



Leveraging the Global Innovation Index to Boost Manufacturing Efficiency in Algeria: An ARDL Model Study (2011-2022)

Souleyman Beghni*	Meriyam Gourari
souleyman.beghni@univ-tlemcen.dz	miryamgourari@yahoo.fr
MECAS Laboratory, University of Tlemcen (Algeria)	MECAS Laboratory, University of Tlemcen (Algeria)

Submitted:18/06/2024

Accepted:11/10/2024

Published: 19/12/2024

Abstract:

This study investigates the impact of innovation inputs and outputs on the growth of Algeria's manufacturing sector from Q1 2011 to Q4 2022, employing an ARDL model to analyze 44 quarterly observations. The results indicate that innovation inputs, such as institutions, human capital and research, infrastructure, market sophistication, and business sophistication, have a statistically significant negative impact on manufacturing growth, suggesting inefficiencies or delays in realizing the benefits of innovation investments. Conversely, innovation outputs, including knowledge and technology outputs and creative outputs, exhibit a weaker and statistically insignificant negative correlation with manufacturing growth. The error correction term is highly significant, indicating a rapid adjustment towards long-run equilibrium, with 47.2% of deviations corrected each quarter. The model's strong fit, reflected by an R-squared value of 0.693658, underscores its explanatory power. However, the ARDL model oversimplifies the complex economic interactions in Algeria, potentially overlooking numerous mediating factors and the influence of regional stability and security issues on manufacturing performance. Furthermore, the context-specific findings may not be applicable to countries with different economic structures. Enhancing the efficiency of innovation investments could lead to significant growth in Algeria's manufacturing industries, with potential social impacts including broader economic development, increased employment, and social stability. This study offers valuable insights into the relationship between innovation and manufacturing growth in Algeria, highlighting the importance of efficient innovation strategies for economic development.

Key words: Innovation, Knowledge, Manufacturing, ARDL Model, Algeria.

JEL Classification Codes : O32, D83, O14, B23.

* Corresponding author

International journal of economic performance/ © 2024 The Authors. Published by the University of Boumerdes, Algeria.
This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>)

1 Introduction

The continuous renewal of ideas, products, and services is a critical factor for achieving success. By fostering an environment that encourages creativity and the development of novel solutions, organizations can maintain their competitive edge, drive economic growth, and adapt to changing market demands. Schumpeter contended that innovation goes beyond merely introducing new technologies or products; it involves a fundamental restructuring of the economy itself. By disrupting conventional production and distribution methods, innovation paves the way for new models that enhance economic efficiency and improve living standards. He defined innovation as a process that triggers profound and sophisticated changes in production and distribution practices, driven by advancements in technology, management strategies, or shifts in social and cultural norms (Ziemnowicz, 2013). Schumpeter's seminal contribution lies in his recognition of innovation as a central driver of economic and social progress. Through his analysis of economic shifts and transformations in market structures, he deepened our understanding of how economies and societies evolve over time (Śledzik, 2013). There appears to be an inherent human inclination toward contemplating new and improved ways of doing things and experimenting with them. Despite its evident importance, innovation has not always received the scientific attention it deserves (Fagerberg, 2006). In the post-Schumpeterian era, new classical and evolutionary schools of thought emphasized public policies aimed at fostering innovation for growth and development (Mejía, 2017), thereby significantly shaping the concept of innovation. Before the twentieth century, innovation was often viewed negatively as a deviation and resistance to change (Nikitin, 2022). However, during the Enlightenment era, innovation began to be seen positively as a catalyst for progress and change, particularly in economics, where it reshaped the economic system and became a pivotal concept (Ciałowicz, 2023). This evolution led to the recognition of innovation as a crucial driver of success in competitive environments, with innovative competition being essential for economic development and evolution. The contemporary stage of innovative development theories is characterized by a focus on institutional models and the impact of scientific and technological advancements on financial and economic activities (Vlados, 2019). The rise of this novel trend has spurred researchers to investigate the multifaceted effects of innovation factors on various economic undertakings, particularly within industrial sectors. Innovation within individual firms is seen as a critical step toward enhancing productivity, reforming industrial frameworks, and strengthening the competitive edge of manufacturing enterprises in the global market (Mairesse et al., 2012). Through innovation, a nation's competitive advantage can be fully harnessed, yielding substantial returns on capital, facilitating the importation of intermediate goods, and amplifying capital returns in less developed economies (Rahman

et al., 2023) , such as Algeria. Our research examines Algerian innovation, specifically innovation input and output, and their relationship with the manufacturing sector. This study stems from the long-standing observation that Algeria has lagged in innovation and creativity, highlighting a significant research gap. Investigating the influence of factors such as "Institutions, Human capital & research, Infrastructure, Market sophistication, and Business sophistication, Knowledge & technology outputs, and Creative outputs" on productivity across various industrial contexts promises to yield a more detailed understanding. In-depth investigations or comparative analyses to determine why innovation impacts Algerian industries differently could inform more effective policy strategies aimed at fostering innovation within Algeria's economic framework. The lack of comprehensive research data poses a substantial challenge to this endeavor. According to the World Intellectual Property Organization's evaluation, Algeria ranks 119th out of 132 economies in global innovation (wipo, 2023). The 2023 Global Innovation Index (GII) report, which measures international financial openness using 80 innovation metrics, reveals a consistent decline in Algeria's innovation performance. Specifically, Algeria is ranked 118th for innovation input and 116th for innovation output.

2 Literature Review

A wide range of research has delved into innovation from a theoretical standpoint, while other studies have explored its relationships with various factors at both the macroeconomic and microeconomic levels. Table 1 presents a summary of the essential studies that examine the impact of innovation on different industries.

Table 1 Summary Key Elements of 6 Studies.

Title	Research objective	Results	Methods Used	Authors
Firm Level Innovation and Productivity - is There a Common Story Across Countries?	This paper analyzes the role of innovation in firm performance using data from the Community Innovation Survey (CIS) across Europe, focusing on Germany and Sweden. It uses a knowledge production function to examine the relationship between innovation inputs, outputs, and productivity, finding significant similarities and some country-specific variations among knowledge-intensive manufacturing firms.	Innovation increases with firm size; market orientation influences product innovations. Common cross-country story for knowledge-intensive manufacturing firms.	Analyzed the relationship between productivity, innovation output, and spending on R&D and other innovation activities for a pooled sample of 1,049 German and Swedish knowledge-intensive firms with 10-999 employees, with	(Janz et al., 2003)

			558 (53%) classified as innovative firms.	
Innovation Technology Transfer and Labor Productivity Linkages: Evidence from a Panel of Manufacturing Industries	This study investigates the connections between labor productivity, innovation, and technology spillovers in manufacturing industries. It examines the roles of R&D, human capital, and international trade in fostering innovation and technology transfer, identifying a long-term equilibrium relationship between these variables and their significant impact on labor productivity.	Existence of a single long-run equilibrium relation between labor productivity, innovation, and technology transfer. R&D, trade, and human capital have significant effects on labor productivity.	Panel-based unit root tests, Cointegration analysis	(Apergis et al., 2008)
Long-Run Convergence in Manufacturing and Innovation-Based Models	This research explores productivity convergence in OECD manufacturing from 1870 to 2006, providing evidence of both unconditional β -convergence and σ -convergence. It attributes this convergence to factors such as domestic and international R&D spillovers and financial development, aligning with Schumpeterian growth theories.	Strong evidence of unconditional β -convergence and σ -convergence in manufacturing. Convergence driven by domestic R&D, international R&D spillovers, and financial development.	Unconditional β -convergence, σ -convergence	(Madsen & Timol, 2011)
Globalization, Innovation, and Productivity in Manufacturing Firms: A Study of Four Sectors of China	This paper examines the relationship between innovation inputs, outputs, and labor productivity in four major manufacturing sectors in China. Using firm-level data and a structural model, it shows that innovation positively impacts firm performance, with globalization influencing innovation efforts differently across the sectors.	Positive effects from innovation input to output and firm performance. Globalization has varying impacts on innovation depending on the sector.	Structural model estimation, Firm level micro data analysis	(Mairesse et al., 2012)

