ICT AND MANUFACTURING SECTOR PERFORMANCE: INSIGHTS FROM APPLICATION OF ARDL BOUNDS TEST APPROACH WITH A STRUCTURAL BREAK TO NIGERIA

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ABSTRACT

This study investigates the impact of Information and Communication Technology (ICT) on Nigeria's manufacturing sector using an annual time series dataset for the period 1981-2021. This is necessitated by the fact that although manufacturing sector plays a catalytic role in economic transformation and industrialization, but in Nigeria, the sector has continued to experience a decline output, prompting a search for solutions. To achieve its objective, the study employs both descriptive and inferential methods of data analyses. For the inferential analysis, the Autoregressive Distributed Lag (ARDL) bounds test with a structural break examines the long-run and short-run effects of ICT on manufacturing performance, controlling for human capital, foreign direct investment (FDI), and capacity utilization. The findings reveal a significant long-run positive impact of ICT and FDI, even after accounting for a structural break in 1993. In the short run, human capital enhances manufacturing output, while FDI has a negative effect in the short-run. These results underscore the importance of strengthening ICT infrastructure, attracting FDI, and enhancing human capital to drive manufacturing growth. Thus, policymakers should foster a conducive environment for digital adoption and foreign investment while prioritizing skills development to maximize the sector's potential.

Keywords: ARDL Bounds Test, Cointegration, Error Correction Model, ICT, Manufacturing Sector Performance, Nigeria

INTRODUCTION

The manufacturing sector has historically been a key driver of economic transformation and industrialisation, fostering national income growth and economic prosperity. Opaluwa, Umeh, and Ameh (2010) emphasise the sector's critical role in economic growth, particularly in advanced economies, through import substitution, export expansion, employment generation, and investment growth. Similarly, Obasan and Adediran (2010) underscore its importance in Nigeria's economic advancement. However, despite its potential, Nigeria's manufacturing sector has faced significant downturns, particularly in the late 1980s, 1990s, and more recently in 2016 and 2017, leading to productivity declines (CBN, 2018). Challenges such as inadequate technological infrastructure, low human capital development, poor foreign investment inflows, and suboptimal capacity utilisation have constrained the sector. Real output declined by approximately 40% between 1994 and 1996, with capacity utilisation peaking at 73.26% in 1981 before falling to 30.40% in 1994 (CBN, 2021).

The role of information and communication technology (ICT) in enhancing Nigeria's manufacturing sector performance has gained increasing attention. Recognised by the United Nations as a strategic pillar under the Sustainable Development Goals (SDGs), ICT is acknowledged by Nigeria's Federal Government as a catalyst for industrial growth (Jadesimi, 2015; Isa, et al, 2026). Measured by internet penetration, ICT influences manufacturing performance through multiple channels. Internet usage enhances information access, knowledge sharing, and market intelligence, enabling firms to adopt advanced technologies and improve productivity (Chinn & Fairlie, 2010). It also streamlines supply chains, optimises production, and reduces transaction costs (OECD, 2017). Furthermore, internet penetration facilitates digitalisation, automation, and e-commerce, boosting operational efficiency and product customisation (Brynjolfsson & McAfee, 2014). Digital platforms enable small and medium-sized enterprises (SMEs) to integrate into global value chains, lowering entry barriers (UNCTAD, 2019). Additionally, internet access fosters workforce skills development through online training, enhancing innovation capacity (Autor, 2015). Increased internet usage also supports research and development (R&D) collaborations, accelerates technological progress, and improves regulatory processes such as business registration and tax compliance (Castells, 2010; World Bank, 2020). Despite these benefits, ICT adoption in Nigeria's manufacturing sector remains suboptimal due to outdated technologies and infrastructural deficiencies, limiting its potential to drive economic growth.

Despite the growing literature on ICT's role in manufacturing performance in Nigeria, several gaps persist. First, empirical studies such as Jatto (2013), Onu, Ibrahim, and Segun (2015), and Madu (2016) remain limited. Second, methodological shortcomings exist. For example, Rahmani, Asil, and Kenari (2015) rely on descriptive analysis without establishing causal relationships, while Shaukat and Zafarullah (2009) employ pooled ordinary least squares (OLS) without considering fixed or random effects. Similarly, Castorena, Enriquez, and Adame (2014) use correlation and chi-square tests, which fail to capture causality, whereas Pohjola (2002) applies correlation analysis to panel data, a methodologically inadequate approach. Empirical findings are also inconclusive; while some studies (e.g., Ghorbanzad & Beig, 2012; Sharma & Singh, 2012; Castorena et al., 2014; Abri & Mahmoudzadeh, 2015) find a significant positive impact of ICT, others (e.g., Kiley, 1999) report a negative relationship, and Pohjola (2002) finds no significant link.

This study aims to bridge these gaps by employing the autoregressive distributed lag (ARDL) bounds test approach

while incorporating structural breaks to analyse the short- and long-run effects of ICT on Nigeria's manufacturing sector. Unlike previous studies that utilise static models or overlook structural shifts, this research integrates break analysis to account for exogenous shocks such as economic recessions, policy changes, or technological advancements. This methodological advancement provides a more nuanced understanding of ICT's impact on manufacturing sector performance over time. Then the question is: Does ICT influence manufacturing sector performance in Nigeria in both the short and long run? To answer this question, the study formulates and tests a null hypothesis that ICT does not have a significant impact on manufacturing sector performance in Nigeria. The study contributes to the literature on innovation and economic development by offering fresh insights into ICT as a driver of industrial transformation. The rest of the paper is structured as follows: Section 2 presents the theoretical framework, Section 3 reviews the literature, Section 4 details the data and methodology, Section 5 discusses the empirical results, and Section 6 concludes with policy recommendations and future research directions.

