

Can Innovation Drive Industrial Growth? A Sectoral Analysis of Algeria's Manufacturing Performance (2013–2024)

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Abstract :

This study applies the ARDL model to explore the long-run and short-run effects of knowledge diffusion, intangible assets, and creative goods and services on Algeria's manufacturing performance. The model employs quarterly data from 2013Q1 to 2024Q4. Results indicate that both knowledge diffusion and intangible assets negatively influence manufacturing output in the long run, with significant coefficients of -0.6061 and -0.2972, respectively. Creative goods and services show a positive but statistically insignificant effect. The model confirms a strong cointegration relationship among variables, with an error correction term of -0.4817, suggesting that 48% of short-run disequilibrium adjusts each quarter toward long-run equilibrium. The model explains 67.56% of the variation in manufacturing performance, indicating good overall fit. These findings highlight the complex role of intangible factors in industrial development and suggest the need for more effective strategies to convert knowledge and intangible assets into productive outcomes within Algeria's manufacturing sector.

Keywords: Innovation Output, knowledge diffusion, Manufacturing, WIPO Index.

Jel Classification Codes : O32, D83, O14, B23

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1. Introduction

In his influential book "The Theory of Economic Development," which was first published in 1911, Joseph Schumpeter introduced the concept of "Creative Destruction." This concept illustrates how innovation disrupts existing market structures and established businesses, ultimately leading to the emergence of newer, more advanced economic frameworks. Schumpeter argued that innovation transcends the mere introduction of new technologies or products; it involves a fundamental restructuring of the economy itself. By disrupting conventional production and distribution methods, innovation creates pathways for new models that enhance economic efficiency and elevate living standards. Schumpeter defined innovation as a process that triggers profound and sophisticated changes in production and distribution practices, stemming from advancements in technology, management strategies, or shifts in social and cultural norms. 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 focused on public policies aimed at fostering innovation for growth and development (Mejía, 2017), thereby significantly shaping the concept of innovation. Innovation was associated with negative connotations of deviation and resistance to change before the twentieth century (Nikitin, 2022). However, during the Enlightenment era, innovation began to be viewed positively as a catalyst for progress and change, particularly in economics, where it reshaped the economic system and became a pivotal concept (Cialowicz, 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 delve into the multifaceted effects of innovation factors on diverse economic undertakings, notably within industrial sectors. Innovation within individual firms stands as a pivotal stride toward enhancing productivity, bolstering the reformation of industrial frameworks, and fortifying the competitive edge of manufacturing enterprises in the global arena (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 focuses on Algerian innovation, Knowledge diffusion, intangible assets, creative goods and services, as well as their correlation with the manufacturing sector. It stemmed from the persistent observation that Algeria has lagged behind in innovation and creativity for an extended period. This observation further underscores the validity of the identified research gap. Exploring the impact of unique knowledge diffusion and diverse intangible assets on innovation and productivity across various industrial contexts holds the potential for a more nuanced comprehension.

Undertaking thorough investigations or comparative analyses to elucidate the reasons behind the varying effects of innovation on Algerian industries could lay the groundwork for more efficient policy strategies aimed at fostering innovation within the Algerian economic landscape. The dearth of definitive research data presents a considerable impediment to any research undertaking. Algeria's global innovation ranking, based on the evaluation conducted by the World Intellectual Property Organization, positioned it as the 119th among 132 economies (wipo, 2023). The country's innovation

performance, as unveiled in the 2023 Global Innovation Index (GII) report, assessing international financial openness with 80 innovation metrics, indicates a steady decline. More specifically, Algeria is situated at the 128th spot for Knowledge and technology outputs and the 107th spot for Creative outputs. Through all this, we will try to answer the following question: What is the impact of innovation output in Algeria on the growth of manufacturing industries in Algeria during the period (2013-2024)?

2. Literature Review

Research on manufacturing innovation has focused on its impact on productivity, efficiency, competitiveness, and sustainability. Scholars have explored how advancements in technology, organizational structures, and strategic approaches drive innovation in the manufacturing industry. For example, (Gautam et al., 2024) highlighted how AI, IoT, and robotics are transforming intelligent manufacturing by improving automation and productivity while also addressing challenges like workforce reskilling. Similarly, Stoettrup Schioenning (Larsen et al., 2023) developed a heuristic model for Industry 4.0 that allows for experimentation and complexity management, helping manufacturing firms transition smoothly.

Many studies emphasize the crucial role of technology in manufacturing success. (Plinta & Radwan, 2023) explored how small-batch production can effectively implement technological innovations through strong management and strategic planning. (Leng & Zhang, 2024) discussed the benefits of university-industry partnerships in driving patent development and boosting innovation, particularly in emerging industries. (Tang et al., 2024) reinforced this idea by stressing the importance of collaboration between government, industry, and academia to achieve breakthroughs in key manufacturing technologies.

A recurring theme in research is the challenge of overcoming innovation barriers. (Castaneda et al., 2023) identified limited funding and a shortage of skilled workers as major obstacles to innovation in manufacturing. (Zhang et al., 2021) studied China's institutional environment and found that government support plays a critical role in strengthening manufacturing performance through innovation. These findings suggest that policy interventions and financial support are essential for fostering innovation.

Process innovation has proven to be a key factor in improving efficiency and competitiveness. (Kim et al., 2024) examined the FOM system in film manufacturing and demonstrated how it enhances productivity. (Riesener et al., 2022) proposed a framework for continuous innovation in manufacturing, highlighting the importance of adaptability in fast-changing markets. Meanwhile, (Nandakumar et al., 2022) explored the benefits of modularizing chemical manufacturing processes, which allows for quicker adoption of new technologies and greater efficiency.

The rise of data-driven and AI-powered innovations has gained significant attention in recent years (Babu et al., 2024) introduced a seven-step data-driven innovation (DDI) model that helps commercialize big data analytics. (Li & Han, 2022) expanded on this by integrating AI into green manufacturing innovation systems, showing how it can support sustainable production and environmental protection. (Medhi et al., 2022) also examined design thinking as a strategy for managing innovation in manufacturing, demonstrating its role in driving organizational transformation.