Relationship between the Innovation and the Labor Production in the Mexico Manufacturer	The study investigates the correlation between innovation and labor productivity in Mexico's manufacturing industry. It finds that while innovation positively affects labor productivity, gross fixed capital formation has a more substantial impact. The study attributes declining labor productivity levels to structural issues and outdated production systems.	Innovation has a relative influence on labor productivity in the manufacturing industry. Gross fixed capital formation contributes more to labor productivity.	Quantitative descriptive-correlational-causal approach, Empirical analysis: Pearson correlation, multiple linear regression	(Rodríguez et al., 2019)
Causality Nexus between Economic Growth, Inflation, and Innovation	This paper examines the causal relationships between inflation, innovation, and economic growth in 25 countries from 1990 to 2014 using a panel vector error-correction model. It suggests that innovation productivity is more influenced by inflation in highly innovative countries, while innovation funding is more affected by inflation in less innovative countries.	Innovation productivity more responsive to inflation in most innovative countries. Innovation funding more sensitive to inflation in less innovative countries.	Panel vector error-correction model, Causality analysis using panel VEC model	(Ramzi & Wiem, 2019)

Source : Created by the authors

Detailed Critique Based on Provided Summaries:

Firm-Level Innovation and Productivity: The study by Janz et al. effectively utilizes harmonized survey data to enable a cross-country comparison, providing a robust analysis of innovation and productivity at the firm level across different national contexts. However, its geographical focus is limited to Germany and Sweden, raising concerns about the generalizability of its findings to firms in other countries, The study may have limited generalizability beyond knowledge-intensive manufacturing firms and the specific countries studied. Potential biases from self-reported survey data are not addressed.

Innovation Technology Transfer and Labor Productivity: Apergis et al. employ comprehensive panel data analysis, successfully identifying long-term equilibrium relationships between innovation, technology transfer, and labor productivity. On the downside, the study does not delve deeply into the specific mechanisms through which technology spillovers occur, leaving a gap in understanding the detailed processes involved, the study's focus on manufacturing industries may limit its applicability to

other sectors. The long-term nature of the relationships examined may overlook short-term dynamics and policy implications.

Long-Run Convergence in Manufacturing: By adopting a long historical perspective, Madsen and Timol provide robust evidence of convergence in manufacturing productivity among OECD countries. Nevertheless, their focus on OECD countries excludes emerging economies, limiting the applicability of the findings to a broader global context. The study may oversimplify the complexities of convergence by focusing predominantly on R&D and financial development, potentially overlooking other influential factors.

Globalization, Innovation, and Productivity in China: The sector-specific analysis in the study by Mairesse et al. offers valuable insights into the impact of globalization on innovation and productivity within China's manufacturing sectors. However, the research is confined to manufacturing, excluding the service and high-tech industries, which are crucial for understanding the full spectrum of innovation impacts. The study's findings may not be generalizable beyond the specific sectors and context of China. The structural model's assumptions and limitations are not fully addressed.

Innovation and Labor Productivity in Mexico: Rodríguez et al. highlight significant structural issues within the Mexican industry and employ robust empirical methods to analyze the relationship between innovation and labor productivity. Yet, the research does not provide specific strategies to address the identified structural issues, limiting its practical applicability for policymakers and industry stakeholders. The study's focus on Mexico's manufacturing sector may limit its generalizability. The potential for omitted variable bias and endogeneity issues in the regression analysis is not fully addressed.

Causality Nexus between Economic Growth, Inflation, and Innovation: Ramzi and Wiem conduct a broad cross-country analysis using advanced econometric models to examine the relationships between economic growth, inflation, and innovation. However, they do not explore the underlying reasons for the differential impacts of inflation on innovation, leaving an important aspect of the causality nexus unaddressed. The study's reliance on macroeconomic data may obscure firm-level dynamics and sector-specific variations. The potential for model misspecification and sensitivity to initial conditions is not fully addressed.

What sets this study apart from previous research?

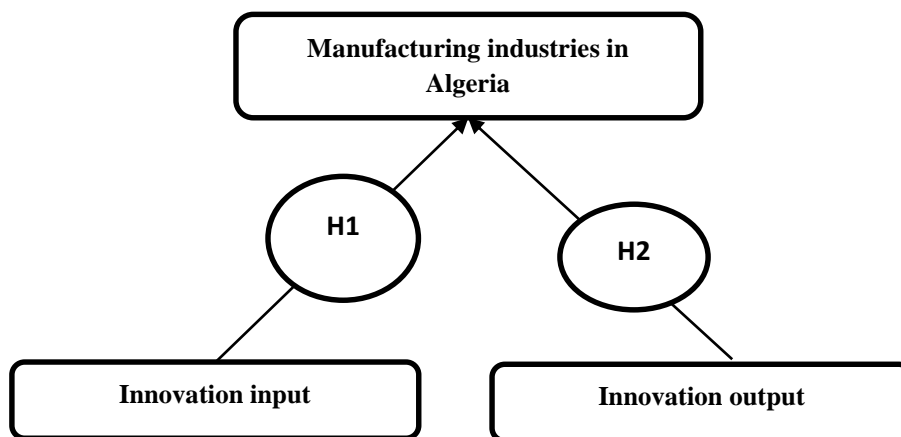
A comprehensive review of past studies and literature related to econometrics was conducted to develop a thorough understanding of the variables and issues pertinent to the present research. This review also aimed to pinpoint significant advancements, summarize the outcomes achieved by these studies, and identify potential avenues for future research. The review concluded that the current study aligns with previous research in assessing the influence of the Global Innovation Index on economic growth.

However, it diverges in the methodological approach used and the time span analyzed. Additionally, this study is unique in its focus on Algeria, utilizing innovation input and output exclusively as independent variables, with the manufacturing industries serving as the dependent variable. As a result, we formulated research hypotheses to examine the relationships between innovation input and output and the manufacturing sector in Algeria. Our conceptualization of these variables offers a novel perspective not previously explored in academic studies, employing the Autoregressive Distributed Lag (ARDL) model. Thus, we propose the following hypotheses: innovation impacts manufacturing industries in Algeria. Our research framework is visually represented through a model (Figure 1), where manufacturing industries and their corresponding predictors are illustrated within separate rectangles. The directional arrows between these rectangles represent the specific hypotheses to be empirically tested in the subsequent phases of our study:

H1: Innovation input impacts manufacturing industries in Algeria.

H2: Innovation output impacts manufacturing industries in Algeria.

Figure 1. Conceptual model



Source : Created by the authors

3 Methodology

The study has effectively managed aspects such as the design of the study and sample, techniques employed for data collection, specifying the model, and conducting data analysis. Its primary aim is to investigate the correlation between innovation in Algeria and the manufacturing sector.