Theoretical Framework

The relationship between ICT and manufacturing sector performance is best analysed using Endogenous Growth Theory, which attributes economic growth to internal factors such as technological innovation, human capital, and knowledge spillovers (Romer, 1994). Within this framework, ICT enhances productivity, efficiency, and innovation by improving information flow and automation in manufacturing. Empirical evidence supports this perspective. Kamwela (2013) finds that ICT adoption significantly improves productivity and information management in Malawi's manufacturing industry. Similarly, Elsaadani (2014) demonstrates that ICT positively affects workforce productivity in Egyptian industrial organisations. Endogenous Growth Theory is particularly relevant to this study for several reasons. Firstly, ICT drives economic growth by enhancing productivity in manufacturing. Secondly, human capital, measured by average years of schooling, is crucial for innovation and technological adoption. Thirdly, FDI, a key control variable, facilitates technology transfer and capital accumulation. Lastly, manufacturing capacity utilisation reflects internal efficiency, central to the theory's premise.

Alternative theories, such as the Diffusion of Innovation Theory (Rogers, 2003) and the Technology-Organisation-Environment (TOE) Framework (Tornatzky & Fleischer, 1990), offer insights into ICT adoption but do not fully capture the integrated role of ICT, human capital, FDI, and capacity utilisation, making Endogenous Growth Theory the most suitable for this study.

MATERIALS AND METHODS

Literature Review

This section reviews empirical studies examining the influence of Information and Communication Technology (ICT), and other control variables [human capital, Foreign Direct Investment (FDI), and manufacturing capacity utilisation] on manufacturing sector performance. The studies reviewed employ various econometric datasets, including cross-sectional, panel, and time series data, and apply diverse analytical methods to assess these relationships.

Influence of ICT on Manufacturing Sector Performance

Numerous studies have examined the impact of ICT on the performance of various industries, including manufacturing.

This interest is driven by empirical evidence highlighting ICT's role in enhancing productivity (Kamwela, 2016).

Several studies confirm a positive association between ICT investment and firm performance, productivity, and economic growth. Zehir et al. (2010) analyse 81 Turkish firms using correlation and OLS, finding ICT spending significantly improves performance. Castorena et al. (2014) examine 120 Mexican SMEs using chi-square tests, reporting a strong correlation between ICT expenditure and supply chain management. However, these studies do not establish causality.

Hawash and Lang (2010) employ fixed-effects panel models on data from 33 developing countries (2002–2006), finding ICT spending enhances total factor productivity (TFP) growth. Similarly, Abri and Mahmoudzadeh (2015) apply DEA and fixed-effects models to Iran's 23 manufacturing industries (2002–2006), showing a positive impact of IT labour productivity on performance. Shaukat and Zafarullah (2009) analyse 48 Pakistani firms (1994–2005) using OLS and ANOVA, concluding ICT investment significantly improves organisational output, with the banking sector outperforming manufacturing.

Ghorbanzad and Beig (2012) employ structural equation modelling, finding ICT investment enhances productivity in Iran Behnoush Company. Similarly, Sharma and Singh (2012) report a positive relationship between IT capital stock and productivity using OLS and GMM on 8000 Indian manufacturing plants.

Onu et al. (2015) find a strong positive relationship between IT investment and worker productivity in Lagos' sachet water sector, while Dawodu and Osundu (2013) report significant ICT-driven profitability in Nigerian banks. Madu (2016) reveals a strong interaction between technological orientation and performance in 10 Nigerian firms. Jatto (2013) and Sigilai (2020) confirm ICT's long-run benefits using time-series data in Nigeria and Kenya, respectively.

Conversely, some studies highlight limitations. Kiley (1999) finds ICT investment negatively impacts output growth due to adjustment costs, while Pohjola (2002) reports no significant link between ICT investment and output growth in 43 developing countries. Overall, while most studies confirm ICT's positive impact, mixed findings highlight unresolved methodological challenges, necessitating further research.

Influence of Human Capital as a control variable on Manufacturing Sector Performance

Human capital development has been recognised as a crucial factor in enhancing manufacturing sector performance. Several empirical studies confirm a positive impact. For example, Adeyemi and Oseni (2021) apply a Johansen's (1988) cointegration approach to a Nigerian time series dataset covering 1981 to 2020 and find that an increase in average years of schooling significantly enhances manufacturing sector output in the long-run. Likewise, using generalised method of moments (GMM) estimation on a panel dataset of 50 developing countries (1990–2018), Rahman (2020) demonstrates that improvements in human capital proxied by secondary school enrolment rates lead to increased manufacturing productivity.

However, some studies challenge these findings. Bello and Okonkwo (2019) employ a fully modified ordinary least squares (FMOLS) regression on annual data for Ghana from 1980 to 2017 and find no significant impact of human capital on manufacturing growth.