Digital transformation is another major area of focus. (Ivanov, 2020) explored how smart connected products are being integrated into manufacturing firms, highlighting the challenges traditional companies face when adapting to digitalization. (Ladokun, 2019) found that product innovation significantly boosts sales and customer satisfaction in Nigerian manufacturing firms, providing them with a competitive edge. Similarly, (Kiveu et al., 2019) studied SMEs in Nairobi and

found that incremental improvements in processes, marketing, and organizational structures greatly enhance competitiveness.

Manufacturing resilience and strategic innovation planning have also been widely studied. (Romero et al., 2021) introduced a conceptual framework for manufacturing resilience, emphasizing the role of production innovation in maintaining long-term competitiveness. In a related study, (Romero et al., 2017) developed a strategic planning model to assess the readiness of new technologies and work methods. These findings highlight the importance of proactive innovation strategies in helping manufacturing firms navigate market uncertainties.

Despite extensive research, some critical gaps remain. One major gap is the lack of studies examining the relationship between innovation and industrialization in developing countries like Algeria, where cultural, economic, and political factors may shape how innovation is understood and applied. Additionally, while much research has focused on technological and process innovations, less attention has been given to their socio-economic impacts, such as changes in workforce dynamics and labor markets. Although AI and big data have been widely discussed, their ethical and security implications in manufacturing require further exploration. Furthermore, most studies focus on large-scale manufacturing firms, while research on innovation strategies for SMEs in developing economies is relatively limited. Addressing these gaps would offer a more comprehensive understanding of manufacturing innovation and its broader effects on industry and society.

In summary, existing research provides valuable insights into manufacturing innovation, covering technological advancements, strategic frameworks, and barriers to progress. However, further studies are needed to explore socio-economic impacts, ethical concerns, and SME-specific innovation strategies, particularly in developing countries like Algeria. By filling these research gaps, future studies can contribute to more inclusive and sustainable innovation models for the manufacturing sector. **What sets this study apart from previous research?**

A group of previous studies and literature related to the subject of the study was reviewed to gain a general understanding of the variables and problems pertinent to the current study. This review also aimed to identify the most important developments, the results achieved by these studies, and the research prospects they highlighted. It was concluded that the current study aligns with previous studies in examining the impact of the Global Innovation Index on economic growth. However, it differs in terms of the standard model adopted and the time period covered. Additionally, the current study is distinguished by its application to Algeria, relying solely on innovation output as the independent variables and manufacturing industries as the dependent variable.

Our study takes a fresh approach to understanding these variables, exploring a perspective that has not yet been thoroughly examined in academic research. Using the Autoregressive Distributed Lag (ARDL) model, we investigate how innovation affects Algeria's manufacturing industries. To illustrate our research framework, we have developed a visual model where manufacturing industries and their key influencing factors are represented within distinct rectangles. The arrows connecting these elements indicate the relationships we aim to test empirically in the next stages of our study.

Our core hypotheses are as follows:

H1: Knowledge diffusion impacts Algeria's manufacturing industries.

H2: Intangible assets impact Algeria's manufacturing industries.

H3: Creative goods and services impact Algeria's manufacturing industries.

3. Methods and Materials

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.

1.1. Data sources

In our study, we collected data for the independent variables from the Global Innovation Index (GII) website., also referred to as the WIPO Index, is a collaborative initiative involving WIPO, Cornell University, and INSEAD. Its purpose is to evaluate how countries perform in terms of innovation using various indicators and to analyze how innovation-focused policies impact economic growth and development. This index assists both developed and developing nations in monitoring progress driven by innovation through a variety of strategies. By simplifying the assessment of innovation inputs, outputs, and efficiency, the GII enables comparisons of innovation performance across countries (Todeva, 2020) .

Furthermore, by prioritizing the enhancement of innovation capacity and recognizing the complex relationships between academic research, business innovation, and government investments, the GII enhances our understanding of global innovation dynamics (WIPO, 2024). The manufacturing industry involves the process of making changes to the nature of the materials used. These materials are transformed from their raw form into a state that makes them ready for use or consumption, whether in the form of finished or semi-finished goods. This transformation is achieved through the combination of several factors, including manpower, technology, and capital (ZORMAN & GHARDI, 2020). The data regarding the dependent variable “**manufacturing industry**” was obtained from the website of the National Bank of Algeria (Bank of Algeria, 2024).

3.2. Data Overview

Duration: The dataset covers 12 years, from Q1 2013 to Q4 2024.

Observations: 44 quarterly observations.

Software Used: The econometric analysis was conducted using EViews 12 (x64), which offers robust tools for estimating dynamic models such as ARDL, conducting cointegration tests, and implementing error correction models.

Variables: **Y** (Manufacturing Industries - MI): Measures the quarterly growth rate of value added at chained prices (Base 2001) for manufacturing industries in Algeria.

X1 (Knowledge Diffusion - KWD): Measures knowledge diffusion through intellectual property receipts, production and export complexity, high-tech exports, ICT services exports, and ISO 9001 quality certifications.

X2 (Intangible Assets - INA): Measures intangible assets through intangible asset intensity, trademarks, global brand value, and industrial designs.

X3 (Creative Goods and Services - CGS): Measures creative goods and services through cultural and creative services exports, national feature films, entertainment and media market, and creative goods exports.

In this study, the dependent variable (Y) is Manufacturing Industries (MI), measured by the quarterly growth rate of value added at chained prices (base year 2001) in Algeria, serving as an indicator of real economic output in the industrial sector (Bank of Algeria, 2024). The first independent variable (X1) is Knowledge Diffusion (KWD), operationalized through a composite score derived from several components: intellectual property receipts, production and export complexity, high-technology exports, ICT services exports, and the number of ISO 9001 certifications (WIPO, 2024).

