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Political Risk, Energy Supply, and Manufacturing Performance in Nigeria: A Bayesian ARDL Analysis of Internet Search Behaviour and Traditional Macroeconomic Indicators

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ABSTRACT

This paper investigates both the long and short-run effects of political risk, energy availability, and traditional macroeconomic indicators on manufacturing performance in Nigeria using monthly data from January 2010 to December 2025. The relationships are estimated using a Bayesian Error Correction Autoregressive Distributed Lag (ECM-ARDL) model, which provides probabilistic inference through posterior distributions and credible intervals. The findings indicate that energy availability is the strongest positive determinant of manufacturing performance, providing decisive posterior evidence that reliable electricity supply enhances industrial productivity. In contrast, political risk and exchange rate depreciation exert persistent negative effects on manufacturing performance, while inflation, oil prices, and monetary policy exhibit comparatively weaker posterior evidence after accounting for structural and institutional factors. The Bayesian results further revealed a slow adjustment towards long-run equilibrium, suggesting that shocks to Nigeria's manufacturing sector are highly persistent. Methodologically, the study demonstrates the value of integrating internet search behaviour with Bayesian econometric modelling to capture evolving political uncertainty. The findings suggest that sustainable manufacturing growth requires coordinated improvements in electricity reliability, political stability and macroeconomic management, providing important evidence for industrial policy and manufacturing development in Nigeria and other developing economies.

Keywords: Bayesian ECM-ARDL, Energy Availability, Internet, Manufacturing performance, Nigeria, Political risk.

JEL Classification: C11, C32, E32, Q43, O55

1. Introduction

Manufacturing occupies a distinctive position in economic development because it generates productivity gains, technological learning, structural transformation and strong linkages with other productive sectors (Szirmai, 2012; Rodrik, 2013; Haraguchi et al., 2017). The expansion of manufacturing facilitates the reallocation of labour and capital from low-productivity activities towards higher value-added production, supporting income growth and long-run economic development (Lewis, 1954; Kuznets, 1966). Industrial development therefore remains an important policy objective across developed and developing economies as governments seek to strengthen productive capacity, create employment and build resilience against economic and environmental shocks (UNIDO, 2024). Manufacturing performance also depends on the institutional and political conditions governing firms' investment and production decisions, since credible institutions can reduce uncertainty and transaction costs while political risk can constrain industrialisation (North, 1990; Acemoglu & Robinson, 2012; Kafoo Fotio & Karim, 2024). Political uncertainty, unreliable energy systems, supply chain disruptions and macroeconomic instability increasingly influence investment decisions, production planning and industrial competitiveness (Moradlou et al., 2024; Shu et al., 2024; Sohail et al., 2025; Hossain et al., 2026).

In Nigeria, manufacturing continues to operate under persistent structural constraints. The country possesses one of Africa's largest manufacturing markets and substantial industrial potential, yet manufacturing value added has remained below expectations despite decades of economic reforms. Frequent electricity interruptions, dependence on imported industrial inputs, exchange rate instability, inflationary pressures and recurring political uncertainty continue to increase production costs and discourage long-term industrial investment (Aliyu et al., 2013; Mukhtar et al., 2021; Magazzino et al., 2023). Energy shortages compel many firms to rely on self-generation, while policy uncertainty and security concerns increase operational risks across manufacturing value chains. These conditions make Nigeria an appropriate setting for examining how political risk, energy availability and macroeconomic conditions interact to influence manufacturing performance.

Although an extensive empirical literature has examined these relationships, three important limitations remain. First, most studies investigate political risk, energy supply and macroeconomic conditions independently, providing limited evidence on their combined influence on manufacturing performance. Second, political risk is typically measured using conventional institutional indices or expert assessments that may not capture rapidly changing public perceptions of political uncertainty. Internet search behaviour has recently emerged as a useful behavioural indicator of uncertainty in studies of climate risk, commodity markets and economic expectations (Fahmy, 2025; Zhao et al., 2023), yet its application to political risk and manufacturing performance remains largely unexplored. Third, Bayesian applications have expanded rapidly across energy and environmental economics because they provide probabilistic inference and more flexible treatment of parameter uncertainty than conventional estimation methods (Abbasi et al., 2022; Ngoc & Awan, 2022; Salakpi et al., 2022). Evidence applying Bayesian ECM–ARDL models to manufacturing performance, particularly in developing economies, remains limited.

This study addresses these limitations by examining the effects of political risk, energy availability and traditional macroeconomic indicators on manufacturing performance in Nigeria using monthly data covering January 2010 to December 2025. Political risk is measured through a novel Political Risk

Index constructed from Google Trends search intensity, while electricity conditions are represented by a composite Energy Availability Index. Long-run and short-run relationships are estimated using a Bayesian Error Correction Autoregressive Distributed Lag (ECM–ARDL) model, allowing parameter uncertainty to be evaluated through posterior distributions and credible intervals instead of relying solely on classical hypothesis testing.

Research Question

The study seeks to answer the following research question:

How do political risk, energy availability, and traditional macroeconomic indicators jointly influence manufacturing performance in Nigeria?

Objective of the Study

The objective of this study is to examine the combined effects of political risk, energy availability, and traditional macroeconomic indicators on manufacturing performance in Nigeria using a Bayesian Error Correction Autoregressive Distributed Lag (ECM–ARDL) model.