3.1 Data Overview

In our study, we sourced data for the independent variables from the Global Innovation Index (GII) website, also known as the WIPO Index. This index is a collaborative effort between WIPO, Cornell University, and INSEAD, aimed at assessing countries' innovation performance using a range of indicators. It also analyzes how innovation-oriented policies influence economic growth and development. The GII aids both developed and developing countries in tracking progress driven by innovation

through diverse strategies. By streamlining the evaluation of innovation inputs, outputs, and efficiency, the GII facilitates comparisons of innovation performance across nations (Todeva, 2020). Additionally, by focusing on enhancing innovation capacity and acknowledging the intricate relationships between academic research, business innovation, and government investments, the GII enriches our comprehension of global innovation dynamics (WIPO, 2024). The manufacturing industry pertains to the process of altering the nature of materials used, transforming them from their raw state into forms suitable for use or consumption, whether as finished or semi-finished goods. This transformation is accomplished through the integration of various factors, including labor, technology, and capital ((ZORMAN & GHARDI, 2020). Data for the dependent variable, the "manufacturing industry," was retrieved from the National Bank of Algeria's website (Bank of Algeria, 2024).

The dataset spans a period of 12 years, commencing from the first quarter of 2011 and concluding with the fourth quarter of 2022. Data Points: There are a total of 44 quarterly observations available for analysis. Variables: As detailed in Table 2,

- Y (Manufacturing Industries - IND): Quantifies the quarterly growth of value added at chained prices (Base 2001) within the manufacturing sector in Algeria.
- X1 (Innovation Input -Index): Evaluates Innovation Input Encompassing Institutions, Human capital & research, Infrastructure, Market sophistication, and Business sophistication.
- X2 (Innovation Output -Index): Gauges Innovation Output by considering Knowledge & technology outputs and Creative outputs.

Table 2: Description of Variables

Variable	Description	Symbols	Definition	Source
Y	Manufacturing industries	IND	Value that is calculated based on this data: Manufacturing industries Quarterly growth value added at chained prices In Algeria	(Bank of Algeria, 2024)
X ₁	Innovation Input	INPU	Score/Value that is calculated based on this data: Institutions, Human capital & research, Infrastructure, Market sophistication, and Business sophistication	(WIPO, 2024)
X ₂	Innovation Output	OUTP	Score/Value that is calculated based on this data: Knowledge & technology outputs and Creative outputs	

Source: Created by the authors.

The mathematical formula for the model is as follows:

$$IND = f(INPU, OUTP, Dum) \quad Dum: \text{Dummy Variables}$$

Through the ARDL model, it is possible to ascertain the integrative relationship between the dependent variable and the independent variables, as well as determine the

magnitude of the impact of each independent variable on the dependent variable, with its estimated parameters for both short and long terms being more consistent than those estimated by other methods for testing cointegration. The general formula of the model comprises the dependent variable " Manufacturing industries " and the explanatory variables "Innovation Input, Innovation Output " Regarding the standard model, it is structured as follows:

Utilizing the Autoregressive Distributed Lag (ARDL) model enables the identification of the integrated association between the dependent variable and the independent variables, along with quantifying the influence of each independent variable on the dependent variable. The estimated parameters for both short and long terms tend to exhibit greater consistency compared to alternative methods for examining cointegration(H. Pesaran & Shin, 1995). The basic formulation of the model involves the dependent variable "Manufacturing industries" and the explanatory variables "Innovation Input" and "Innovation Output." As for the standard model, its structure follows:

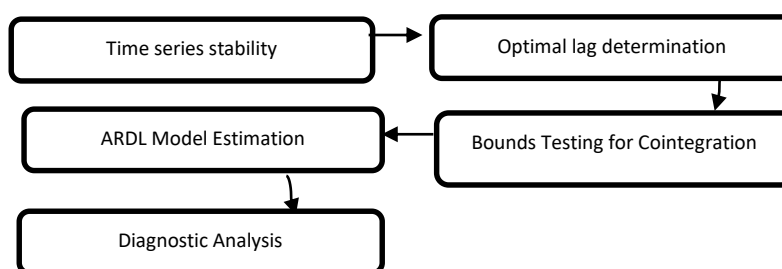
$$\Delta \text{IND}_t = \alpha_0 + \sum_{j=1}^{p1} \alpha_j \Delta \text{IND}_{t-j} + \sum_{j=0}^{p2} \beta_j \Delta \text{INPU}_{t-j} + \sum_{j=0}^{p3} \delta_j \Delta \text{OUTP}_{t-j} + \pi_1 \text{IND}_{t-1} + \pi_2 \text{INPU}_{t-1} + \pi_3 \text{OUTP}_{t-1} + \mu_t$$

- The short-term dynamics of the model are represented by $(\alpha_j, \beta_j, \delta_j, Y_j)$
- Long-term relationship coefficients of the model are represented by $(\pi_1, \pi_2, \pi_3, \pi_4)$
- α_0 : is the constant term.
- Δ : is the first difference operator.
- μ_t : represents white noise.

3.2 Methods

The diagram in Figure 2 illustrates the methodology flow. Initially, a Unit Root Test is conducted to evaluate the stationarity of the variables. Next, the Akaike Information Criterion (AIC) is employed to select the appropriate lags for both dependent and independent variables. Following this, cointegration is tested using bounds tests, culminating in the application of the ARDL model to analyze both long- and short-term effects.

Figure 2: Steps for the methodology



Source: Created by the authors

3.2.1. Time series stability

To determine the stationarity of time series variables, researchers typically use the Augmented Dickey-Fuller (ADF) test or the Phillips-Perron (PP) test. These tests evaluate whether the variables are stationary or non-stationary. The null hypothesis in both tests suggests that the variables have a unit root (non-stationarity), whereas the alternative hypothesis indicates stationarity. If the null hypothesis is rejected, implying non-stationarity, the variables can be rendered stationary through differencing. The ADF test is generally regarded as more reliable than the PP test (Fabozzi et al., 2014).

3.2.2. Optimal lag determination

Various methods exist to determine the optimal number of lag lengths (Fabozzi et al., 2014). In this study, the Akaike Information Criterion (AIC) was chosen for its suitability in smaller sample sizes. AIC evaluates the information loss; hence, a model with a lower AIC score indicates a better fit.

3.2.3. Bounds Testing for Cointegration

The ARDL methodology utilizes the ordinary least squares technique, where $(\alpha_j, \beta_j, \delta_j, Y_j)$ represent short-run coefficients, and $\pi_1, \pi_2, \pi_3, \pi_4$ correspond to long-run dynamics. Additionally, α_0 signifies a constant term, and μ_t denotes the error term. In ARDL regression, the null hypothesis (H_0) posits that all long-run coefficients are zero ($\pi_1 = \pi_2 = \pi_3 = \pi_4 = 0$), indicating no long-term relationship between dependent and independent variables. Conversely, the alternative hypothesis (H_1) asserts that the long-run coefficients are non-zero ($\pi_1 \neq \pi_2 \neq \pi_3 \neq \pi_4 \neq 0$), suggesting a long-term relationship (M. H. Pesaran et al., 2001). The F-Bounds Test is used to test this hypothesis; if the F-statistic exceeds the critical values of both lower and upper bounds, the null hypothesis is rejected, indicating a relationship between the variables (Gómez & Irewole, 2023)

3.2.4. ARDL Model Estimation

If cointegration among the variables is established, both long-term and short-term equilibrium relationships are estimated using the ARDL model.