The second independent variable (X2) is Intangible Assets (INA), measured using indicators such as the intensity of intangible assets, trademark registrations, global brand valuations, and industrial design registrations. The third independent variable (X3) is Creative Goods and Services (CGS), which reflects a composite score based on cultural and creative services exports, the production of national feature films, performance of the entertainment and media market, and exports of creative goods (WIPO, 2024). These variables have been selected to capture diverse innovation-related dimensions that may influence industrial performance in the Algerian context.

The mathematical formula for the model is as follows:

MI_t = f (KWD, INA, CGS, Dum). **Dum: 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 (H. Pesaran & Shin, 1995). The general formula of the model comprises the dependent variable " **Manufacturing industries** " and the explanatory variables " **Knowledge diffusion, Intangible assets, Creative goods services**" Regarding the standard model, it is structured as follows:

$$\Delta MI_t = \alpha_0 + \sum_{j=1}^{p1} \alpha_j \Delta MI_{t-j} + \sum_{j=0}^{p2} \beta_j \Delta KWD_{t-j} + \sum_{j=0}^{p3} \delta_j \Delta INA_{t-j} + \sum_{j=0}^{p4} \gamma_j \Delta CGS_{t-j} + \pi_1 MI_t - 1 + \pi_2 KWD_{t-1} + \pi_3 INA_{t-1} + \pi_4 CGS_{t-1} + \mu_t$$

- The short-term dynamics of the model are represented by ($\alpha_j, \beta_j, \delta_j, \gamma_j$)
- 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.

3.3. Methods

The methodology unfolds in a structured sequence. It initiates with the Unit Root Test, which is employed to evaluate whether the variables are stationary. After establishing stationarity, the Akaike Information Criterion (AIC) is applied to select the optimal lag lengths for the dependent and independent variables. Once lag selection is complete, the bound's testing approach is used to investigate the presence of cointegration relationships among the variables. Finally, the ARDL simulations model is implemented to analyze both the short-run dynamics and long-run equilibrium effects.

a. stationarity of time series

To assess the stationarity of time series variables, researchers commonly employ the Augmented Dickey-Fuller test or the Phillips-Perron test. These tests aim to determine whether the variables exhibit stationarity or non-stationarity. In both tests, the null hypothesis posits that the variables possess a unit root, indicating non-stationarity, while the alternative hypothesis suggests the absence of a unit root, signifying stationarity. If the null hypothesis is rejected, implying non-stationarity, the variable can be made stationary through differencing. Notably, the Augmented Dickey-Fuller (ADF) test is generally considered more dependable than the Phillips-Perron (PP) test (Fabozzi et al., 2014).

b. Optimal lag

The ideal number of lag lengths is determined through various methods (Fabozzi et al., 2014). In this study, we opted for the Akaike information criterion (AIC) to ascertain the optimal lag.

AIC is preferred in situations involving smaller sample sizes, making it a more suitable choice for our research compared to other criteria. AIC measures the information lost, so the model with a lower AIC score indicates a better fit.

c. ARDL Bounds Test

The ARDL method primarily relies on employing the ordinary least squares technique. It suggests that $(\alpha_j, \beta_j, \delta_j, \Upsilon_j)$ function as short-run amplifiers, while $\pi_1, \pi_2, \pi_3, \pi_4$ are associated with long-run dynamics. Additionally, δ_0 denotes a constant run, and μ_t signifies the error run. In ARDL regression analysis, the null hypothesis (H_0) posits that all long-run amplifiers are zero ($\pi_1 = \pi_2 = \pi_3 = \pi_4 = 0$), suggesting no enduring connection between dependent and independent variables. Conversely, the alternative hypothesis (H_1) suggests that long-run amplifiers differ and are non-zero ($\pi_1 \neq \pi_2 \neq \pi_3 \neq \pi_4 \neq 0$), indicating the existence of a lasting relationship between these variables (M. H. Pesaran et al., 2001). So we use F-Bounds Test. If the F-statistic is greater than the critical value of both lower and upper bound the null hypothesis is rejected, and it is concluded that there is a relationship between the variables (Gómez & Irewole, 2023).

d. Estimate ARDL model

If the findings validate the presence of cointegration among the variables under examination, it becomes imperative to estimate both the long-term and short-term equilibrium relationships using the ARDL model. The Short-Run Autoregressive Distributed Lag (ARDL) Model, as explained by, (Banerjee et al., 1998) delves into the dynamics of error correction (EC) and its role in gauging the adjustment speed of a dependent variable towards its long-term equilibrium position following a shock. This model elucidates how swiftly a variable moves to restore equilibrium within a dynamic framework, typically manifested by a statistically significant coefficient bearing a negative sign. The significance of the “EC” run not only confirms the existence of a stable long-term relationship but also underscores the process by which deviations from long-term equilibrium levels in the current period are rectified by a certain percentage, typically denoted as the Error Correction Mechanism (ECM), in subsequent periods to re-establish equilibrium.

e. Diagnostic Test

Autocorrelation in a time series occurs when each observation is correlated with its preceding one, resulting in the variance of each observation being partially explained by regressing it on its predecessor. Consequently, the validity of T-tests, F-tests, or confidence intervals may be compromised, as the estimators' variances tend to be either underestimated or overestimated. This invalidation of hypothesis testing can lead to misleading conclusions regarding the significance of parameters in the model (abibo et al., 2022).

• Test serial correlation problem

Advantage of this test is that it allows researchers to test for serial correlation through a number of lags besides one lag which is a correlation between the residuals between time t and $t-k$ (where k is the number of lags) (Okunade, 2020).

• Heteroskedasticity Test

Both the Breusch-Pagan-Godfrey test and the ARCH test were implemented with the same approach to pinpoint and address any potential causes of the heteroscedasticity issue (Jan et al., 2023).

• Stability Diagnostics

The CUSUM test and CUSUMQ test are utilized on model residuals to evaluate the consistency of long-run coefficients, which contribute to the error-correction run, alongside short-run dynamics. Ensuring stability in both short-run dynamics and long-run parameters necessitates that the CUSUM and CUSUMQ statistics stay below a 5% critical threshold (abibo et al., 2022).