2. Literature Review

2.1 Conceptual Literature Review

Manufacturing performance generally refers to the ability of the manufacturing sector to generate sustained improvements in output, productivity, value added and industrial competitiveness. Although previous studies have measured manufacturing performance using manufacturing value added, industrial production, labour productivity and capacity utilisation, no single indicator fully captures the multidimensional nature of manufacturing activity (Szirmai, 2012; Haraguchi et al., 2017). Similar conceptual diversity exists in the literature on political risk. Earlier studies defined political risk primarily as the possibility that political events or government actions could adversely affect business operations and investment decisions (Howell, 2001). More recent literature adopts a broader interpretation, viewing political risk as uncertainty arising from political institutions, governance quality, security conditions, regulatory changes and geopolitical developments that influence firms' expectations and economic behaviour (Kaya et al., 2025; Kafo Fotio & Karim, 2024). This broader perspective recognises that political risk extends beyond observable political events to include changes in perceived uncertainty that shape production and investment decisions.

The concept of energy availability has also evolved beyond conventional measures of electricity generation and installed capacity. Recent studies argue that reliable, accessible and secure electricity supply provides a more comprehensive representation of energy conditions because industrial production depends on the continuous availability of usable energy rather than electricity generation alone (Magazzino et al., 2023; Afolabi et al., 2025). These developments have encouraged the use of composite indicators that capture multiple dimensions of energy systems. Consistent with this perspective, the present study conceptualises manufacturing performance as the outcome of interactions between political risk, energy availability and macroeconomic conditions. Manufacturing performance is proxied by the Manufacturing Output Index, political risk is measured through a Google Trends-based Political Risk Index that captures changes in public attention to political uncertainty, while energy availability is represented by a composite Energy Availability Index combining conventional electricity indicators with behavioural information. This conceptualisation provides a broader representation of

the production environment than approaches relying exclusively on traditional macroeconomic indicators.

2.2 Theoretical Review

Manufacturing performance depends on the interaction between productive inputs and the institutional environment in which firms operate. Neoclassical and endogenous growth theories argue that output depends on the accumulation and efficient utilisation of productive inputs, including physical capital, labour, technological progress and knowledge, which jointly determine long-run productive capacity and economic growth (Solow, 1956; Romer, 1990). Electricity constitutes an essential intermediate input in modern production systems, as reliable supply can raise productive efficiency by reducing interruptions, lowering operating costs and increasing capacity utilisation. Exchange rates, inflation, oil prices and monetary conditions also influence production decisions through input costs, investment incentives, aggregate demand and access to finance. Production theory therefore provides the basis for examining how energy availability and macroeconomic conditions affect manufacturing performance over time.

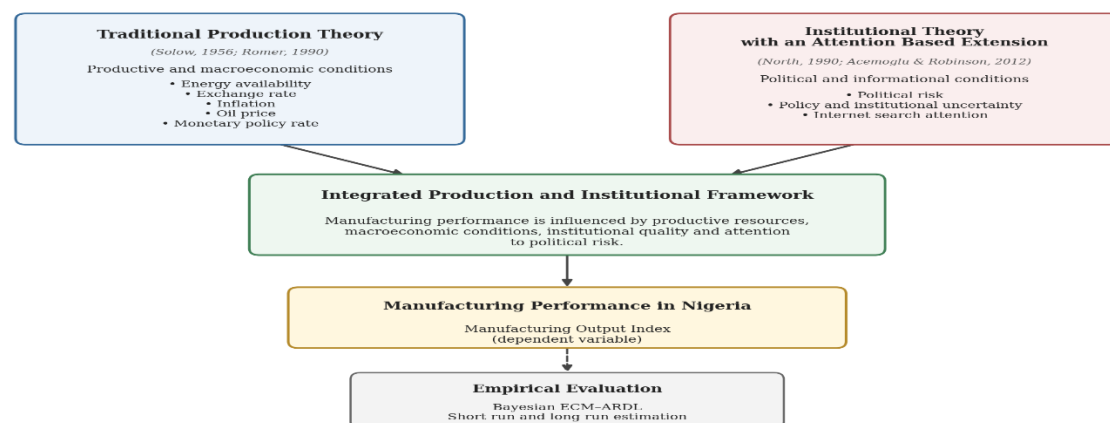


Figure 1. Integrated Production and Institutional Framework for Manufacturing Performance in Nigeria.

Source: Authors' conceptualisation.

The Solid arrows denote the proposed theoretical relationships linking productive and macroeconomic conditions, political and informational conditions, and manufacturing performance. The dashed arrow denotes the empirical evaluation of these relationships using the Bayesian ECM–ARDL model. Internet search attention is used as a timely indicator of attention to political risk rather than as a direct measure of public anxiety. FX denotes the exchange rate, and MPR denotes the monetary policy rate.

2.3 Empirical Literature Review

The empirical literature is organised into five strands. The first strand reviews studies on political risk, uncertainty and manufacturing performance. The second examines the relationship between energy supply and manufacturing performance. The third considers the role of traditional macroeconomic indicators in manufacturing performance, while the fourth and fifth strands review studies on internet search behaviour and Bayesian ARDL applications, respectively. The section concludes by identifying the research gaps addressed by this study.

The empirical literature consistently identifies political risk has consistently been identified as an important determinant of productive economic activities because it influences investment decisions,

financing conditions, production continuity and business confidence. Empirical evidence generally shows that heightened political uncertainty discourages productive investment, weakens operational resilience and constrains industrial expansion. Existing evidence shows that political risk reduces corporate investment, research and development expenditure, labour productivity and access to finance, thereby weakening firm performance and productive capacity (Banerjee & Dutta, 2022; Boah & Ujah, 2024; Choi et al., 2022; Gad et al., 2024; Orlova & Sun, 2024). Similar findings have been reported at broader economic levels. Fotio and Karim (2024) found that political risk significantly constrains industrialisation across African economies, while Kaya et al. (2025) showed that geopolitical risk increases corporate financial fragility. Evidence also suggests that political uncertainty disrupts supply chains and reduces firms' operational resilience, further limiting manufacturing activities (Liu et al., 2025; Moradlou et al., 2024). Although these studies provide strong evidence that political uncertainty affects productive activities, they focus predominantly on firm-level outcomes or cross-country analyses, with relatively limited attention given to manufacturing performance in Nigeria or to real-time measures of political risk derived from internet search behaviour.