Error Correction Model (ECM)

The Short-Run ARDL Model, as described by Banerjee et al (Banerjee et al., 1998) investigates the error correction dynamics, which measure the speed at which a dependent variable returns to its long-term equilibrium after a disturbance. This model shows how quickly a variable adjusts back to equilibrium, typically indicated by a statistically significant, negatively signed coefficient. The significance of the Error Correction (EC) term not only confirms a stable long-term relationship but also highlights the process by which deviations from long-term equilibrium are corrected by a certain percentage in subsequent periods, known as the Error Correction Mechanism (ECM).

3.2.5. Diagnostic Analysis

Autocorrelation in a time series indicates that each observation is correlated with its predecessor, leading to potential issues with the validity of T-tests, F-tests, or confidence intervals, as the variances of estimators may be underestimated or overestimated. This could result in misleading conclusions about the significance of parameters (abibo et al., 2022).

Assess autocorrelation issues

This test allows researchers to check for serial correlation over multiple lags, not just a single lag, by examining the correlation between residuals from time t and $t-k$ (where k is the number of lags) (Okunade, 2020).

Heteroscedasticity examination

Both the Breusch-Pagan-Godfrey test and the ARCH test are applied to identify and address potential heteroskedasticity issues (Jan et al., 2023)

Model stability assessment

The CUSUM and CUSUMQ tests are used to assess the stability of long-run coefficients and the error-correction term alongside short-run dynamics. Stability in these parameters is confirmed if the CUSUM and CUSUMQ statistics remain below the 5% critical threshold (abibo et al., 2022).

Normally distribute

To interpret the results, we assess whether the p-value is below the significance level of 0.05. If the p-value falls below 0.05, we infer that the dataset does not follow a normal distribution. Conversely, if the p-value exceeds 0.05, we infer that the dataset adheres to a normal distribution (Thadewald & Buning, 2007).

4 Result And Discussion

4.1 Stationarity Test

Table 3 Unit Root Test - for each variable at $I(0)$, $I(1)$

UNIT ROOT TEST TABLE (PP)				
<u>At Level</u>				
		Y_INDUSTRIE	X1_INNOV_INPUT	X2_INNOV_OUTPU T
With Constant	t-Statistic	-2.9671	-0.3798	-1.3417
	Prob.	0.0455	0.9041	0.6025
		**	n0	n0
With Constant & Trend	t-Statistic	-2.9184	-1.0013	-2.8051
	Prob.	0.1662	0.9340	0.2028
		n0	n0	n0
Without Constant & Trend	t-Statistic	0.0297	-0.9220	-0.4228
	Prob.	0.6873	0.3119	0.5253
		n0	n0	n0
<u>At First Difference</u>				

Leveraging the Global Innovation Index to Boost Manufacturing Efficiency in Algeria: An ARDL Model Study (2011-2022)

Souleyman Beghni, Meriyam Gourari

		d(Y_INDUSTRIE)	d(X1_INNOV_INPUT)	d(X2_INNOV_OUTPUT)
With Constant	t-Statistic	-6.8082	-6.7526	-6.6342
	Prob.	0.0000	0.0000	0.0000
		***	***	***
With Constant & Trend	t-Statistic	-6.6965	-7.2044	-7.8030
	Prob.	0.0000	0.0000	0.0000
		***	***	***
Without Constant & Trend	t-Statistic	-6.8932	-6.7082	-6.7082
	Prob.	0.0000	0.0000	0.0000
		***	***	***
UNIT ROOT TEST TABLE (ADF)				
<u>At Level</u>				
		Y_INDUSTRIE	X1_INNOV_INPUT	X2_INNOV_OUTPUT
With Constant	t-Statistic	-2.9671	-0.3798	-1.3110
	Prob.	0.0455	0.9041	0.6169
		**	n0	n0
With Constant & Trend	t-Statistic	-2.9184	-1.0156	-2.5445
	Prob.	0.1662	0.9319	0.3065
		n0	n0	n0
Without Constant & Trend	t-Statistic	-0.0052	-0.9165	-0.4228
	Prob.	0.6759	0.3142	0.5253
		n0	n0	n0
<u>At First Difference</u>				
		d(Y_INDUSTRIE)	d(X1_INNOV_INPUT)	d(X2_INNOV_OUTPUT)
With Constant	t-Statistic	-6.6253	-6.7526	-6.6342
	Prob.	0.0000	0.0000	0.0000
		***	***	***
With Constant & Trend	t-Statistic	-6.5392	-7.0179	-7.2266
	Prob.	0.0000	0.0000	0.0000
		***	***	***
Without Constant & Trend	t-Statistic	-6.6938	-6.7082	-6.7082
	Prob.	0.0000	0.0000	0.0000
		***	***	***

Notes: (*)Significant at the 10%; (**)Significant at the 5%; (***) Significant at the 1%. and (no) Not Significant

Sources: Eviews 12 result

Based on the information presented in Table 3, at the original level, we find no grounds to reject the null hypothesis concerning the presence of a unit root in the variables. However, upon transitioning to the first differences, we do refute the null hypothesis, signaling that all dependent (Y_Manufacturing industries) and independent

(X1_INNOV_INPUT, X2_INNOV_OUTPUT) variables are integrated of order (I)1, achieving stationarity at the I(1) level. Specifically, all dependent (Y_INDUSTRIE) and independent (X1_INNOV_INPUT and X2_INNOV_OUTPUT) variables display integration of order 1, becoming stationary at the first difference. This suggests the potential existence of a cointegration relationship among the series.

4.2 Model Determination

Table 4 Akaike information criterion Top 10 Models

Model	LogL	AIC*	BIC	HQ	Adj. R-sq	Specification
30	-85.965015	4.362046	4.767544	4.512424	0.750651	ARDL(3, 4, 0)
80	-88.400967	4.381862	4.706260	4.502165	0.736930	ARDL(1, 4, 0)
29	-85.731174	4.396872	4.842919	4.562287	0.745812	ARDL(3, 4, 1)
5	-85.782480	4.399204	4.845251	4.564620	0.745218	ARDL(4, 4, 0)
55	-87.829597	4.401345	4.766293	4.536686	0.736351	ARDL(2, 4, 0)
79	-88.126366	4.414835	4.779783	4.550175	0.732771	ARDL(1, 4, 1)
4	-85.502314	4.431923	4.918521	4.612377	0.740581	ARDL(4, 4, 1)
54	-87.558778	4.434490	4.839988	4.584868	0.731917	ARDL(2, 4, 1)
28	-85.685912	4.440269	4.926866	4.620722	0.738407	ARDL(3, 4, 2)
78	-88.100606	4.459118	4.864616	4.609497	0.725233	ARDL(1, 4, 2)

Sources: Eviews 12 result

Based on the findings presented in Table 4, the ARDL model (3, 4,0) emerges as the preferred choice due to its lower AIC score (4.362046). The equation can be expressed as follows:

$$IND_t = a + \alpha_1 IND_{t-1} + \alpha_2 IND_{t-2} + \alpha_3 IND_{t-3} + \beta_1 INPU + \beta_2 INPU_{t-1} + \beta_3 INPU_{t-2} + \beta_4 INPU_{t-3} + \beta_5 INPU_{t-4} + \delta_1 OUTP + \mu t$$

4.3 Bounds Testing for Cointegration

Table 5 ARDL Bounds Test for Co-integration

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	10.64324	10%	2.63	3.35
k	2	5%	3.1	3.87
		2.5%	3.55	4.38
		1%	4.13	5

Sources: Eviews 12 result

From the results of Table 5, it is evident that there is a long-run link between the model variables, as the value of the F-statistic (10.64) exceeds the upper critical value of (5) at a significance level of 1 %, as shown in the table. Therefore, the null hypothesis H0 is rejected, In summary, based on the AF-Bounds Test results, we can conclude that there is evidence of cointegration among the variables in the equation. This suggests a long-run relationship between the dependent (Y_ industries) and independent variables

(X1_INNOV_INPUT, X2_INNOV_OUTPUT), indicating the presence of a stable equilibrium relationship among them.