Influence of Foreign Direct Investment as control variable on Manufacturing Sector Performance

Foreign direct investment (FDI) has been widely studied for its role in stimulating the manufacturing sector. Many studies document a positive impact. For instance, using an error correction model (ECM) on annual data for India (1980–2019), Gupta and Sharma (2021) find that FDI inflows significantly increase manufacturing value added in the long-run. Similarly, employing a panel quantile regression approach on data for 20 Latin American countries (1995–2020), Rodriguez (2022) finds that FDI positively affects manufacturing output, but the impact is more pronounced in countries with higher absorptive capacities.

On the other hand, some research identifies limited or no significant effects of FDI on manufacturing. For example, employing a pooled mean group (PMG) estimator on a panel dataset covering 25 African economies from 1985 to 2019, Mensah and Boateng (2020) report no significant relationship between FDI and manufacturing sector output.

Influence of Manufacturing Capacity Utilisation as a control variable on Manufacturing Sector Performance

Manufacturing capacity utilisation is an important determinant of sectoral performance. Several studies report a strong positive relationship between capacity utilisation and manufacturing output. For instance, Owusu and Amankwah (2020) use a dynamic panel data approach on a dataset covering 40 African countries from 1990 to 2018 and establish that higher capacity utilisation rates significantly enhance manufacturing productivity.

Nevertheless, other studies present contrasting findings. For example, Kamau and Njoroge (2022) apply a Markov-switching model on quarterly data for Kenya (1995Q1–2020Q4) and find that the effect of capacity utilisation on manufacturing performance varies across different economic regimes. In contrast, Adams and Mensah (2021) use a Bayesian vector autoregressive (BVAR) model on a panel of West African economies (1985–2019) and find no significant relationship between capacity utilisation and manufacturing sector growth.

Research Gaps

While several studies have examined the impact of ICT, human capital, FDI, and capacity utilisation on manufacturing sector performance, gaps remain. First, most existing studies either exclude structural breaks in the relationships. Second, many studies focus on developed economies, with limited attention to Nigeria's unique economic and policy context. Third, the literature presents mixed findings, highlighting the need for further investigation using robust methods such as the ARDL bounds test with structural breaks. Finally, few studies integrate ICT with other explanatory variables to assess its combined effect on manufacturing sector performance. This study, therefore, fills these gaps by employing a comprehensive econometric approach that incorporates structural break.

Methodology

This section outlines the data sources, sample size, variable measurement, and the methodological approach employed in this study. It provides a detailed justification for the application of the Autoregressive Distributed Lag (ARDL) bounds test with a structural break, alongside the model specification and post-estimation tests. The methods adopted ensure robustness in capturing the relationship between information and communication technology (ICT) and manufacturing sector performance in Nigeria. Relatedly, for the purpose of this study, causal research design which is primarily to determine the cause-effect relationship between variables quantitative research approach has been employed to test the respective hypotheses from the secondary data obtained.

Data

This study has sourced its annual time series dataset from the Quality of Government (QoG) (2023) annual time series dataset of the QoG Institute of the University of Gothenburg, Sweden; the Central Bank of Nigeria (CBN) (2022) statistical bulletin; and the World Bank Development Indicators (2023) for the period 1981-2021(41 observations for each variable used). These sources provide comprehensive and credible data for analysing the impact of ICT on manufacturing sector performance in Nigeria. Dataset on manufacturing sector performance (output) and capacity utilisation has been obtained directly from CBN statistical bulletin. On the other hand, dataset on FDI and exchange rate has been sourced from World Bank development indicators (2023). While ICT and human capital index dataset has been sourced from the archive of Quality of Government (QoG) Institute, University of Gothenburg, Sweden.

Sample Size and Sampling Technique

The study covers the period from 1981 to 2021, chosen based on data availability for all the variables of interest. The use of a 41-year dataset ensures sufficient observations to capture both short-run and long-run relationships while accounting for structural changes in Nigeria's manufacturing sector.

Variables Measurement

The study employs the following variables:

Dependent Variable

Manufacturing sector performance: This has been measured as total contribution of manufacturing sector industries to nominal Gross Domestic Product (GDP) in billions of naira. This measurement aligns with previous studies, such as Adebayo and Dada (2021), which assess industrial contributions to economic growth using similar indicators.

Independent Variable

Information and communication technology (ICT): This has been measured as individuals using the internet as a percentage of the population.

Control Variables

Human capital: This has been measured as average years of schooling; Foreign direct investment (FDI): This has been measured as total net inflows of investment in trillions of naira, following the method adopted by Akinlo (2004), who examines FDI inflows and their effect on sectoral performance; and Manufacturing capacity utilisation has been measured as the percentage of manufacturing industries' total possible production capacity. This measure is in line with Ali and Mnafo (2019), who assess industrial efficiency through capacity utilisation rates.

Methods of Data Analyses

This subsection presents the analytical techniques used to achieve the objectives of the study. The study employs both descriptive and inferential statistical methods.

Descriptive Analysis

Descriptive statistics, including the mean, standard deviation, minimum, and maximum values, have been computed for

each variable to provide insights into their distribution and variability over the study period.

Inferential Analysis
Inferential analysis is conducted to examine the impact of ICT on manufacturing sector performance while controlling for human capital, foreign direct investment, and manufacturing capacity utilisation.