The second strand demonstrates that reliable energy supply is fundamental to manufacturing performance because electricity availability supports production efficiency, technological adoption and industrial competitiveness. Empirical studies consistently demonstrate that improvements in electricity supply enhance productive activities, while electricity shortages, transmission losses and inadequate infrastructure reduce industrial performance (Adom & Bekoe, 2012; Asaleye et al., 2025; Hossain et al., 2026; Sheikh et al., 2026). Similarly, Etensa et al. (2025) and Sohail et al. (2025) found that stable energy systems support long-run economic performance by encouraging investment and improving production efficiency. Studies also show that geopolitical uncertainty and energy investment constraints weaken energy security, indirectly limiting industrial productivity (Javed et al., 2025; Shu et al., 2024; Waheed, 2026).

The third strand highlights the importance of macroeconomic stability for manufacturing performance. Existing studies generally report that inflation, exchange rate volatility, oil prices and monetary policy have all been shown to influence production costs, investment decisions and industrial competitiveness (Geyikçi et al., 2021; Iqbal et al., 2023; Wang & Peng, 2025; Zhao et al., 2023). Recent evidence further suggests that macroeconomic variables interact closely with energy markets and uncertainty, reinforcing their combined influence on productive activities (Foye, 2023; Sohail et al., 2025; Zhao et al., 2023). However, the literature remains fragmented because these macroeconomic variables are frequently investigated separately or in relation to aggregate economic growth rather than manufacturing performance. Consequently, empirical evidence on their combined effects alongside political risk and energy supply remains limited.

The final strand reflects recent methodological developments in Bayesian econometrics and the growing application of internet search behaviour in economic research. Bayesian ARDL models provide richer probabilistic inference than conventional ARDL approaches by estimating posterior distributions, credible intervals and posterior probabilities rather than relying solely on classical significance tests (Błazejowski & Kwiatkowski, 2020; Ngoc & Awan, 2022; Salakpi et al., 2022). Similar advantages have been demonstrated in studies employing Bayesian and dynamic ARDL techniques to investigate industrial performance, energy systems and macroeconomic relationships (Abbasi et al., 2022; Iqbal et al., 2023; Kartal et al., 2023). At the same time, internet search behaviour has emerged as a valuable source of real time information for measuring uncertainty and improving economic forecasting. Studies by Zhao et al. (2023), Geyikçi et al. (2021) and Fahmy (2025) demonstrate that search intensity captures evolving public expectations that are often unavailable in conventional economic indicators. Despite these advances, very few studies combine Bayesian ARDL estimation with internet search-based

political risk indicators and traditional macroeconomic variables to explain manufacturing performance, particularly in developing economies.

In summary, the empirical literature provides substantial evidence that political risk, energy supply and macroeconomic conditions influence productive economic activities. However, important gaps remain regarding their joint effects on manufacturing performance, the use of internet search behaviour as a real-time measure of political risk and the application of Bayesian ARDL techniques in the Nigerian context. The present study addresses these gaps by integrating behavioural and traditional economic indicators into a unified Bayesian ECM–ARDL framework to examine the determinants of manufacturing performance in Nigeria.

3. Methodology

This section describes the empirical procedures adopted to examine the relationship between political risk, energy availability and manufacturing performance in Nigeria. It presents the research design, data and variables, model specification and Bayesian estimation procedure used to estimate the robust Bayesian ECM–ARDL model.

Research Design

This study adopts a quantitative explanatory research design to investigate the dynamic effects of political risk, energy availability and macroeconomic conditions on manufacturing performance in Nigeria. Monthly time series data covering January 2010 to December 2025 are analysed using a Bayesian Error Correction Autoregressive Distributed Lag (Bayesian ECM ARDL) framework, which permits simultaneous estimation of long-run equilibrium relationships and short-run adjustments while accommodating variables integrated of different orders.

Data and Variable Measurement

The empirical analysis uses monthly observations spanning January 2010 to December 2025. This sample contains 192 observations for model estimation. Monthly data are appropriate because manufacturing activity, political developments, electricity supply, and macroeconomic conditions change more rapidly than annual data can capture. The dataset combines official statistics from the National Bureau of Statistics (NBS), the Central Bank of Nigeria (CBN), the Nigerian Electricity Regulatory Commission (NERC), the U.S. Energy Information Administration (EIA), and Google Trends, integrating conventional macroeconomic indicators with real-time behavioural information on political attention. Table 1 summarises the data sources and sample characteristics, while Table 2 presents the variable definitions, measurement units and expected effects.

Table 1. Summary of Data Sources and Characteristics

Data Category	Variables	Source	Frequency	Coverage
Manufacturing sector	Manufacturing Output Index (MANU)	National Bureau of Statistics (NBS)	Monthly	Jan 2010–Dec 2025
Political risk	Political Risk Index (Google Trends composite)	Google Trends; Authors' computation	Monthly	Jan 2010–Dec 2025
Electricity sector	Energy Availability Index (EAI)	Nigerian Electricity Regulatory Commission (NERC); Authors' computation	Monthly	Jan 2010–Dec 2025
Macroeconomic indicators	Exchange Rate (EXR); Inflation Rate (INF); Monetary Policy Rate (MPR)	Central Bank of Nigeria (CBN); National Bureau of Statistics (NBS)	Monthly	Jan 2010–Dec 2025

International energy market	Brent Crude Oil Price (OIL)	U.S. Energy Information Administration (EIA)	Monthly	Jan 2010–Dec 2025
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Source: Compiled by the authors using data from the NBS, CBN, NERC, EIA, and Google Trends. Note: Google Trends data were aggregated to construct the Political Risk Index (PRI), while the Energy Availability Index (EAI) was computed from monthly electricity sector statistics following the procedure described in Section 3.3.