4.4 ARDL Long-Run Estimation

Table 6 long -run estimate ARDL model

Levels Equation				
Case 2: Restricted Constant and No Trend				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
X1_INNOV_INPUT	-2.841161	0.796924	-3.565161	0.0011
X2_INNOV_OUTPUT	-0.443329	0.401894	-1.103099	0.2777
C	249.0782	28.43228	8.760400	0.0000

Sources: Eviews 12 result

From the results of Table 6, The econometric evaluation of the link between innovation and manufacturing growth in Algeria yields some compelling findings. The coefficient for innovation input (X1_INNOV_INPUT) stands at -2.841161, signifying that a one-unit rise in innovation input corresponds with a notable decline of approximately 2.841161 units in the manufacturing industries' quarterly growth value added at chained prices. This relationship is statistically significant, with a p-value of 0.0011, well within the 1% significance threshold. This inverse relationship is unexpected, indicating that despite increased funding in innovation, these inputs are not efficiently translating into manufacturing growth. Possible reasons could include misallocation of resources, delays in realizing innovation benefits, or flaws in how innovation input is measured.

In contrast, the coefficient for innovation output (X2_INNOV_OUTPUT) is -0.443329, indicating a much weaker negative correlation with manufacturing growth. However, this association is not statistically significant, given the high p-value of 0.2777. Consequently, we cannot assert that innovation output significantly impacts manufacturing growth based on this model. This lack of significance might stem from the quality or relevance of the innovation outputs, or from other external economic or political factors overshadowing their effect.

The constant term (C) is 249.0782, denoting the anticipated value of the manufacturing growth variable when all independent variables are zero. This is highly significant, with a p-value of effectively zero, indicating a substantial baseline level of manufacturing growth, independent of the evaluated innovation inputs and outputs.

Moreover, the potential impact of hydrocarbon prices on manufacturing growth should be considered. Given Algeria's economy's heavy reliance on hydrocarbons, fluctuations in hydrocarbon prices could significantly affect manufacturing industries. Higher hydrocarbon prices might boost overall economic stability and government revenues, potentially increasing investment in manufacturing and innovation. Conversely, lower prices could strain public finances, reducing support for industrial innovation and growth.

In summary, the analysis indicates that while innovation inputs are statistically significant, their adverse impact on manufacturing growth raises concerns about the efficiency of innovation resource utilization. Conversely, innovation outputs do not exhibit a significant effect. These outcomes underscore the necessity for a more detailed understanding of innovation dynamics and their practical implementation within Algeria's manufacturing industries.

4.5 Error Correction Model (ECM)

Table 7 ARDL Error Correction Regression

ECM Regression				
Case 2: Restricted Constant and No Trend				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(Y_INDUSTRIE(-1))	0.073593	0.110328	0.667033	0.5093
D(Y_INDUSTRIE(-2))	-0.248330	0.109490	-2.268069	0.0298
D(X1_INNOV_INPUT)	1.588105	0.316360	5.019926	0.0000
D(X1_INNOV_INPUT(-1))	2.570515	0.461026	5.575642	0.0000
D(X1_INNOV_INPUT(-2))	1.821486	0.513990	3.543813	0.0012
D(X1_INNOV_INPUT(-3))	2.442694	0.447702	5.456068	0.0000
CointEq(-1)*	-0.471858	0.069324	-6.806570	0.0000
R-squared	0.693658	Mean dependent var		0.043044
Adjusted R-squared	0.643981	S.D. dependent var		3.120002
S.E. of regression	1.861621	Akaike info criterion		4.225683
Sum squared resid	128.2284	Schwarz criterion		4.509531
Log likelihood	-85.96502	Hannan-Quinn criter.		4.330947
Durbin-Watson stat	2.104963			

Sources: Eviews 12 result

Examining Table 7, The ECM regression analysis reveals significant insights into the dynamics between innovation inputs and manufacturing growth in Algeria. The current and lagged first differences of innovation input exhibit strong, positive, and statistically significant coefficients, underscoring the pivotal role of innovation investments in driving manufacturing growth. Specifically, the coefficients for the current period and three lags are all significant at the 1% level, indicating that both immediate and past innovation inputs positively influence manufacturing growth. Conversely, the analysis of lagged differences of the dependent variable (manufacturing growth) shows mixed results. While the first lag is positive but statistically insignificant, the second lag is negative and significant, suggesting some degree of negative autocorrelation. This indicates that previous periods' manufacturing growth can have a complex impact on current growth, warranting further investigation. The error correction term is highly significant and negative, with a coefficient of -0.471858, indicating a rapid adjustment towards long-run equilibrium. Approximately 47.2% of any deviation from the equilibrium is corrected within one period, highlighting the robust nature of the adjustment process.

Model fit statistics reinforce the robustness of the regression results. The R-squared value of 0.693658 indicates that approximately 69.4% of the variability in manufacturing growth is explained by the model, which is a strong indication of the model's explanatory power. The Durbin-Watson statistic of 2.104963 suggests no significant autocorrelation in the residuals, which is desirable for model reliability.

In summary, the ECM regression results demonstrate that innovation inputs are crucial for manufacturing growth in Algeria, with significant effects observed both in the immediate term and over multiple periods. The rapid correction towards long-term equilibrium further underscores the effectiveness of innovation investments. However, the mixed results from the lagged dependent variable highlight the need for further research to fully understand the autocorrelation dynamics. Incorporating additional factors, such as hydrocarbon prices, in future analyses could provide a more comprehensive understanding of the drivers of manufacturing growth in Algeria.

4.6 Autocorrelation Testing

Table 8 Breusch-Godfrey Serial Correlation LM Test

Breusch-Godfrey Serial Correlation LM Test:			
Null hypothesis: No serial correlation at up to 2 lags			
F-statistic	0.427366	Prob. F(2,27)	0.6566
Obs*R-squared	1.350155	Prob. Chi-Square(2)	0.5091

Sources: Eviews 12 result

In this study, the widely used Breusch-Godfrey Serial Correlation LM Test was employed to investigate the presence of autocorrelation. The hypothesis for this test was formulated as follows:

Null Hypothesis (H0): There is no issue of autocorrelation in the model.

Alternative Hypothesis (H1): There is a problem of autocorrelation in the model.

Significance Level (α) = 0.05. Decision Rule: Reject H0 if the p-value is less than the significance level; otherwise, do not reject H0.