Pre-Estimation Tests
Before proceeding to analyse the dataset, some tests must be conducted to confirm some time series regression assumptions. These tests include test for trending, optimum lag selection test, unit root test, test for structural break and cointegration test. To ensure robustness, the study has conducted various pre-estimation tests. These include trending analysis, optimum lag selection, unit root tests using the Phillips and Perron (1988) and Clemente, Montañes and Reyes (1998) methods, and a test for structural breaks.

Test for Trending
This is drawing a line graph of a time series variable with a time period. If a series variable appears to be trending together and its mean is not zero, trend variable and constant ought to be incorporated into the unit root testing (Dougherty, 2007). Yet, when the series variables exhibit no discernible curve, but the series mean seems greater than zero, it's advisable to solely include a constant in the unit root regressions (Dougherty, 2007). Conversely, if the series variables reveal no apparent trend and the series mean appears to be zero, there is no need for adding a constant and a trend (Dougherty, 2007).

Optimum Lag Selection Test
In time series models, selecting the appropriate number of lags is crucial to minimise collinearity. Glynn, Perera, and Verma (2007) suggest using the Akaike Information Criterion (AIC) to determine optimal lag length. Dougherty (2007) highlights the popularity of AIC and the Bayes Information Criterion (BIC) in time series analysis, with BIC penalising additional parameters more strictly. While BIC provides more consistent lag length estimates in small samples, neither method is superior in finite samples, and both are widely used in practice (Dougherty, 2007). The optimal model minimises the respective test statistic.

Unit Root Test
Unit root tests are essential for assessing stationarity in time series data. Common methods include the Dickey-Fuller (DF) test (Dickey & Fuller, 1979), the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1981), and the Phillips-Perron (PP) test (Phillips & Perron, 1988). This study employs Clemente, Montañés, and Reyes (1998) to detect structural breaks and PP for cases without significant breaks. The PP test adjusts for serial correlation and heteroscedasticity using the Newey-West covariance matrix (Newey & West, 1987; Vanegas & Croes, 2007). The null hypothesis states that a variable has a unit root, indicating non-stationarity.

Phillips and Perron (1988) unit root unit root test equations can be expressed as:

$$\Delta Y_t = a_0 + a_1 Y_{t-1} + \beta_1 trend_t + \sum_{i=1}^{m} a_i \Delta Y_{t-i} + \varepsilon_t \quad (1)$$
$$\Delta Y_t = a_0 + a_1 Y_{t-1} + \sum_{i=1}^{m} a_i \Delta Y_{t-i} + \varepsilon_t \quad (2)$$
$$\Delta Y_t = a_1 Y_{t-1} + \sum_{i=1}^{m} a_i \Delta Y_{t-i} + \varepsilon_t \quad (3)$$

Where:
Y_t stands for the series variable and αs are the estimated parameters. If a series variable is trending and its mean is not zero, Equation (1) should be applied. However, if the variable is not trending, but the mean is zero, then Equation (2) should be applied. Nonetheless, if the variable is not trending and its mean is zero, Equation (3) should be applied.

The choice of unit root test equations depends on whether a series is integrated of the same order or mixed order. If all variables are integrated of order 1, i.e., I(1), an autoregressive distributed lag (ADL) bounds test model cannot be used to assess long-run relationships. If variables are stationary at level, or some of them are stationary at level and others at first difference, the autoregressive distributed lag (ARDL) bounds test is appropriate for the analysis.

Test for Structural Breaks
A structural break signifies an unexpected shift in a time series, potentially affecting model reliability and forecasting accuracy (Mills & Birks, 2014). Traditional time series models assume stable relationships; however, if a break is suspected, it must be accounted for in the regression model. The Clemente et al. (1998) unit root test examines whether a series is non-stationary with a structural break, rejecting the null hypothesis if the test statistic exceeds the critical value (Glynn, 2007). This test, based on Perron and Vogelsang (1992), allows for up to two structural breaks in the series mean (Parpiev, 2016). Accounting for such breaks enhances econometric analysis and ensures robust results. The test offers two models:

i. An additive outlier (AO) model that captures abrupt adjustments in the average of the series, and
ii. An innovative outlier (IO) model that permits a gradual shift in the average of the series

Clemente et al. (1998) unit root test equation with one structural break can be expressed as:

$$\Delta Y_t = a_0 + a_1 Y_{t-1} + \beta_1 DU_t + \beta_2 DT_t \sum_{i=1}^{m} a_i \Delta Y_{t-i} + \varepsilon_t \quad (4)$$

Where:
DU_t and DT_t break dummy variables represent a average shift and a curve shift, correspondingly. The shift crop up at every potential breakdown point.

ARDL Bounds Test with a Structural Break
The study applies the Autoregressive Distributed Lag (ARDL) bounds test approach with a structural break to examine the long-run relationship between ICT and manufacturing sector performance. The ARDL model is appropriate given the potential mix of stationary and non-stationary variables (Pesaran, Shin, & Smith, 2001). Additionally, the inclusion of a structural break accounts for significant economic events that may have impacted Nigeria's manufacturing sector. This approach has been applied in various studies, such as Narayan (2005), who extends the ARDL framework to account for structural changes in economic modelling.