- **Normally distributed residuals**

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

This section presents the empirical findings of the study and interprets their significance in relation to the research hypotheses. Building on the conceptual framework, we examine the impact of three key innovation-related variables knowledge diffusion, intangible assets, and creative goods and services on Algeria's manufacturing industries.

4.1. Results

In this section, we present the main findings of our study. The goal is to understand how knowledge diffusion, intangible assets, and creative goods and services affect manufacturing industries in Algeria. To do this, we used data from 2013 to 2024 and applied an ARDL model, which helps us study both short-term and long-term relationships between the variables. We start by testing if the data is stable over time. Then, we select the best model, check if there is a long-term connection between the variables, and estimate the results for both the long run and the short run. After that, we test whether the model is statistically valid and stable. These results will help us understand which factors have a strong or weak influence on the performance of Algeria's manufacturing sector.

Before conducting the ARDL estimation, stationarity tests were performed to determine the integration order of the variables. As detailed in [Table 1](#), the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests reveal that most variables namely the dependent variable (Y, representing manufacturing industries) and the independent variables (X1_Knowledge Diffusion, X2_Intangible Assets, and X3_Creative Goods and Services) exhibit non-stationarity at levels but become stationary after first differencing. This implies that all series are integrated of order one, I(1), which satisfies the precondition for testing long-run relationships. Notably, Y is stationary at level with a constant (both in ADF and PP tests), and X1 becomes stationary at level with trend specifications; however, full stationarity across all series is achieved at first differences. Given this, the Bounds Test was employed to verify the existence of a long-run equilibrium relationship among the variables. As shown in [Table 3](#), the calculated F-statistic of 5.167 exceeds the upper bound critical value of 4.66 at the 1% significance level. This leads to rejection of the null hypothesis of no cointegration, confirming that a stable long-term relationship exists between manufacturing performance (Y) and the innovation-related variables (X1, X2, and X3). To ensure the reliability of the ARDL model estimates, a series of diagnostic checks were conducted. The Breusch-Godfrey Serial Correlation LM Test, reported in [Table 6](#), yielded p-values of 0.6566 (F-statistic) and 0.5091 (Chi-Square), both well above the 0.05 significance threshold. This indicates no evidence of autocorrelation in the residuals, validating the model's temporal independence assumptions. To assess heteroskedasticity, both the Breusch-Pagan-Godfrey and ARCH tests were used. As seen in [Table 7](#), the Breusch-Pagan-Godfrey test produced extremely high p-values (0.9995 and 0.9985), and the ARCH test results in [Table 8](#) also show high p-values (0.6547 and 0.6453), leading to the conclusion that the residuals exhibit constant variance over time. Model stability was further examined through CUSUM and CUSUMSQ plots ([Figures 1 and 2](#)), where all values remained within the 5% significance bands, confirming coefficient stability throughout the study period. Residual diagnostics also support model adequacy, as illustrated in [Figure 3](#), which shows a close alignment between actual and fitted values, implying strong predictive performance. Lastly, normality of the residuals was confirmed using the Jarque-Bera test; with a p-

value of 0.516 shown in Figure 4, the residuals follow a normal distribution, further affirming the model's statistical soundness. Collectively, these results confirm that the data and model meet the core econometric assumptions necessary for valid inference, thereby strengthening confidence in the long-run and short-run findings.

a. Model Selection

The model ARDL(1, 4, 4, 2), with a lower AIC score(4.646564), indicates a better fit [Table 2](#).

$$\begin{aligned} \text{Mlt} = & a + c\text{MI}_{t-1} + d_1\text{KWD} + d_2\text{KWD}_{t-1} + d_3\text{KWD}_{t-2} + d_4\text{KWD}_{t-3} + d_5\text{KWD}_{t-4} + e_1\text{INA} \\ & + e_2\text{INA}_{t-1} + e_3\text{INA}_{t-2} + e_4\text{INA}_{t-3} + e_5\text{INA}_{t-4} + f_1\text{CGS} + f_2\text{CGS}_{t-1} + f_3\text{CGS}_{t-2} + \mu t \end{aligned}$$

The long-run estimates from the ARDL model, as reported in [Table 4](#), demonstrate distinct directional relationships between the explanatory variables and the dependent variable (Y_Manufacturing industries). The coefficient for X1_Knowledge Diffusion is negative and statistically significant at the 1% level ($p = 0.0368$), with a magnitude of -0.606053. This implies that a 1% rise in knowledge diffusion is associated with a long-term decline of approximately 60.60% in manufacturing industry performance, indicating a strong inverse equilibrium effect. Similarly, X2_Intangible Assets also exhibits a negative coefficient (-0.297165), significant at the 1% level ($p = 0.0492$), suggesting that a 1% increase in intangible assets leads to a 29.71% reduction in manufacturing performance over the long run. Conversely, X3_Creative Goods and Services has a positive coefficient (0.501919), yet it lacks statistical significance at the 5% level ($p = 0.2445$), indicating no robust evidence of a long-run equilibrium relationship with the dependent variable. The short-run dynamics, examined through the ARDL Error Correction Model in [Table 5](#), offer further insights. The model specification ARDL(1,4,4,2) covers quarterly data from 2013Q1 to 2024Q4 and includes lags for all explanatory variables. The error correction term is both negative and significant, with a coefficient of -0.481676, implying that nearly 48% of the deviation from long-run equilibrium is corrected each quarter, signifying a reversion to equilibrium within about two quarters. The model's explanatory power is reflected in the R-squared value of 0.675610, meaning that approximately 67.56% of the variability in Y is accounted for by X1, X2, and X3, while the remaining variance is attributed to stochastic disturbances. Regarding the interpretation of short-term coefficients, the immediate change in X1 shows a significantly negative impact on Y (-0.3185; $p = 0.0041$), while some lagged differences such as $D(X1(-3))$ are also statistically significant ($p = 0.0011$), albeit with varying signs. For X2, both the contemporaneous and lagged differences ($D(X2)$, $D(X2(-1))$, $D(X2(-3))$) consistently exhibit positive and significant impacts, reflecting short-run positive elasticity. In the case of X3, the immediate effect is highly significant and positive (coefficient = 0.7397; $p = 0.0019$), while the first lag ($D(X3(-1))$) lacks statistical significance ($p = 0.1348$). Collectively, these findings illustrate complex short- and long-run interactions between innovation-related inputs and industrial manufacturing output, reinforcing the critical importance of dynamic modeling in uncovering nuanced relationships in applied econometric studies.