Table 2. Variable Definitions, Measurement Units and Expected Relationship

Variable	Symbol	Unit	Expected Sign	Source
Manufacturing Output	MANU	Index	Dependent	CBN
Political Risk	PRI	Search Index	–	Google Trends
Energy Availability	EAI	Composite Index	+	Authors/NERC
Exchange Rate	EXR	NGN/USD	–	CBN
Inflation	INF	%	–	NBS
Oil Price	OIL	USD/barrel	±	EIA

Source: Compiled by the authors from NBS, CBN, NERC, EIA, Google Trends, and authors' computations. Note: (+) denotes an expected positive relationship with manufacturing performance, (–) denotes an expected negative relationship, and (±) indicates that the expected effect is theoretically ambiguous.

Model Specification

The relationship between political risk, energy availability and manufacturing performance is estimated using a Bayesian Error Correction Autoregressive Distributed Lag (Bayesian ECM–ARDL) framework. The ARDL approach is particularly appropriate because it permits the joint estimation of short-run dynamics and long-run equilibrium relationships when the variables are integrated of order zero or one, provided none is integrated beyond the first order (Pesaran et al., 2001). The Bayesian extension replaces point estimation with posterior probability distributions, allowing parameter uncertainty to be incorporated directly into statistical inference through credible intervals and posterior probabilities (Koop, 2003; Gelman et al., 2013; Salakpi et al., 2022).

The empirical specification models manufacturing performance as a function of political risk, energy availability and selected macroeconomic indicators, namely the exchange rate, inflation rate, international crude oil prices and the monetary policy rate. The Bayesian ECM–ARDL specification estimates both the long-run equilibrium relationship and the short-run adjustment process, while the associated error correction term measures the speed at which manufacturing output returns to equilibrium following temporary shocks.

General Bayesian ARDL Model

The long-run relationship is specified as

$$MANU_t = \alpha_0 + \sum_{i=1}^p \phi_i MANU_{t-i} + \sum_{j=0}^{q_1} \beta_j PRI_{t-j} + \sum_{j=0}^{q_2} \gamma_j EAI_{t-j} + \sum_{j=0}^{q_3} \delta_j EXR_{t-j} + \sum_{j=0}^{q_4} \eta_j INF_{t-j} + \sum_{j=0}^{q_5} \kappa_j OIL_{t-j} + \sum_{j=0}^{q_6} \lambda_j MPR_{t-j} + \varepsilon_t \quad \text{eq. 1}$$

where

- *MANU* denotes the Manufacturing Output Index;
- *PRI* is the Political Risk Index;
- *EAI* represents the Energy Availability Index;
- *EXR* denotes the exchange rate;
- *INF* is the inflation rate;
- *OIL* represents Brent crude oil prices;

- MPR denotes the monetary policy rate.

Bayesian Error Correction Representation

The corresponding Bayesian ECM–ARDL model is

$$\begin{aligned} \Delta MANU_t = & \alpha + \sum_{i=1}^{p-1} \psi_i \Delta MANU_{t-i} + \sum_{i=0}^{q_1-1} \beta_i \Delta PRI_{t-i} + \sum_{i=0}^{q_2-1} \gamma_i \Delta EAI_{t-i} \\ & + \sum_{i=0}^{q_3-1} \delta_i \Delta EXR_{t-i} + \sum_{i=0}^{q_4-1} \eta_i \Delta INF_{t-i} + \sum_{i=0}^{q_5-1} \kappa_i \Delta OIL_{t-i} + \sum_{i=0}^{q_6-1} \lambda_i \Delta MPR_{t-i} \\ & + \rho ECT_{t-1} + \varepsilon_t \end{aligned} \quad \text{eq. 2}$$

where

- Δ denotes the first difference operator;
- ECT_{t-1} is the lagged error correction term;
- ρ is the speed of adjustment coefficient, expected to be negative and statistically meaningful.

Bayesian Estimation

Parameter estimation is based on Bayes' theorem,

$$p(\theta | y) = \frac{p(y|\theta)p(\theta)}{p(y)} \quad \text{eq. 3}$$

where

- $p(\theta | y)$ denotes the posterior distribution,
- $p(y | \theta)$ represents the likelihood,
- $p(\theta)$ is the prior distribution,
- $p(y)$ is the marginal likelihood.

The posterior distribution was obtained using Markov Chain Monte Carlo (MCMC) sampling under a Student-t likelihood, allowing robust inference in the presence of non-normal residuals and potential outliers. Posterior summaries are reported using posterior means, 95% credible intervals and posterior directional probabilities. Convergence was assessed using trace plots, Gelman-Rubin convergence statistics and effective sample sizes.

Bayesian Estimation Procedure

Bayesian estimation followed a six-stage procedure that links data preparation, conventional time series analysis and posterior inference. Monthly observations from the selected sources were first aligned and checked for consistency. The study variables and composite indices were then constructed before conducting descriptive analysis, unit root testing and lag order selection. The preferred ARDL specification was subsequently estimated in error correction form using Bayesian inference. Figure 2 presents the complete empirical procedure.