Model Specification
The ARDL bounds test model for this study is specified as follows:

$$\Delta \ln MANUFACTOUTP_t = \beta_0 + \sum_{i=1}^{m} b_i \Delta \ln MANUFACTOUTP_{t-i} + \sum_{i=1}^{m} c_i \Delta WDI\_INTERNET_{t-i} +$$
$$\sum_{i=1}^{m} d_i \Delta PWT\_HCI_{t-i} + \sum_{i=1}^{m} e_i \Delta \ln FDI_{t-i} + \sum_{i=1}^{m} f_i \Delta MANUFACAPUTZ_{t-i} + \sum_{i=1}^{m} g_i \Delta BREAKDUM_{t-i} +$$
$$\theta_1 \ln MANUFACTOUTP_{t-1} + \theta_2 \ln WDI\_INTERNET_{t-1} + \theta_3 PWT\_HCI_{t-1} + \theta_4 \ln FDI_{t-1} + \theta_5 MANUFACAPUTZ_{t-1} +$$
$$\theta_6 BREAKDUM_{t-1} + \mu_{1t} \quad (5)$$

Where:

Δ is the first difference operator and m is the optimal lag length. The optimal lag length m in the equations has been selected using Likelihood Ration Criterion (LR), Akaike Information Criterion (AIC), Bayes Information Criterion (BIC), also known as the Schwartz Information Criterion (SIC), Hannan-Quinn Information criterion (HQIC), and Final Prediction Error (FPE) using varsoc Stata command. *MANUFACTOUTP* is the natural log of manufacturing output as a gauge of manufacturing performance. *WDI_INTERNET* is a proxy for ICT, *PWT_HCI* is human capital index as a control variable measuring human capital development, BREAKDUM is the break period dummy, and *lnFDI* is natural log of FDI in naira (as another control variable). β0 is the constant parameter included in the equation. But parameters *b, c, d, e, and g,* represent vectors containing coefficients derived from the first-difference lagged values of the variables incorporated in the system, signifying the short-term movement of the model's coming to equilibrium. Furthermore, β1 to β5 in the equation stand for the coefficients of the level lagged values of the explanatory variables included in the model, indicating long phase crescendos of the model's coming to equilibrium.

The null hypothesis stating no cointegration midst the variables in Equation 5 where manufacturing sector output is the dependent variable is: H_0: $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$ against the alternative hypothesis H1 H_1: $\beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq \beta_5 \neq 0$. This is denoted as *F(lnMANUFACTOUTP| WDI_INTERNET, PWT_HCI, lnFDI,* MANUFACAPUTZ*).* Should the cyphered F statistic surpass the upper critical value, it permits the rejection of the null hypothesis of no cointegration. Conversely, should it fall below the lower critical value, the null hypothesis remains unaltered. If, however, the F statistic value lies between the lower and upper critical values, the outcome becomes inconclusive (Oktayer & Oktayer, 2013).

Error Correction Model

The establishment of cointegration and the subsequent estimation of the long-run relationships will pave way for the specification and estimation of the error correction model to determine the short-run movement of the model. This can be applied only if there is evidence of cointegration. The ECM entails regressing the first difference of each variable in the cointegrating equation against the first lagged values of the first difference of all variables, along with one lagged level value of the ect (error correction term) derived from the cointegrating equation (Miller, 1991). The error correction term encapsulates the short-phase model's dynamics, illustrating the pace of adjustment as of short-phase equilibrium to long-phase equilibrium. A higher absolute rate of the adjustment parameter signifies a swifter adjustment as of short-phase to long-phase equilibrium, with an anticipated negative insignia for the coefficient of the ect (Johansen, 1988).

In the final step of the bounds testing procedure according to Oktayer and Oktayer (2013), short-lane parameters mechanics are gotten by assessing an ECM allied with the long-lane ballpark figures of the lag level cointegrated variables. This can be done by estimating the ect from the cointegrated variables model. To gauge the rate at which the dependent variable adjusts to independent variable(s), one must consider the lagged level variables in Equation (5) that indicates the existence of cointegration are replaced by ectt-1 (one lag level value of ECM) in Equation (6):

$$\Delta lnMANUFACTOUTP_t = \beta_0 + \sum_{i=1}^{m} b_i \Delta lnMANUFACTOUTP_{t-i} + \sum_{i=1}^{m} c_i \Delta WDI\_INTERNET_{t-i} + \sum_{i=1}^{m} d_i \Delta PWT\_HCI_{t-i} + \sum_{i=1}^{m} e_i \Delta lnFDI_{t-i} + \sum_{i=1}^{m} f_i \Delta MANUFACAPUTZ_{t-i} + \sum_{i=1}^{m} g_i \Delta BREAKDUM_{t-i} + \lambda ect_{t-1} + \mu_t$$

$$(6)$$

In Equation (6), bi to gi are the short-lane patterns coefficients of the system's merging to equilibrium while λ is the coefficient of speed of adjustment and ect is the error correction term (ECT) gotten from the long-phase interactions. If the fallout of the error correction term (ECT) is zero, it portends that there exists no long-phase interactions (Oktayer & Oktayer, 2013). Moreover, if it is between -0.99 and -0.01, partial adjustment is present (Oktayer & Oktayer, 2013). But, a value of -1 indicates complete adjustment. A less value than "-1" (i.e., -1.1, -1.5, -2.0, etc.) shows that the model is over adjusting at the moment (Oktayer & Oktayer, 2013). However, A positive insignia indicates that the structure diverges from long-term equilibrium (Oktayer & Oktayer, 2013).