4.2. Discussion

a. Long-Run Estimates from the ARDL Model

The long-run coefficients derived from the ARDL model estimation provide critical insights into the enduring relationships between innovation-related variables and the performance of Algeria's manufacturing industries. As demonstrated in [Table 4](#), the empirical results indicate that both Knowledge Diffusion (X1) and Intangible Assets (X2) have statistically significant negative impacts on manufacturing output in the long run, while Creative Goods and Services (X3) show a non-significant positive effect.

More specifically, the coefficient associated with Knowledge Diffusion is negative (-0.606053) and statistically significant at the 1% level ($p = 0.0368$). This implies that a 1% increase in the Knowledge Diffusion index leads to a 0.606% decline in the growth rate of value added in manufacturing

industries. This counterintuitive finding suggests that the current structure or absorption capacity of Algeria's manufacturing sector might not yet be adequately equipped to translate increased knowledge diffusion measured through intellectual property receipts, high-tech exports, and ICT services into productivity gains. It may also indicate structural mismatches, a weak national innovation system, or inefficiencies in knowledge application mechanisms within industrial processes.

Similarly, the coefficient for Intangible Assets stands at -0.297165, also statistically significant at the 5% level ($p = 0.0492$). This implies that for every 1% increase in intangible asset intensity (e.g., brand value, trademarks, industrial designs), the manufacturing industry's output declines by approximately 0.297%. This suggests that intangible capital in Algeria may still be concentrated in non-industrial sectors or is underutilized in industrial processes. These findings warrant a closer examination of how intangibles are integrated into industrial policy and capacity-building strategies, particularly in low- and middle-tech manufacturing segments.

Contrarily, the coefficient for Creative Goods and Services is positive (0.501919) but statistically insignificant ($p = 0.2445$). While the direction of influence suggests that creative sectors might support industrial growth potentially through design, branding, and cultural value addition the lack of statistical significance implies that this relationship remains weak or underdeveloped. The creative economy's contribution to manufacturing may be at an early stage, or its effects may be indirect and hence harder to capture within a conventional linear ARDL framework.

Together, these long-run results highlight a paradox: while innovation inputs are generally regarded as growth-enhancing, their current configuration or deployment within Algeria's manufacturing sector appears misaligned with long-term industrial performance. This reinforces the need for policies that not only promote innovation inputs but also enhance firms' absorptive capacities, cross-sectoral linkages, and innovation governance structures.

b. The Short-Run ARDL Model (ECM Regression)

The short-run dynamics of the model, assessed through the ARDL Error Correction Model (ECM), further illuminate the temporal adjustment processes between the dependent and independent variables. As summarized in [Table 5](#), the short-run regression captures both the immediate effects of changes in X_1 , X_2 , and X_3 on Y , as well as the speed at which deviations from long-run equilibrium are corrected.

A key finding is the highly significant and negative error correction term ($ECM = -0.481676$, $p < 0.01$). This coefficient signifies a strong correction mechanism whereby approximately 48% of the disequilibrium from the previous quarter is adjusted in the current period. This rapid convergence toward equilibrium underscores a well-behaved model and provides evidence of a stable long-run relationship among the variables. The implication is that while some innovation-related activities may initially have destabilizing effects, the system self-corrects over a relatively short horizon two quarters suggesting institutional responsiveness or adaptability within the industrial sector.

The short-run coefficients provide additional nuance:

- **Knowledge Diffusion (X_1):** The immediate change (ΔX_1) negatively affects manufacturing output (coefficient = -0.3185, $p = 0.0041$). This aligns with the long-run result and suggests that surges in knowledge diffusion without proper assimilation may disrupt current production systems. Interestingly, the third lag of X_1 ($\Delta X_1(-3)$) is significantly positive ($p = 0.0011$), hinting at a delayed beneficial impact. This temporal pattern implies a learning curve or gestation period required for knowledge-based inputs to translate into productivity improvements.
- **Intangible Assets (X_2):** Contrary to its long-run behavior, X_2 exhibits a positive and significant short-run effect, both at the current level (coefficient = 0.4497, $p = 0.0007$) and across multiple lags (e.g., $\Delta X_2(-1)$, $p = 0.0000$; $\Delta X_2(-3)$, $p = 0.0018$). This suggests that intangible investments may provide immediate innovation-driven advantages, such as enhanced marketing, reputation, or process innovation. However, these benefits might dissipate or reverse over time if not accompanied by structural and technological upgrades, explaining the negative long-run coefficient.
- **Creative Goods and Services (X_3):** The short-run coefficient is also positive and statistically significant (coefficient = 0.7397, $p = 0.0019$), indicating that immediate changes in creative industry

outputs stimulate manufacturing sector performance. This result may reflect the synergistic effects of creativity on product design, consumer engagement, and cultural value embedded in manufactured goods. However, the first lag of X3 is insignificant ($p = 0.1348$), indicating a lack of consistent short-term persistence.

Furthermore, the R-squared value of 0.675610 indicates that the model explains approximately 67.56% of the variability in manufacturing performance. This is relatively high for time-series econometric models and suggests a strong explanatory capacity of the innovation-related variables, while the remaining variance can be attributed to exogenous shocks, policy changes, or structural constraints.