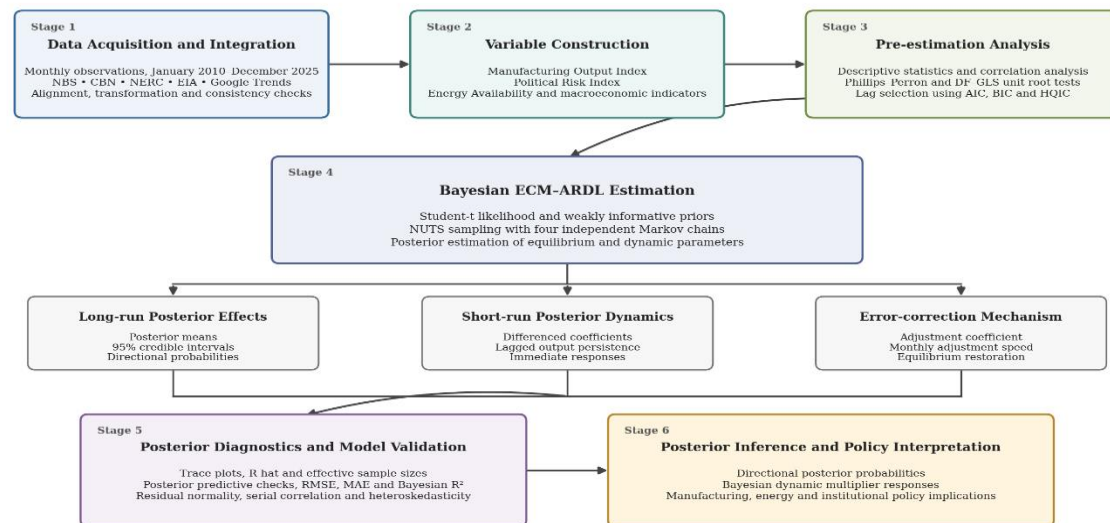


Figure 2. Bayesian ECM–ARDL Empirical Estimation Framework

Source: Authors’ conceptualisation.

The framework above presents the six stages of data acquisition, variable construction, pre-estimation analysis, Bayesian ECM–ARDL estimation, posterior validation and policy interpretation. AIC, BIC and HQIC denote the Akaike, Bayesian and Hannan–Quinn information criteria. NUTS denotes the No U Turn Sampler, while $\hat{R}$ and effective sample size assess posterior convergence.

4. Results and Discussion of Findings

This section presents and interprets the empirical findings of the Bayesian ECM–ARDL analysis. The discussion begins with preliminary estimation procedures before examining the long-run and short-run posterior estimates, model diagnostics, and Bayesian validation results. The final part provides a comprehensive discussion of the findings to establish structural recommendations for industrial development and energy policy in Nigeria.

Descriptive Statistics

Table 3 presents the descriptive statistics for the variables used in the empirical analysis. The reported measures summarise the central tendency, dispersion, and distributional characteristics of each series. The evidence establishes the statistical profile of the data before estimating the Bayesian ARDL model.

Table 3: Descriptive Statistics

Variable	Mean	Median	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
Manufacturing Output Index	91.818	99.085	18.708	65	118.994	-0.415	-1.425
Industrial Production Index	91.81	98.665	19.162	60.907	123.04	-0.366	-1.378
Political Risk Index	50	48.803	6.909	35.999	69.085	0.592	-0.142
Energy Availability Index	63.61	62.104	8.933	46.702	82.062	0.447	-0.832
Electricity Generation	3,232.81	3,237.31	320.432	2,495.38	3,904.78	0.015	-0.697
Inflation Rate	14.382	12.651	5.01	9.033	29.735	1.928	2.513
Exchange Rate (NGN/USD)	306.921	251.661	166.574	150	896.025	1.785	2.759
Oil Price	74.163	73.775	16.657	28.842	119.442	0.149	0.246
Monetary Policy Rate	13.791	13.485	2.294	6	20.55	0.519	2.551

Source: Authors' compilation

Stationarity Analysis

The integration properties of the variables were assessed using the Phillips–Perron (PP), Dickey–Fuller Generalised Least Squares (DF–GLS) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests. PP and DF–GLS evaluate the null hypothesis of a unit root, whereas KPSS tests the null hypothesis of stationarity. This provides complementary evidence on the stochastic properties of the series. The results are presented in Table 4.

Table 4. Conventional Unit Root Test Results

Panel A. Level					
Variable	PP	DF-GLS	KPSS	Decision	
Manufacturing Output	-0.2005	-0.089	1.5692***	Non stationary	
Political Risk	-6.5903***	-2.7339***	1.3303***	Stationary	
Energy Availability	-2.6656*	-2.1380**	1.4547***	Non stationary	
Inflation	0.8079	1.6845	0.8919***	Non stationary	
Exchange Rate	4.5761	3.1594	1.8745***	Non stationary	
Oil Price	-2.4105	-2.3109**	0.3894*	Stationary	
Monetary Policy Rate	-2.3352	1.6043	1.1698***	Non stationary	
Panel B. First Difference					
Variable	PP	DF-GLS	KPSS	Decision	Integration
Manufacturing Output	-8.4758***	-3.2390***	0.2836	Stationary	I(1)
Political Risk	-31.1174***	-11.5268***	0.069	Stationary	I(0)
Energy Availability	-17.3391***	-11.4908***	0.0528	Stationary	I(1)
Inflation	-13.8942***	-10.4831***	0.4986**	Stationary	I(1)
Exchange Rate	-9.7723***	-3.1047***	1.0365***	Stationary	I(1)
Oil Price	-10.3993***	-10.0661***	0.07	Stationary	I(0)
Monetary Policy Rate	-12.7455***	-5.9598***	0.2564	Stationary	I(1)

Source: Authors' computation. Note: PP denotes the Phillips–Perron unit root test, DF–GLS denotes the Elliott–Rothenberg–Stock Dickey–Fuller Generalised Least Squares test, and KPSS denotes the Kwiatkowski–Phillips–Schmidt–Shin stationarity test. PP and DF–GLS test the null hypothesis that the series contains a unit root, whereas KPSS tests the null hypothesis of stationarity. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. All tests include a constant but no deterministic trend.