Based on the results provided in Table 8, all variations of the Breusch-Godfrey serial correlation LM test statistic, such as the F-statistic and Chi-Square, yielded a consistent outcome: there was no indication of autocorrelation detected in this particular investigation. With p-values of 0.6566 for the F-statistic and 0.5091 for the Chi-Square, both surpassing the significance threshold of 0.05, there is insufficient evidence to reject the null hypothesis.

4.7 Heteroskedasticity Test

Table 9 Heteroskedasticity/BPG Test

Heteroskedasticity Test: Breusch-Pagan-Godfrey			
Null hypothesis: Homoskedasticity			
F-statistic	0.57072	Prob. F(9,34)	0.8112
Obs*R-squared	5.77480	Prob. Chi-Square(9)	0.7622
Scaled explained SS	3.26726	Prob. Chi-Square(9)	0.9527

Sources: Eviews 12 result

Table 10 Heteroskedasticity/ ARCH Test

Heteroskedasticity Test: ARCH			
F-statistic	0.34497	Prob. F(1,41)	0.5602
Obs*R-squared	0.35878	Prob. Chi-Square(1)	0.5492

Sources: Eviews 12 result

In this research, the Breusch-Pagan-Godfrey and ARCH tests, renowned for their effectiveness in identifying heteroskedasticity, were utilized to examine whether this issue was present. The hypotheses for these tests are as follows:

- Null Hypothesis (H0): The model does not exhibit heteroskedasticity.
- Alternative Hypothesis (H1): The model does exhibit heteroskedasticity.
- Significance Level (α): 0.05.
- Decision Rule: Reject H0 if the p-value is less than the significance level; otherwise, do not reject H0.

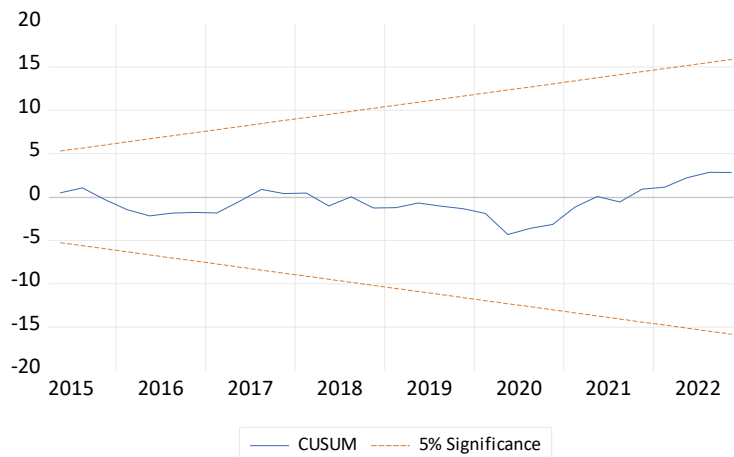
A) From the results in Table 9, it is clear that all measures of the Breusch-Pagan-Godfrey test, including the F-statistic and Chi-Square, indicate a consistent conclusion: there is no evidence of heteroskedasticity in this analysis. The F-statistic of 0.57072 with a p-value of 0.8112, and the Obs*R-squared of 5.77480 with a p-value of 0.7622, both exceed the significance threshold of 0.05, providing insufficient grounds to reject the null hypothesis. Additionally, the Scaled explained SS with a p-value of 0.9527 further supports this conclusion.

B) From the results in Table 10, all measures of the ARCH test, including the F-statistic and Chi-Square, consistently show no evidence of heteroskedasticity. The F-statistic of 0.34497 with a p-value of 0.5602, and the Obs*R-squared of 0.35878 with a p-value of 0.5492, both exceed the 0.05 significance threshold, indicating insufficient grounds to reject the null hypothesis.

In summary, both the Breusch-Pagan-Godfrey and ARCH test results demonstrate no significant evidence of heteroskedasticity within the model. Thus, the assumption of constant error variance holds, ensuring the reliability of regression outcomes under the assumption of homoskedasticity. Nonetheless, using heteroskedasticity-robust standard errors in future analyses could further enhance the robustness of these findings.

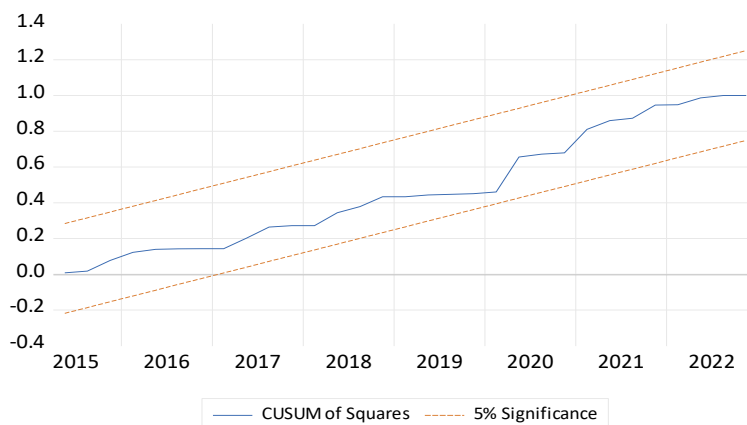
4.8 CUSUM and CUSUMSQ Analysis

Figure 3 : CUSUM test



Sources: Eviews 12 result

Figure 4 : CUSUMSQ test

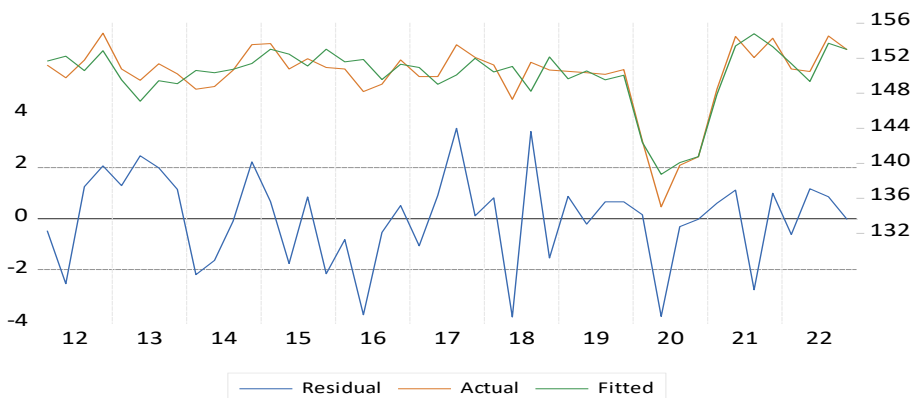


Sources: Eviews 12 result

Figures (3) and (4) reveal that the CUSUM and CUSUMQ plots remain within the 5% critical boundaries, indicating that the estimated coefficients exhibit consistent stability over the study period. This lack of intersection with the threshold lines reinforces the robustness and dependability of the regression coefficients, as it suggests that they are not subject to significant variation over time.