5. Conclusion and Policy suggestions

5.1. Conclusions

The analysis revealed that the model ARDL applied to Algeria demonstrated considerable stability and established a long-term relationship between the independent and dependent variables. The ARDL Error Correction Regression analysis highlighted a complex interaction among the factors impacting Algeria's manufacturing sector. Notably, "knowledge diffusion" and "intangible assets" showed statistically significant negative impacts, with increases in these factors correlating to 60.60% and 29.71% reductions in manufacturing performance, respectively. This surprising outcome suggests that higher levels of knowledge diffusion and intangible assets might lead to short-term disruptions or inefficiencies. In contrast, "creative goods and services" displayed a positive yet statistically insignificant effect, indicating their uncertain benefits on manufacturing performance within this analysis. The model, with a robust R-squared value of 0.675610, also indicated a strong long-term equilibrium among the variables, with a significant error correction coefficient of -0.481676. This coefficient reflects a correction rate of 48% per quarter for deviations from equilibrium, underscoring the model's capability to capture the dynamic adjustments within Algeria's manufacturing sector. From these results, we can further understand these relationships by analyzing the following:

Impact of Knowledge diffusion on Manufacturing Industries in Algeria: The variable X1 (knowledge diffusion) has a significant negative long-term impact on Y (Manufacturing Industries) in Algeria, with a coefficient of -0.6061. This indicates that increases in knowledge diffusion activities, such as intellectual property receipts and high-tech exports, are associated with a decrease in the growth rate of manufacturing industries. This could suggest potential misalignment or inefficiencies in how knowledge diffusion is being integrated into Algeria's manufacturing sector.

Influence of Intangible Assets: The variable X2 (Intangible Assets) also shows a significant negative long-term impact on manufacturing industries in Algeria, with a coefficient of -0.2972. This suggests that higher investments in intangible assets, like trademarks and global brand value, correlate with a decrease in manufacturing growth. This could be due to possible underutilization or ineffective deployment of these assets in enhancing manufacturing productivity in Algeria.

Role of Creative Goods and Services: The variable X3 (Creative Goods and Services) has a positive coefficient of 0.5019, though it is not statistically significant. This implies that while there might be a positive relationship between creative goods and services and manufacturing growth in Algeria, the evidence is not strong enough to confirm a definitive impact in the long term.

Error Correction Mechanism: The error correction term is highly significant, indicating a robust adjustment mechanism that corrects 48.17% of any deviation from the long-term equilibrium each quarter. This suggests that Algeria's manufacturing sector is fairly responsive in adjusting towards equilibrium after short-term shocks.

Integration with Hydrocarbons Prices: Algeria's economic structure is significantly dependent on hydrocarbons. This reliance has historically led to a concentration on the hydrocarbon sector, often at the detriment of other industries. The preeminence of the hydrocarbon industry tends to result in insufficient investment in sectors driven by knowledge and intangible assets.

Consequently, this reliance can create inefficiencies and mismatches when attempting to integrate advanced knowledge dissemination and intangible assets into the manufacturing industry. The dominance of the hydrocarbon sector can overshadow the advantages that creative goods and services could bring to the economy. Although these sectors have the potential to make positive contributions, their impact often remains uncertain and minimal. This situation is likely due to inconsistent investment and development, which are heavily influenced by the fluctuating revenues from hydrocarbons.

5.2. Policy suggestions

Strategies for Boosting Innovation in Algeria's Manufacturing Sector:

Reevaluate Knowledge Diffusion Strategies: Given the negative impact of knowledge diffusion on manufacturing, Algeria needs to reassess these activities' implementation. Policymakers and industry leaders should align knowledge diffusion efforts with the manufacturing sector's specific needs and capacities to foster growth.

Optimize Utilization of Intangible Assets: The negative impact of intangible assets suggests inefficiencies or underutilization. Algerian companies should integrate intangible assets more effectively into their operational and strategic frameworks. This may involve training, product development innovation, and better brand value management.

Enhance the Role of Creative Goods and Services: While the positive impact of creative goods and services is not statistically significant, there is potential for benefits. Algeria should foster stronger links between the creative industries and manufacturing through collaborative projects and cross-sector innovation initiatives.

Strengthen Policy Frameworks: Policies should support the integration of knowledge and intangible assets in manufacturing. This includes incentives for innovation, improved intellectual property rights management, and tailored research and development activities.

Continuous Monitoring and Adjustment: Given the dynamic nature of the relationships between these variables, continuous monitoring and periodic reassessment of strategies are necessary. This will help address emerging inefficiencies and capitalize on new opportunities.

Promote Cross-Sector Collaboration: Encouraging collaboration between manufacturing and sectors responsible for knowledge diffusion, intangible assets, and creative goods can create synergies that enhance productivity and growth. Joint ventures, public-private partnerships, and innovation hubs can facilitate this collaboration.

Focus on Capacity Building: Investing in capacity building within Algeria's manufacturing sector is essential for better utilization of knowledge diffusion and intangible assets. This could involve technical training, management education, and fostering a culture of innovation within manufacturing enterprises.

Targeted Investment: When hydrocarbon prices are elevated, there is an opportunity to boost investment in creative industries. However, for these investments to have a lasting positive effect on the manufacturing sector, they must be deliberate and maintained over time.

Investment in Diverse Sectors: Policymakers should prioritize promoting investments in sectors beyond hydrocarbons to reduce the adverse effects of reliance on this industry. This effort involves creating conditions that successfully incorporate knowledge dissemination and intangible assets into the manufacturing sector.

By addressing these areas, Algeria can improve the positive impacts of knowledge diffusion and intangible assets on its manufacturing sector and leverage potential benefits from creative goods and services.