Bayesian ARDL Estimation

The Bayesian ECM–ARDL estimates provide posterior evidence on the long-run relationship, short-run dynamics and speed of equilibrium adjustment between manufacturing output and the selected political-risk, energy and macroeconomic variables. The analysis reports posterior means, 95% credible intervals and directional posterior probabilities, which permit direct assessment of coefficient magnitude, uncertainty and sign. The Student-t likelihood also reduces the influence of unusually large monthly shocks that may arise from policy changes, energy disruptions and macroeconomic crises.

Long-Run Posterior Estimates

Table 5 presents the long-run posterior estimates, while Figure 5 displays the posterior means and their 95% credible intervals. The estimates show that energy availability provides the clearest long-run support for manufacturing output. Political risk, inflation and exchange-rate depreciation have negative posterior means, although their credible intervals contain zero. Oil prices and the monetary policy rate have positive posterior means, but uncertainty remains substantial.

Table 5. Bayesian Long-Run Posterior Estimates

Variable	Posterior Mean	Posterior SD	95% Credible Interval	Direction	Posterior Probability
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Political Risk Index	-0.0150	0.0126	[-0.0402, 0.0092]	Negative	0.8876
Energy Availability Index	0.0207	0.0089	[0.0035, 0.0381]	Positive	0.9873
Inflation Rate	-0.0065	0.017	[-0.0395, 0.0277]	Negative	0.6556
Log Exchange Rate	-0.2161	0.2073	[-0.6128, 0.1985]	Negative	0.851
Log Oil Price	0.4127	0.3042	[-0.1703, 1.0237]	Positive	0.9239
Monetary Policy Rate	0.0304	0.0392	[-0.0501, 0.1041]	Positive	0.7837

Source: Authors' computation using the study dataset. Note: Posterior probability refers to the probability of the dominant coefficient direction. The reported intervals are 95% posterior credible intervals.

Short Run Posterior Dynamics

The long run posterior estimates describe the equilibrium relationship between manufacturing output and the explanatory variables. The short run estimates reported in this subsection examine how monthly changes in political risk, energy availability and macroeconomic conditions affect manufacturing output before the long run equilibrium is restored. The Bayesian short-run estimates are presented using posterior means, 95% credible intervals and directional posterior probabilities, allowing the immediate effects of each variable to be evaluated while accounting for parameter uncertainty.

Table 6. Bayesian Short-Run Posterior Dynamics

Variable	Posterior Mean	Posterior SD	95% Credible Interval	Direction	Posterior Probability
Δ Log Manufacturing Output (t-1)	0.4719	0.0650	[0.3463, 0.5986]	Positive	1.0000
Δ Political Risk Index	-0.0008	0.0001	[-0.0010, -0.0005]	Negative	1.0000
Δ Energy Availability Index	0.0001	0.0002	[-0.0003, 0.0004]	Positive	0.6251
Δ Inflation Rate	-0.0022	0.0009	[-0.0040, -0.0005]	Negative	0.9937
Δ Log Exchange Rate	0.0909	0.0709	[-0.0499, 0.2289]	Positive	0.9025
Δ Log Oil Price	0.0096	0.0110	[-0.0122, 0.0305]	Positive	0.8033
Δ Monetary Policy Rate	-0.0021	0.0017	[-0.0053, 0.0012]	Negative	0.8950

Source: Authors' computation using the study dataset. Note: Δ denotes the first difference. Posterior probability is the probability of the dominant coefficient direction.

Bayesian Error Correction Mechanism

The Bayesian Error Correction Mechanism (ECM) evaluates the speed at which manufacturing output returns to its long-run equilibrium following short-run disturbances. A valid ECM requires the adjustment coefficient to be negative, indicating that temporary deviations from equilibrium are gradually eliminated over time. In the Bayesian framework, inference is based on the posterior distribution of the adjustment coefficient rather than conventional hypothesis testing.

Table 7. Bayesian Error-Correction Estimate

Parameter	Posterior Mean	Posterior SD	95% Credible Interval	$\Pr(\lambda < 0)$	Monthly Adjustment Speed
Error-Correction Term	-0.0086	0.0029	[-0.0147, -0.0031]	1	0.86%

Source: Authors' computation using the study dataset. Note: λ denotes the Bayesian error correction coefficient. The adjustment speed is the absolute posterior mean of the error-correction coefficient expressed as a percentage. A negative coefficient indicates movement towards the long-run equilibrium. Posterior probability refers to the probability that the adjustment coefficient is negative.

Table 8. Comparison of Bayesian and Frequentist Adjustment Coefficients

Estimator	Adjustment Coefficient	95% Interval	Inferential Evidence
Bayesian ECM	-0.0086	[-0.0147, -0.0031]	$\Pr(\lambda < 0) = 1.0000$
Frequentist UECM	0.0049	[-0.0047, 0.0145]	p-value = 0.3168

Source: Authors' computation using the study dataset. Note: The Bayesian interval is a posterior credible interval, while the frequentist interval is a confidence interval. The posterior probability and p-value are conceptually different and should not be interpreted as equivalent measures.