4.9 Analysis of Residuals

Figure 5 Actual, Fitted, Residual Graphs

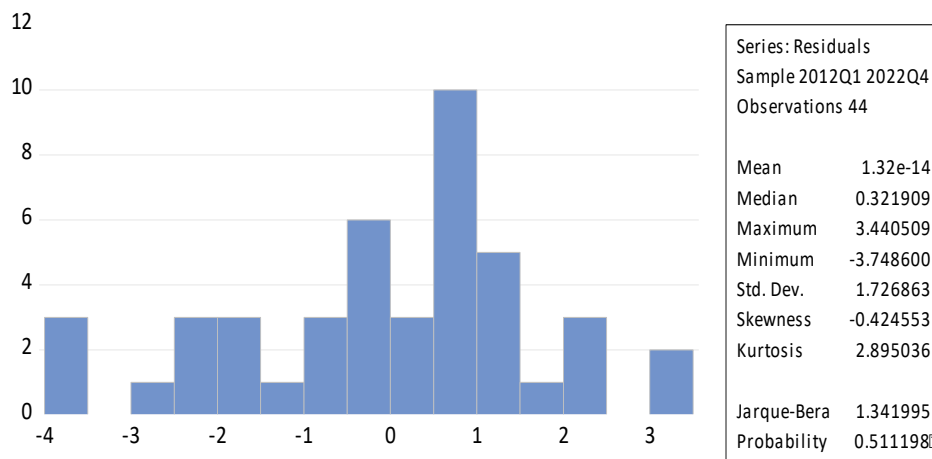


Sources: Eviews 12 result

A review of Figure 5 shows a strong congruence between the actual data points and the predicted values, demonstrating the model's high level of accuracy. This close match implies that the model is highly effective in capturing the underlying data patterns, thereby validating its predictive capability and reliability. The minimal divergence between observed and fitted values also suggests that the model's residuals are likely well-behaved, further supporting the overall validity and robustness of the econometric model.

4.10 Test for Normal Distribution

Figure 6 : Actual, Fitted, Residual Graphs



Sources: Eviews 12 result

After examining the figure 6, The Jarque-Bera test evaluates whether sample data exhibit skewness and kurtosis consistent with a normal distribution. When the p-value exceeds the significance threshold (0.05 in this context), the null hypothesis of normality cannot be rejected. Hence, a p-value of 0.511 strongly indicates that the dataset meets the normality assumption. This is particularly important in econometrics because numerous inferential techniques, such as hypothesis testing and confidence intervals, depend on the normality of residuals. Furthermore, the histogram of residuals visually corroborates this finding by displaying a bell-shaped curve characteristic of a normal distribution. This visual evidence is crucial as it intuitively demonstrates the distributional properties of the data. The normality of residuals signifies that the regression model's estimates are unbiased and efficient, as per the Gauss-Markov theorem. This significantly enhances the reliability and validity of the model's results, making it a dependable tool for prediction and inference

5 Conclusion and Policy suggestions

5.1 Conclusions

The econometric analysis of the relationship between innovation and manufacturing growth in Algeria, spanning 12 years from 2011 to 2022 with 44 quarterly observations, reveals several significant insights. The analysis utilizes ARDL and ECM regression models to examine the complex interactions between innovation inputs and outputs and

their impact on manufacturing industries. The ARDL Error Correction Regression analysis underscores the intricate dynamics among the factors influencing Algeria's manufacturing sector. Notably, the analysis finds that innovation inputs, encompassing institutions, human capital & research, infrastructure, market sophistication, and business sophistication, have statistically significant positive impacts on manufacturing growth, with coefficients indicating strong immediate and lagged effects. Conversely, innovation outputs, gauged by considering knowledge & technology outputs and creative outputs, show a weaker, statistically insignificant negative relationship with manufacturing growth.

Impact of Innovation Inputs: The coefficient of -2.841161 indicates a significant negative impact on manufacturing growth, with a p-value of 0.0011. This suggests that increased investments in innovation input are not translating effectively into manufacturing growth, possibly due to resource misallocation, time lags, or measurement issues.

The ECM regression shows strong, positive, and statistically significant coefficients for current and lagged innovation inputs, underscoring their pivotal role in driving manufacturing growth over multiple periods.

Impact of Innovation Outputs: The coefficient of -0.443329 is not statistically significant (p-value of 0.2777), indicating that innovation outputs do not have a meaningful impact on manufacturing growth within this model. This might be due to the quality or relevance of the outputs or overshadowing external factors.

Error Correction Mechanism: The error correction term is highly significant and negative, with a coefficient of -0.471858, indicating a rapid adjustment towards long-term equilibrium. Approximately 47.2% of any deviation from the equilibrium is corrected within one period, highlighting the robust nature of the adjustment process. The R-squared value of 0.693658 indicates that approximately 69.4% of the variability in manufacturing growth is explained by the model, demonstrating strong explanatory power. The Durbin-Watson Statistic of 2.104963 suggests no significant autocorrelation in the residuals, which supports the reliability of the model.

Integration with Hydrocarbon Prices: Given Algeria's heavy reliance on hydrocarbons, fluctuations in hydrocarbon prices significantly impact manufacturing industries. Higher hydrocarbon prices can boost economic stability and government revenues, potentially increasing investments in manufacturing and innovation. Conversely, lower prices can strain public finances, reducing support for industrial innovation and growth. The dominance of the hydrocarbon sector often leads to insufficient investment in other sectors, hindering the effective integration of advanced knowledge dissemination and intangible assets into manufacturing.

5.2 Policy suggestions

Efficient Allocation of Innovation Resources: Addressing the negative impact of innovation inputs requires improving the efficiency of resource allocation. Policymakers should ensure that investments in innovation are strategically directed towards high-impact areas and that the benefits of innovation inputs are effectively realized.

Enhancing Innovation Output Quality: To mitigate the insignificant impact of innovation outputs, efforts should be made to improve the quality and relevance of innovation outputs. This can involve fostering stronger links between research institutions and the manufacturing sector to ensure that innovation outputs are practically applicable and beneficial.

Economic Diversification: Reducing the economy's reliance on hydrocarbons by diversifying into other sectors, including manufacturing, can create a more balanced and resilient economic structure. Diversification strategies should focus on integrating knowledge dissemination and intangible assets more effectively.

Monitoring and Adjusting Policies: Continuous monitoring of the innovation ecosystem and manufacturing sector performance is essential. Policymakers should be prepared to adjust strategies based on real-time data and emerging trends to maintain alignment with long-term growth objectives.

Foster Interdisciplinary Cooperation: Encouraging collaborative efforts between the manufacturing industry and sectors involved in disseminating knowledge, managing intangible assets, and producing creative goods can generate synergies that amplify productivity and foster economic expansion. Collaborative initiatives such as joint ventures, public-private partnerships, and innovation centers can serve as effective facilitators of such cooperation.

Prioritize Skill Development: Allocating resources towards enhancing skill sets within Algeria's manufacturing sector is paramount for maximizing the utilization of knowledge dissemination and intangible assets. This endeavor may entail investment in technical training programs, managerial education initiatives, and cultivating a culture of innovation within manufacturing enterprises.

Strategic Investment Allocation: During periods of elevated hydrocarbon prices, there exists an opportunity to direct investments towards creative industries. However, for these investments to yield enduring positive outcomes for the manufacturing sector, they must be purposeful and sustained over time, ensuring their alignment with broader economic objectives.

Exploring the Complex Interactions: Future research endeavors should embrace a comprehensive methodology, integrating temporal delays, a diverse array of variables, and leveraging advanced econometric methodologies. This approach will enable researchers to delve further into the nuanced interconnections among innovation input,

manufacturing sector outcomes, and hydrocarbon price dynamics. Such endeavors are pivotal not only for enriching scholarly understanding but also for guiding data-driven policy formulations in energy markets and manufacturing policy arenas.