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 knowledge diffusion and intangible assets 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
 CE Co-integrating Equation
 CGS Creative Goods and Services -
 Dum Dummy Variables
 EC Error Correction
 ECM Error Correction Mode
 INA Intangible Assets -
 KWD Knowledge Diffusion -
 LM Lagrange Multiplier
 MI Manufacturing Industries -
 PP Phillips Perron

Appendices:

Table 1 Unit Root Test –

UNIT ROOT TEST TABLE (PP)					
	<u>At Level</u>				
		Y	X1	X2	X3
With Constant	t-Statistic	-2.9671	-2.5533	-1.3195	-2.2296
	Prob.	0.0455	0.1099	0.6129	0.1989
		**	n0	n0	n0
With Constant & Trend	t-Statistic	-2.9184	-3.8721	-1.1465	-3.1900
	Prob.	0.1662	0.0212	0.9097	0.0988
		n0	**	n0	*
Without Constant & Trend	t-Statistic	0.0297	-1.2108	-0.7468	-1.3341
	Prob.	0.6873	0.2039	0.3876	0.1662
		n0	n0	n0	n0
<u>At First Difference</u>					
		d(Y)	d(X1)	d(X2)	d(X3)
With Constant	t-Statistic	-6.8082	-6.6360	-6.6562	-6.6342
	Prob.	0.0000	0.0000	0.0000	0.0000
		***	***	***	***
With Constant & Trend	t-Statistic	-6.6965	-6.7015	-6.6998	-6.6722
	Prob.	0.0000	0.0000	0.0000	0.0000
		***	***	***	***
Without Constant & Trend	t-Statistic	-6.8932	-6.7082	-6.7082	-6.7082
	Prob.	0.0000	0.0000	0.0000	0.0000
		***	***	***	***
UNIT ROOT TEST TABLE (ADF)					
	<u>At Level</u>				
		Y	X1	X2	X3
With Constant	t-Statistic	-2.9671	-1.0338	-1.2414	-0.2651
	Prob.	0.0455	0.7316	0.6487	0.9210
		**	n0	n0	n0
With Constant & Trend	t-Statistic	-2.9184	-26.2281	-1.1200	-2.0775
	Prob.	0.1662	0.0000	0.9146	0.5417
		n0	***	n0	n0
Without Constant & Trend	t-Statistic	-0.0052	-2.4467	-0.7468	-1.2581

	Prob.	0.6759	0.0157	0.3876	0.1882
		n0	**	n0	n0
At First Difference					
		d(Y)	d(X1)	d(X2)	d(X3)
With Constant	t-Statistic	-6.6253	-2.6323	-6.6562	-5.0982
	Prob.	0.0000	0.0953	0.0000	0.0002
		***	*	***	***
With Constant & Trend	t-Statistic	-6.5392	-2.5887	-6.7003	-4.9660
	Prob.	0.0000	0.2873	0.0000	0.0014
		***	n0	***	***
Without Constant & Trend	t-Statistic	-6.6938	-1.2624	-6.7082	-4.9319
	Prob.	0.0000	0.1868	0.0000	0.0000
		***	n0	***	***
Notes: (*)Significant at the 10%; (**)Significant at the 5%; (***) Significant at the 1%. and (no) Not Significant					

Table 2 Akaike information criterion Top 10 Models

Model	LogL	AIC*	BIC	HQ	Adj. R-sq	Specification
378	-87.224403	4.646564	5.254810	4.872131	0.690437	ARDL(1, 4, 4, 2)
128	-85.225595	4.646618	5.335964	4.902261	0.696383	ARDL(3, 4, 4, 2)
379	-88.518489	4.659931	5.227628	4.870461	0.682626	ARDL(1, 4, 4, 1)
129	-86.574424	4.662474	5.311270	4.903079	0.688715	ARDL(3, 4, 4, 1)
377	-86.807744	4.673079	5.321875	4.913684	0.685396	ARDL(1, 4, 4, 3)
3	-85.109189	4.686781	5.416677	4.957462	0.686370	ARDL(4, 4, 4, 2)
254	-88.154912	4.688860	5.297106	4.914427	0.677063	ARDL(2, 4, 4, 1)
253	-87.169484	4.689522	5.338318	4.930127	0.680181	ARDL(2, 4, 4, 2)
127	-85.170604	4.689573	5.419469	4.960253	0.685493	ARDL(3, 4, 4, 3)
4	-86.550319	4.706833	5.396179	4.962475	0.677540	ARDL(4, 4, 4, 1)

Table 3 ARDL Bounds Test for Co-integration

Test Statistic	Value	K
F-statistic	5.167010	3
Critical Value Bounds		
Signif.	I(0)	I(1)
10%	2.37	3.2
5%	2.79	3.67
2.5%	3.15	4.08
1%	3.65	4.66

Table 4 long -run estimate ARDL model

*Levels Equation				
Case 2: Restricted Constant and No Trend				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
X1	-0.606053	0.276843	-2.189159	0.0368
X2	-0.297165	0.144755	-2.052889	0.0492
X3	0.501919	0.422515	1.187931	0.2445
C	161.5444	4.314506	37.44216	0.0000

Table 5 ARDL Error Correction Regression

ARDL Error Correction Regression				
Dependent Variable: D(Y)				
Selected Model: ARDL(1, 4, 4, 2)				
Case 2: Restricted Constant and No Trend				
Date: 05/12/24 Time: 19:24				
Sample: 2013Q1 2024Q4				
Included observations: 44				
ECM Regression				
Case 2: Restricted Constant and No Trend				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(X1)	-0.318507	0.102298	-3.113510	0.0041
D(X1(-1))	0.016394	0.098120	0.167078	0.8685
D(X1(-2))	0.124817	0.065393	1.908717	0.0662
D(X1(-3))	0.237439	0.065464	3.626998	0.0011
D(X2)	0.449662	0.119038	3.777473	0.0007
D(X2(-1))	0.682815	0.132344	5.159395	0.0000
D(X2(-2))	0.246331	0.140379	1.754762	0.0899
D(X2(-3))	0.448596	0.130199	3.445459	0.0018
D(X3)	0.739699	0.216120	3.422632	0.0019
D(X3(-1))	0.334605	0.217506	1.538373	0.1348
CointEq(-1)*	-0.481676	0.088837	-5.422039	0.0000
R-squared	0.675610	Mean dependent var		0.043044
Adjusted R-squared	0.577310	S.D. dependent var		3.120002
S.E. of regression	2.028457	Akaike info criterion		4.464746
Sum squared resid	135.7830	Schwarz criterion		4.910793
Log likelihood	-87.22440	Hannan-Quinn criter.		4.630161
Durbin-Watson stat	1.961873			