The comparison demonstrates an important methodological advantage of Bayesian estimation. The Bayesian ECM identifies clear evidence of equilibrium adjustment despite the relatively small adjustment speed, whereas the frequentist benchmark fails to detect convergence because the estimated confidence interval includes zero. The Bayesian framework therefore appears better suited for identifying long-run equilibrium relationships in macroeconomic time series characterised by relatively short samples, structural uncertainty and highly persistent economic shocks. In summary, the Bayesian Error Correction Mechanism confirms that manufacturing output, political risk, energy availability and the selected macroeconomic variables share a stable long-run equilibrium relationship. Short-run deviations are temporary and gradually diminish over time, supporting the validity of the Bayesian ECM–ARDL specification adopted in this study.

Bayesian Model Diagnostics and Model Validation

The credibility of Bayesian estimates depends not only on the posterior coefficients but also on the adequacy of the fitted model, the predictive accuracy of the posterior distribution, the statistical behaviour of the residuals, and the convergence of the Markov Chain Monte Carlo (MCMC) algorithm. This subsection evaluates the performance of the Bayesian ECM–ARDL model using model fit statistics, posterior predictive checks, residual diagnostic tests, posterior density distributions and formal MCMC convergence diagnostics. These procedures determine whether the estimated posterior distributions provide a reliable basis for statistical inference.

Table 10. Bayesian Model Fit Diagnostics

Statistic	Value
RMSE	0.0083
MAE	0.0063
Bayesian R ²	0.502
Mean Residual	0.000
Residual Standard Deviation	0.0083

Source: Authors' computation using the study dataset. Note: RMSE denotes the Root Mean Squared Error, MAE denotes the Mean Absolute Error, and Bayesian R² measures the proportion of variation in monthly manufacturing output explained by the Bayesian ECM–ARDL model.

The Bayesian ECM–ARDL model demonstrates satisfactory predictive performance over the sample period. The Root Mean Squared Error (RMSE) equals 0.0083, while the Mean Absolute Error (MAE) equals 0.0063, indicating that prediction errors remain relatively small after accounting for monthly changes in manufacturing output. The Bayesian coefficient of determination (Bayesian R²) equals 0.5020, implying that approximately 50.2% of the variation in monthly manufacturing output growth is explained by the estimated model.

Although approximately half of the monthly variation remains unexplained, this level of predictive performance is reasonable for monthly macroeconomic time series characterised by policy uncertainty, external shocks and structural changes. Manufacturing activity is influenced by numerous factors that are difficult to observe or quantify, including firm-specific investment decisions, supply-chain disruptions, institutional reforms and international economic conditions. Therefore, moderate explanatory power is expected even when the principal macroeconomic determinants are included.

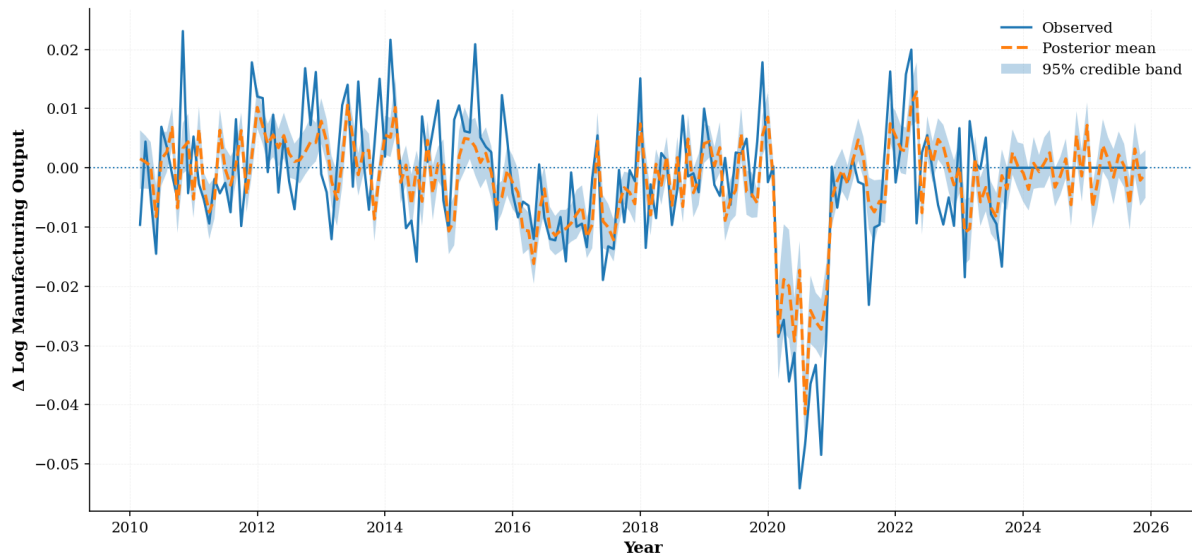


Figure 7. Posterior Predictive Performance of the Bayesian ECM-ARDL Model. The solid blue line represents the observed monthly change in manufacturing output, the dashed orange line represents the posterior predictive mean, and the shaded region denotes the 95% posterior credible interval. **Note:** Wider credible intervals indicate greater posterior uncertainty in model predictions. The increased uncertainty observed during the 2020 economic disruption reflects the model's recognition of heightened macroeconomic volatility during the COVID-19 period.

Figure 7 compares the observed monthly manufacturing output growth with the posterior mean predictions and the associated 95% credible interval. The posterior mean closely follows the principal movements observed in manufacturing output throughout the sample period, while the credible interval captures much of the realised variability. Larger deviations occur during periods of heightened macroeconomic instability, particularly around the COVID-19 pandemic and episodes of exchange rate adjustment, when abrupt economic shocks temporarily increase forecast uncertainty. Nevertheless, the posterior predictions continue to reproduce the underlying direction of manufacturing activity, indicating that the Bayesian ECM-ARDL model successfully captures the principal dynamics of the series.