Post-Estimation Tests

Post-estimation diagnostic tests include the Ramsey RESET test for omitted variables bias, the Lagrange Multiplier (LM) test for autoregressive conditional heteroskedasticity (ARCH), the Breusch and Godfrey (1979) LM test for autocorrelation, the Durbin and Watson (1950) d-statistic, commonly known as Durbin-Watson d-statistic, the Jarque and Bera (1987) normality test, commonly known as Jarque-Bera normality test, and stability tests such as the CUSUM and CUSUMSQ tests. These tests ensure the reliability and validity of the estimated model.

RESULTS AND DISCUSSION

This section presents and discusses the empirical findings derived from the application of the ARDL bounds test approach with a structural break, providing insights into the relationships between the variables under study.

Results

Descriptive Results

Table 1 presented the summary statistics of the variables used in the study, including the number of observations, mean values, and the minimum and maximum values for each variable. The manufacturing sector output had an average value of ₦3.88 trillion, with a minimum of ₦28.23 billion and a maximum of ₦25.73 trillion over the study period. These figures suggested that the manufacturing sector exhibited substantial growth over time, although significant variability existed across the years.

ICT, measured as the percentage of individuals using the internet, had a mean value of 7.41%, with a minimum of 0% and a maximum of 35.50%. This indicated that internet penetration in Nigeria increased considerably during the study period, reflecting improvements in digital infrastructure and accessibility. The human capital index from the Penn World Table recorded an average of 1.51, ranging from 1.2 to 1.97. This relatively low variation suggested a gradual improvement in human capital development, though the overall level remained relatively modest.

Table 1: Results of Descriptive Analysis

Items	No. of Observations	Mean	Minimum	Maximum
Manufacturing sector output	41	3,879,580,000,000	28,230,000,000	25,725,870,000,000
ICT (Individuals using internet as a % of population)	41	7.41	0	35.50
Penn world table human capital index	41	1.51	1.2	1.97
Foreign direct investment in trillions of naira	41	386,700,000,000	145,700,000	1,360,285,925,376
Manufacturing capacity utilization	41	47.96	30.4	73.26

Foreign direct investment (FDI) inflows, measured in trillions of naira, showed substantial variation, with a mean of ₦386.7 billion, a minimum of ₦145.7 million, and a maximum of ₦1.36 trillion. The large disparity between the minimum and maximum values suggested that FDI inflows fluctuated significantly over time, possibly due to changes in economic policies, global investment trends, and domestic macroeconomic conditions.

Manufacturing capacity utilisation averaged 47.96%, with a minimum of 30.4% and a maximum of 73.26%. This indicated that, on average, the manufacturing sector operated below full capacity, with some periods of relatively high utilisation. The low minimum value suggested periods of economic downturn or infrastructural challenges that constrained industrial output.

Overall, the descriptive analysis revealed notable variations in the key variables, highlighting trends such as the increasing role of ICT, fluctuating FDI inflows, and underutilisation of manufacturing capacity. These findings underscored the importance of policies aimed at enhancing digital adoption, improving industrial productivity, and stabilising investment inflows to support the manufacturing sector's performance.

Inferential Analysis and Interpretation of Results
This subsection deals with inferential analysis and interpretation of results, consisting of pre-estimation tests (tests for trending, optimum lag selection, and unit root with and without structural breaks), ARDL bounds test with structural breaks, and post-estimation tests (diagnostic tests).

Pre-Estimation Test Results
This subsection also dwells on pre-estimation tests, consisting of tests for trending, optimum lag selection, structural breaks, and unit root.

Results of the test for trending
The results the test indicate that at their level values, all variables exhibit a trending pattern, suggesting potential non-stationarity. Additionally, the mean of each variable at its level is greater than zero, reinforcing the presence of long-term growth trends. However, after first differencing, foreign direct investment (FDI) and manufacturing capacity utilisation cease to trend, whereas manufacturing sector output, ICT usage, and the human capital index continue to exhibit a trending pattern.

In terms of mean values, the first difference transformation reduces the mean of FDI and manufacturing capacity utilisation to zero, suggesting that these variables exhibit characteristics of a stationary process after differencing. Meanwhile, the persistence of a mean greater than zero for the other variables implies that they may still exhibit some degree of trend even after differencing.

Results of the test for optimum lag selection
The results of the optimum lag selection at the level values of the variables based on multiple selection criteria in the form of Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Hannan-Quinn Information Criterion (HQIC), and Schwarz/Bayesian Information Criterion (SBIC) indicate that the natural log of manufacturing sector output requires two lags, while ICT usage and the Penn World Table human capital index both require four lags at their level values. Similarly, the natural log of foreign direct investment (FDI) and manufacturing capacity utilisation are best modelled with two lags. These findings highlight varying degrees of persistence, with ICT usage and human capital exhibiting longer lag structures, while manufacturing sector output, FDI, and capacity utilisation respond more quickly to past changes. These results underscore the importance of appropriate lag selection in econometric modelling, ensuring robust estimations, minimising autocorrelation, and reducing misspecification errors in vector autoregression (VAR) or autoregressive distributed lag (ARDL) models.

The results of the optimum lag selection at the first differenced values of the variables, using multiple selection criteria reveal that the first differenced values of natural log of manufacturing sector output and foreign direct investment (FDI) require one lag, while ICT usage and the Penn World Table human capital index are best modelled with three lags. Manufacturing capacity utilisation is optimally lagged at two periods.