By implementing these policy suggestions, Algeria can better harness the potential of innovation to drive sustainable growth in its manufacturing industries, ultimately contributing to a more diversified and resilient economy.

Limitations of the Research

Simplified Relationships: Although the ARDL model is useful for exploring relationships between variables, it oversimplifies the intricate economic interactions in Algeria, potentially missing out on numerous mediating factors affecting the real-world impact of innovation on manufacturing performance.

Regional Instability: The model does not account for the influence of regional stability and security issues on Algeria's manufacturing performance.

Context-Specific Findings: The research findings are tailored to Algeria's economic context and might not be applicable to countries with different economic structures and dependencies.

Abbreviations

ADF Augmented Dickey-Fuller test

AIC Akaike Information Criteria

ARDL Autoregressive Distributive Lag

Dum Dummy Variables

ECM Error Correction Mode

IND Manufacturing industries

INPU Innovation Input

OUTP Innovation Output

PP Phillips Perron

Referrals and references:

- abibo, abebaw, Muchie, M., Sime, zerayehu, & Ezezew, W. (2022). Analysis of the Relationship between Innovation and Ethipian Economic Growth. <https://doi.org/10.21203/rs.3.rs-1576170/v1>
- Apergis, N., Economidou, C., & Filippidis, I. (2008). Innovation, Technology Transfer and Labor Productivity Linkages: Evidence from a Panel of Manufacturing Industries. *Review of World Economics*, 144(3), 491–508. <https://doi.org/10.1007/s10290-008-0157-9>
- Banerjee, A., Dolado, J., & Mestre, R. (1998). Error-correction Mechanism Tests for Cointegration in a Single-equation Framework. *Journal of Time Series Analysis*, 19(3), 267–283. <https://doi.org/10.1111/1467-9892.00091>
- Bank of Algeria. (2024). Croissance du PIB. <https://www.bank-of-algeria.dz/croissance-du-pib/>

- Cialowicz, B. (2023). Formal Modeling of Innovative Competition in a Production System—An Evolutionary Approach. *Journal of the Knowledge Economy*. <https://doi.org/10.1007/s13132-023-01301-0>
- Fabozzi, F., Modigliani, F., & Jones, F. (2014). *Foundations financial markets and institutions*. Pearson. <https://thuvienso.hoasen.edu.vn/handle/123456789/6946>
- Fagerberg, J. (2006). Innovation: A Guide to the Literature. In J. Fagerberg & D. C. Mowery (Eds.), *The Oxford Handbook of Innovation* (p. 0). Oxford University Press. <https://doi.org/10.1093/oxfordhb/9780199286805.003.0001>
- Gómez, M., & Irewole, O. E. (2023). Economic growth, inflation and unemployment in Africa: An autoregressive distributed lag bounds testing approach (1991–2019). *African Journal of Economic and Management Studies*. <https://doi.org/10.1108/AJEMS-09-2022-0378>
- Jan, A., Xin-gang, Z., Babar, S. F., & Khan, M. K. (2023). Role of financial development, foreign direct investment inflow, innovation in environmental degradation in Pakistan with dynamic ARDL simulation model. *Environmental Science and Pollution Research*, 30(17), 49381–49396. <https://doi.org/10.1007/s11356-023-25631-3>
- Janz, N., Lööf, H., & Peters, B. (2003). Firm Level Innovation and Productivity—Is There a Common Story Across Countries? (SSRN Scholarly Paper 416444). <https://doi.org/10.2139/ssrn.416444>
- Madsen, J. B., & Timol, I. (2011). Long-Run Convergence in Manufacturing and Innovation-Based Models. *The Review of Economics and Statistics*, 93(4), 1155–1171. https://doi.org/10.1162/REST_a_00147
- Mairesse, J., Mohnen, P., Zhao, Y., & Zhen, F. (2012). Globalization, Innovation and Productivity in Manufacturing Firms: A Study of Four Sectors of China. Working Papers, Article DP-2012-10. <https://ideas.repec.org/p/era/wpaper/dp-2012-10.html>
- Mejía, A. G. (2017). The concept of Technology in the History of Economic Thought. From the Classics to Schumpeter, Evolutionism and today. *Libre Empresa*, 14(2), Article 2. <https://doi.org/10.18041/1657-2815/libreempresa.2017v14n2.3039>
- Nikitin, D. V. (2022). The Theoretical and Methodological Origins of Innovative Theories. *Business Inform*, 5(532), 4–10. <https://doi.org/10.32983/2222-4459-2022-5-4-10>
- Okunade, S. (2020). Effect of Capacity Utilisation on Manufacturing Firms' Production in Nigeria Effect of Capacity Utilisation on Manufacturing Firms' Production in Nigeria. *Global Journal of Management and Business Research*, 18, 28–38.
- Pesaran, H., & Shin, Y. (1995). An Autoregressive Distributed Lag Modeling Approach to Co-integration Analysis. *Econometrics and Economic Theory in the 20st Century: The Ragnar Frisch Centennial Symposium*, 31. <https://doi.org/10.1017/CCOL0521633230.011>
- Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, 16(3), 289–326. <https://doi.org/10.1002/jae.616>
- Rahman, P., Zhang, Z., & Musa, M. (2023). Do technological innovation, foreign investment, trade and human capital have a symmetric effect on economic growth? Novel dynamic ARDL simulation study on Bangladesh. *Economic Change and Restructuring*, 56(2), 1327–1366. <https://doi.org/10.1007/s10644-022-09478-1>
- Ramzi, T., & Wiem, J. (2019). Causality Nexus between Economic Growth, Inflation and Innovation. *Journal of the Knowledge Economy*, 10(1), 35–58. <https://doi.org/10.1007/s13132-016-0432-2>

- Rodríguez, J. F. G., Ramírez, A. A., Pérez, L. M., Meza, J. R., & Ramos, R. R. (2019). Relationship between the innovation and the labor production in the Mexico manufacturer. *Investigacion Operacional*, 40, 249–254.
- Śledzik, K. (2013). Schumpeter's View on Innovation and Entrepreneurship. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.2257783>
- Thadewald, T., & Buning, H. (2007). Jarque-Bera Test and its Competitors for Testing Normality—A Power Comparison. *Journal of Applied Statistics*, 34, 87–105. <https://doi.org/10.1080/02664760600994539>
- Todeva, E. (2020). The Global Innovation Index as a Measure of Triple Helix Engagement (pp. 119–134). https://doi.org/10.1007/978-3-030-23898-8_10
- Vlado, C. (2019). The Conception of Innovation on the Central Theoretical Hubs of Economic Thought (SSRN Scholarly Paper 3495548). <https://papers.ssrn.com/abstract=3495548>
- wipo. (2023). Global Innovation Index 2023. <https://www.wipo.int/publications/en/details.jsp?id=4680&plang=EN>
- WIPO. (2024). WIPO - World Intellectual Property Organization. <https://www.wipo.int/>
- Ziemnowicz, C. (2013). Joseph A. Schumpeter and Innovation. In E. G. Carayannis (Ed.), *Encyclopedia of Creativity, Invention, Innovation and Entrepreneurship* (pp. 1171–1176). Springer. https://doi.org/10.1007/978-1-4614-3858-8_476
- ZORMAN, M., & GHARDI, M. (2020). The reality of the manufacturing industries in Algeria and its development strategy within the framework of the economic diversification program. *Revue d'Economie et de Développement Humain*, 11(3), 7–22.