Table 6 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

Table 7 Heteroskedasticity/BPG Test

Heteroskedasticity Test: Breusch-Pagan-Godfrey			
Null hypothesis: Homoskedasticity			
F-statistic	0.165390	Prob. F(14,29)	0.9995
Obs*R-squared	3.253353	Prob. Chi-Square(14)	0.9985
Scaled explained SS	1.531522	Prob. Chi-Square(14)	1.0000

Table 8 Heteroskedasticity/ ARCH Test

Heteroskedasticity Test: ARCH			
F-statistic	0.203032	Prob. F(1,41)	0.6547
Obs*R-squared	0.211886	Prob. Chi-Square(1)	0.6453

Figure 1 CUSUM test

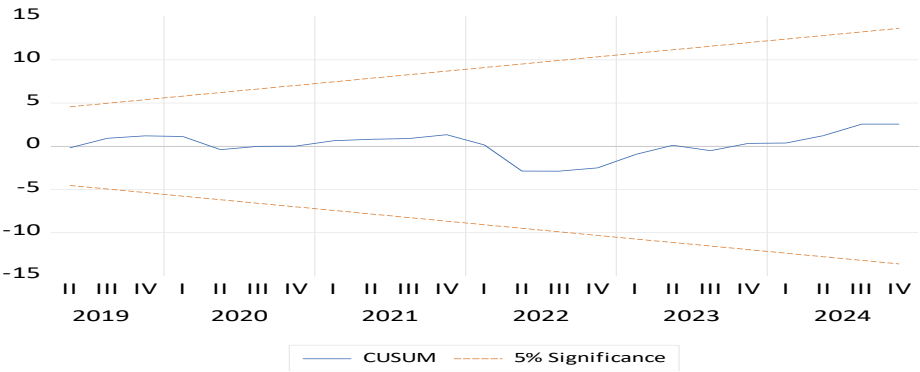


Figure 2 CUSUMSQ test

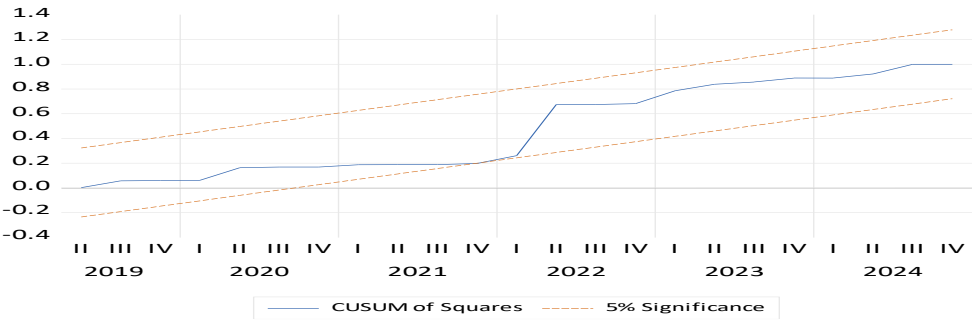


Figure 3 Actual, Fitted, Residual Graphs

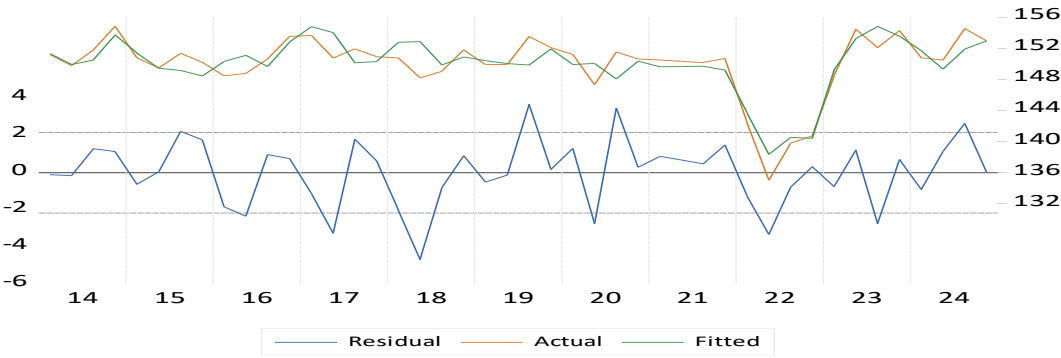
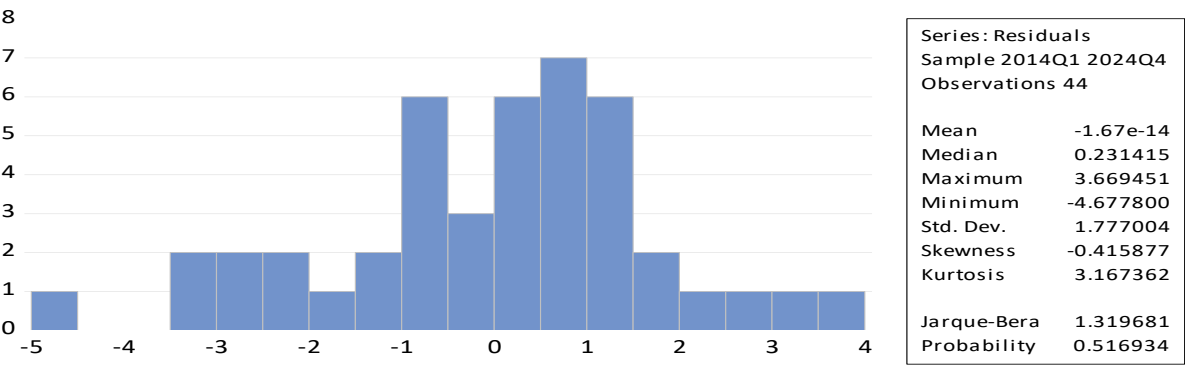


Figure 4 Actual, Fitted, Residual Graphs



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