Bayesian Directional Probability Analysis

Bayesian estimation allows inference to be expressed directly as posterior probabilities rather than statistical significance tests. Instead of evaluating whether a coefficient differs significantly from zero using p-values, Bayesian inference estimates the probability that each coefficient is positive or negative after incorporating the observed data and prior information. This provides a more intuitive measure of evidence regarding the direction and credibility of each macroeconomic relationship.

Table 13. Bayesian Evidence Dashboard

Variable	Mean and 95% CI	Direction	Posterior Probability
Political Risk Index	-0.0150 [-0.0402, 0.0092]	Negative	0.8876
Energy Availability Index	0.0207 [0.0035, 0.0381]	Positive	0.9873
Inflation Rate	-0.0065 [-0.0395, 0.0277]	Negative	0.6556
Log Exchange Rate	-0.2161 [-0.6128, 0.1985]	Negative	0.851
Log Oil Price	0.4127 [-0.1703, 1.0237]	Positive	0.9239
Monetary Policy Rate	0.0304 [-0.0501, 0.1041]	Positive	0.7837

Source: Authors' computation using the study dataset. **Note:** Posterior probability represents the probability that the dominant directional effect (positive or negative) is supported by the posterior distribution. Evidence classifications are based on posterior probability thresholds adopted in this study.

Table 13 summarises the posterior means, ninety-five percent credible intervals, dominant effect direction, posterior probabilities and corresponding evidence classifications. Figure 13 complements these results by ranking the explanatory variables according to the posterior probability supporting their dominant directional effect.

4.2 Discussion of Findings

The Bayesian estimates indicate that political risk exerts a persistent adverse influence on manufacturing performance in Nigeria. This finding suggests that political risk does not necessarily generate immediate production disruptions but gradually reduces manufacturing performance by discouraging investment, increasing operational uncertainty, and weakening firms' willingness to undertake long-term productive activities. This finding supports the broader African evidence reported by several authors such as Fotio and Karim (2024), Banerjee and Dutta (2022), Choi et al. (2022), Boah and Ujah (2024), and Orlova and Sun (2024), while Kaya et al. (2025) found that geopolitical uncertainty increases financial fragility among firms. The present study extends this evidence by demonstrating that a behavioural measure of political risk constructed from internet search behaviour produces similar conclusions at the macroeconomic level.

The Bayesian ARDL estimates further indicate that energy availability exerts a positive effect on manufacturing performance in both the long run and short run. The result is consistent with a growing body of empirical evidence that identifies electricity availability as a major determinant of industrial productivity in Nigeria, Afolabi et al. (2025), Asaleye et al. (2025) also reported that improved electricity availability creates broader economic opportunities by supporting productive activities and employment, while Sohail et al. (2025) concluded that energy indicators constitute important drivers of sustainable economic growth across developing economies.

5. Conclusion and Recommendations

5.1 Conclusion

This study examined the effects of political risk, energy availability, and traditional macroeconomic indicators on manufacturing performance in Nigeria using a Bayesian Error Correction Autoregressive Distributed Lag (ECM–ARDL) framework. Unlike previous studies that rely primarily on conventional political risk indicators, this study constructed a Political Risk Index based on internet search behaviour and integrated it with an Energy Availability Index and conventional macroeconomic variables to evaluate both the long-run and short-run determinants of manufacturing performance. The Bayesian framework further enabled probabilistic inference through posterior distributions and credible intervals, providing a richer assessment of parameter uncertainty than conventional frequentist estimation techniques.

The empirical findings indicate that energy availability is the most important determinant of manufacturing performance, providing the strongest posterior evidence of a positive long-run relationship. The results demonstrate that improvements in electricity availability significantly enhance manufacturing output by reducing production interruptions and improving productive efficiency. In contrast, political risk and exchange rate depreciation exert persistent adverse effects on manufacturing performance, indicating that institutional uncertainty and macroeconomic instability continue to constrain industrial development in Nigeria. Although inflation, oil prices and monetary policy also influence manufacturing activity, their posterior evidence is comparatively weaker once structural and institutional factors are incorporated into the empirical model.

Beyond the substantive findings, the study contributes methodologically by demonstrating the usefulness of combining internet search behaviour with Bayesian ARDL estimation in analysing manufacturing performance. The results show that behavioural indicators derived from online search activity provide valuable real-time information that complements conventional macroeconomic indicators when evaluating political uncertainty. The Bayesian approach further allows policymakers to interpret the probability and uncertainty surrounding estimated relationships rather than relying solely on statistical significance, thereby providing a stronger basis for evidence-based decision-making.

In summary, the findings suggest that sustainable manufacturing growth in Nigeria depends less on isolated macroeconomic interventions and more on coordinated improvements in political stability, electricity reliability and macroeconomic management. Addressing these structural constraints simultaneously is likely to generate greater improvements in industrial productivity than focusing on any single policy instrument in isolation. Consequently, the study provides new empirical evidence supporting the integration of behavioural data, energy policy and macroeconomic management into industrial development strategies aimed at strengthening manufacturing performance in Nigeria.

5.2 Recommendations

a) Government should prioritize reliable electricity supply, exchange rate stability, and investments in energy infrastructure while promoting local industrial inputs and export diversification. These measures will reduce production costs, improve productivity, and enhance the competitiveness and resilience of Nigeria's manufacturing sector.

b) Secondly, government should strengthen political stability, regulatory consistency, and institutional transparency to attract long-term manufacturing investment. In addition, integrating digital behavioural indicators with conventional economic statistics will improve policy monitoring, early warning systems, and evidence-based industrial planning for sustainable industrial development

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