The results indicate generally shorter optimal lag structures after differencing, as expected, though some variables exhibit short-term dependence. These findings are critical for unit root tests and econometric modelling, particularly in determining the order of integration and selecting appropriate lag structures in ARDL or VAR models, ensuring model accuracy while minimising serial correlation and overfitting.

Results of the test for unit root
Table 2 presents the results of the Clemente et al. (1998) and Phillips and Perron (1988) unit root tests, assessing the stationarity of variables at both level and first-differenced values.

Table 2: Results of Clemente et al. (1998) and Phillips and Perron (1988) Unit Root Tests

Variable	Clemente et al. (1998) H0: a series is not stationary with one structural break				Phillips and Perron (1988) H0: a series is not stationary	
	LEVEL		1st difference		LEVEL	1st difference
	Test statistics				Test statistics	
	Unit Root	Structural Break (du1)	Unit Root	Structural Break (du1)		
Manufacturing sector output	-1.712(2)	3.663***	-4.437(1)**	-0.007	-1.628	-3.682**
ICT (individuals using internet as a % of population)	-2.008(4)	26.418***	-6.032(3)**	1.939***	-1.177	-4.457***
Human Capital Index	-2.242(4)	0.481***	-4.938(3)**	0.021***	-3.837**	
foreign direct investment naira in trillions of naira	-2.381(2)	5.048***	-9.005(1)**	-0.146	-2.062	-8.619***
Manufacturing capacity utilisation	-5.211(2)**	13.549***	-	-	-4.416***	

Note: *, ** and *** show levels of acceptance at 10%, 5% and 1% respectively. Also, figures in parenthesis indicate the number of lags inclusion

The Clemente et al. (1998) test accounts for structural breaks, whereas the Phillips-Perron test assumes none. Both tests indicate non-stationarity at levels for most variables but confirm stationarity after first differencing, suggesting they follow an I(1) process. Manufacturing sector output, ICT usage, human capital index, and foreign direct investment (FDI) become stationary after differencing, with significant structural breaks. However, manufacturing capacity utilisation is stationary at levels based on the Clemente et al. (1998) test, rejecting the Phillips-Perron findings.

These results suggest that cointegration techniques like the Johansen test are unsuitable with mixed integration, whereas the ARDL bounds testing approach is appropriate. The presence of structural breaks highlights the need to account for such disruptions to avoid misleading inferences in time series analysis.

Results of the Gregory and Hansen (1996) test for structural break period

The results of the Gregory and Hansen (1996) test for identifying the structural break period for consideration in the ARDL bounds test approach with structural breaks in the constant and the trend indicate the break period was 1993 corresponding to Zt statistic. Hence, we generate a dummy variable for the break period and add it into the ARDL bounds tryout cointegration model since all the variables to be captured in the model are trending and their means are not zero at their level values.

Table 3: Results of ARDL Bounds Test for Cointegration with Structural Break

Dependent Variable = Manufacturing sector output in billions of naira		
	H0: No levels relationship	
Test Statistics		
F-Statistic	28.863	
T-Statistic	-10.342	
	I(0)	I(1)
Critical F Values (1%)	3.41	4.68
Critical T Values (1%)	-3.43	-4.79
Critical F Values (5%)	2.62	3.79
Critical T Values (5%)	-2.86	-4.19
Critical F Values (10%)	2.26	3.35
Critical T Values (10%)	-2.57	-3.86

Table 3 presents the ARDL bounds test for cointegration with a structural break, assessing the long-run relationship between explanatory variables and manufacturing sector output. The null hypothesis of no cointegration is rejected as the absolute F-statistic (28.863) exceeds the upper bound I(1) critical value at even the 1% significance level (4.68). This confirms the existence of a stable long-run relationship. If the statistic had fallen between the lower and upper bounds, the result would be inconclusive, while a value below the lower bound would indicate no cointegration. Additionally, the absolute t-statistic (10.342) surpasses the upper bound I(1) critical value (-4.79) at the 1% level, further validating cointegration and a significant speed of adjustment. The error correction term (ECT) in Table 8 is negative (-0.433) and significant at 1%, reinforcing the presence of a stable long-run equilibrium.

Regression Results
Table 4: Results of ECM for the Long-run Relationship and Diagnostic Tests

Dependent variable = Manufacturing sector output in billions of naira	Long-run Model Coefficients	Short-run Model
ICT (Individuals using internet as a % of population)	0.553***	0.001
	(4.16)	(0.05)
Penn world table human capital index	0.968	5.148***
	(1.10)	(3.74)
Foreign direct investment in naira	0.305***	-0.125***
	(8.59)	(-7.59)
Manufacturing capacity utilisation	0.006	
	(0.78)	
Break period (breakdum93)	2.174***	-0.476***
	(9.44)	(-4.90)
Error Correction Term (ECT)	-0.433***	
	(-10.34)	
Ramsey RESET test for omitted variables	1.64	
	[0.230]	
LM test for autoregressive conditional heteroskedasticity (ARCH)	0.004	
	[0.949]	
Breusch-GodfreyLM test for autocorrelation	0.654	
	[0.419]	
Durbin–Watson d-statistic	1.797	
Jarque-Bera normality test:	1.36	
	[0.507]	
Observations	41	
R^2	0.946	
Adjusted R-squared	0.886	

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Values in brackets are t-ratios, but those in parentheses are p-values for diagnostic tests

Table 4 presents the results of the Error Correction Model (ECM), examining the long-run and short-run dynamics between ICT usage, human capital, foreign direct investment (FDI), and manufacturing sector output. In the long run, ICT usage significantly boosts manufacturing output (0.553, $p<0.01$), while FDI also has a positive effect (0.305, $p<0.01$). However, human capital and manufacturing capacity utilisation are not significant. The structural break in 1993 is significant (2.174, $p<0.01$), indicating a major shift in sectoral performance. In the short run, human capital positively impacts output (5.148, $p<0.01$), while FDI has a temporary negative effect (-0.125, $p<0.01$). The break period also negatively affects short-term output (-0.476, $p<0.01$). The error correction term (-0.433, $p<0.01$) confirms a stable long-run relationship, with 43.3% of deviations corrected each period. Diagnostic tests confirm model robustness, with no omitted variable bias, autocorrelation, or heteroskedasticity. Residuals are normally distributed, and the Durbin-Watson statistic (1.797) suggests no severe autocorrelation. Figure 1 shows the results of the cumulative sum of squares (CUSUM squared) test. This test is used to assess the stability of regression coefficients over time. The graph plots the CUSUM squared values against time, with the horizontal axis representing the years from 1988 to 2019. The two straight lines represent the critical bounds at the 5% significance level. The line continues to fluctuate within the bounds for the remaining period. The line has remained within the bounds since the crossing, suggesting a period of stability following the initial change. The CUSUM squared test suggests that the line has remained within the bounds and indicates that the model has stabilised.
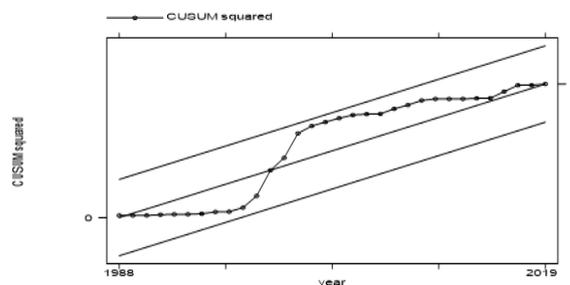

Figure 1: Cumulative Sum Test

Discussion
The empirical findings indicate that ICT positively influences manufacturing sector performance in the long run, aligning with Zehir et al. (2010) and Abri and Mahmoudzadeh (2015), who highlight ICT's role in enhancing productivity, efficiency, and information flow. Similarly, Castorena et al. (2014) confirm that ICT investment strengthens supply chain performance in manufacturing SMEs, reinforcing the argument that sustained ICT investment fosters industrial competitiveness and growth. Human capital, as a control variable, has a positive short-run impact but no significant long-run effect on manufacturing performance. This supports

Adeyemi and Oseni (2021), who assert that human capital investments yield immediate productivity gains but require complementary technological advancements for long-term growth. FDI exerts a negative short-run effect but a positive long-run impact, consistent with Akinlo (2004), who suggests that initial FDI inflows may disrupt domestic industries but later enhance capital accumulation and technology transfer. Ali and Mnafo (2019) find similar evidence in Sub-Saharan Africa. Structural breaks, notably in 1993, further highlight the role of economic policies and external shocks, supporting Gregory and Hansen (1996). Given the evidence of a long-run equilibrium relationship among ICT, human capital, FDI, and manufacturing sector performance, the null hypothesis that ICT does not have a significant long-run impact on manufacturing sector performance in Nigeria is rejected.

CONCLUSION

This study examines the impact of ICT on manufacturing sector performance in Nigeria using an ARDL bounds test approach with a structural break. The findings confirm a significant long-run relationship, with ICT usage and FDI positively influencing manufacturing output. However, human capital and manufacturing capacity utilisation show no long-run effects. In the short run, human capital positively impacts output, while FDI exerts a negative effect. The 1993 structural break significantly affects sectoral performance. Robust diagnostic tests validate the model, underscoring the need for policies that enhance ICT infrastructure, attract FDI, and develop human capital to drive manufacturing growth.

POLICY IMPLICATIONS AND RECOMMENDATIONS

The positive impact of ICT on manufacturing output highlights the need for investments in digital infrastructure, including broadband expansion, lower internet costs, and digital literacy initiatives. To attract FDI, the Nigerian government should streamline investment procedures, ensure political stability, and provide incentives for manufacturing investments. While human capital has no long-run effect, its short-run impact underscores the need for quality education, vocational training, and skills development. The 1993 structural break highlights the importance of stable economic policies. Improving manufacturing capacity utilisation requires infrastructure development, reliable energy supply, and local raw material sourcing to enhance sectoral productivity and growth.

SUGGESTIONS FOR FURTHER RESEARCH

Future studies could conduct a disaggregated analysis of ICT's impact on specific manufacturing sub-sectors for targeted policy insights. Comparative analyses with other developing economies may reveal contextual factors influencing ICT-manufacturing performance links. Extending the study period could capture evolving sectoral dynamics, while exploring alternative ICT measures, such as e-commerce adoption and digital skills, would provide a more comprehensive understanding of ICT's role in manufacturing.

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