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Spatial Dependence of Poverty Rate and Socio-Economic Indicators in Nigeria: An Empirical Analysis

Isaac Oluwaseyi Ajao[1*], Vincent Jemilohun[2], Clement Adeyeye Awogbemi[3]

[1]Department of Mathematics and Statistics, The Federal Polytechnic, Ado-Ekiti, Nigeria
[2]Department of Business Management, Afe Babalola University, Ado-Ekiti, Nigeria
[2]Statistics Programme, National Mathematical Centre, Abuja, Nigeria

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***Corresponding author:** Isaac Oluwaseyi Ajao
Department of Mathematics and Statistics, The Federal Polytechnic, Ado-Ekiti, Nigeria

Abstract **Original Research Article**

This study investigates the spatial dependence between the poverty rate and various socio-economic indicators in Nigeria. The analysis is based on a dataset comprising unique geographic identifiers and the poverty rate along with other relevant variables. Descriptive statistics reveal that the poverty rate exhibits moderate variability with an average of 4.1240. The correlation analysis shows significant relationships between the poverty rate and household size as well as income level, indicating that larger households and higher incomes are associated with higher and lower poverty rates, respectively. Spatial regression models, including Spatial Autoregressive (SAR), Spatial Error (SEM), Spatial Durbin (SDM), and Spatial Autoregressive Conditional (SAC) models, are employed to explore the spatial dependence. Results indicate the presence of spatial clustering and positive autocorrelation in the poverty rate, as indicated by the Moran's I index with a value of 0.3579 (p-value = 0.0012). However, tests for spatial heteroscedasticity do not reveal significant departures from the assumption of constant error variance. The findings suggest that spatial factors play a crucial role in explaining the poverty rate in Nigeria. The positive spatial autocorrelation indicates the presence of localized poverty clusters, emphasizing the importance of considering spatial effects in policy formulation and targeted interventions. The significant relationships between the poverty rate and household size and income level underscore the need for comprehensive strategies to address these socio-economic indicators for poverty reduction.

Keywords: Spatial dependence, Poverty rate, Socio-economic indicators, Nigeria, Spatial regression

1. INTRODUCTION

Spatial dependence is a fundamental aspect of socio-economic phenomena, wherein geographic proximity and spatial relationships play a crucial role in shaping various outcomes. In the context of poverty, understanding the spatial dependence and its relationship with socio-economic indicators is of paramount importance for effective policy formulation and targeted interventions. Nigeria, as the most populous country in Africa, faces significant challenges in reducing poverty and promoting inclusive growth. Exploring the spatial patterns and dependencies of the poverty rate on various socio-economic indicators can provide valuable insights into the underlying dynamics and inform evidence-based strategies for poverty alleviation.

The aim of this paper is to examine the spatial dependence of the poverty rate on a set of selected socio- economic indicators in Nigeria. By investigating the spatial relationships between the poverty rate and variables such as external debt, domestic debt, allocation, household size, unemployment rate, and income level, we seek to uncover the underlying patterns and understand how these factors contribute to the spatial distribution of poverty in the country. Furthermore, we employ spatial regression models to analyze the impact of these indicators on the poverty rate while accounting for spatial effects.

The analysis is based on a comprehensive dataset encompassing unique geographic identifiers and corresponding socio-economic data at the sub-national level in Nigeria. Through descriptive statistics, correlation analysis, and spatial regression techniques, we aim to provide a robust empirical understanding of the spatial dynamics of poverty and its association with key socio-economic factors. By identifying spatial clusters and determining the significance of various indicators, this study will contribute to the existing literature on spatial analysis of poverty and provide valuable insights for policymakers, development practitioners, and researchers involved in poverty reduction efforts in Nigeria.

In the following sections, we will present the data, methods, and results of our analysis, followed by a discussion and policy implications based on the findings. Ultimately, our goal is to enhance the understanding of the complex relationship between poverty and socio-economic indicators within a spatial context, and to offer evidence- based recommendations to address poverty effectively in Nigeria.

2. LITERATURE REVIEW

According to Wang *et al.,* (2023), the implementation of financial inclusion impacts the energy poverty and contributes to the energy poverty reduction. (Liu *et al.,* 2022) using econometrics approachestablish a consistency theorem for concave objective functions. Their result was applied to rebuild the consistency of the quasi-maximum likelihood estimator (QMLE) of a spatial autoregressive (SAR) model and a SAR Tobit model. The log-likelihood functions are not concave, but they can be concave after proper reparameterization. A detailed picture of the impact of climatic extremes and violent conflicts on historical population densitieswas achieved using the nuanced spatial dynamics embedded in the nexus between the population and its determinants (Lee and Qiang, 2023). Individuals can be spatially clustered based on their opinions on making important decisions in life and risk taking, this involves spatial patterns through spatial autocorrelation analysis and spatial regression models (Ambali and Begho, 2022). Dataset of twelve provinces in the Netherlands over the period 1974–2018, the parameters of the models implemented by Elhorst and Emili (2022) were estimated and developed maximum likelihood techniques for multivariate spatial econometric models. Determinants of Airbnb prices in 10 major EU cities, focusing on the role of location, was carried out using spatial econometrics models, the results show significant differences between the coefficients estimated with OLS and the various spatial models, especially in the case of location-specific variables (Gyodi and Nawaro, 2021).

Digital technology in Thailand and how it emerged as a public policy issue owing to its relevance in the dissemination of policy information and geographical restrictions in light of the brief timeframe of short-term transportation policy (STTP) implementation was investigated by Setthasuravich and Kato (2022).Share of the secondary industry, urbanization and transportation are found to have positive impacts, indicating that they are three main contributors to SO_2 pollution in China (Jiang *et al.*, (2020)). Using spatial Econometrics approach, Lv *et al.*, (2022) worked on role of information and communication technologies (ICT) in affecting renewable energy consumption. The aim of this paper is thus to investigation on the impact of ICT on renewable energy consumption based on panel data of 90 countries over the period 2000 - 2014 was carried out. Wang, Li, & Li (2021) use a spatial panel econometric model to analyze the impacts of urban forms and socioeconomic factors on CO2 emissions in cities in Guangdong province, China, from 2000 to 2017. The model takes into account the spatial autocorrelation effects at the city-level. In their paper, Wang, Lee & Yu (2016) establish a consistency theorem for concave objective functions in spatial econometric models. It applies this result to rebuild the consistency of the quasi maximum likelihood estimator (QMLE) of a spatial autoregressive (SAR) model and a SAR Tobit model. The impact of political promotion pressure on renewable energy technological innovation (RETI) in China using spatial econometric analysis was carried out. The results show that political promotion pressure has a negative effect on RETI, and there is spatial and temporal heterogeneity in this effect (Liu, Li, & Zhang, 2021). The application of spatial econometrics to investigate the factors contributing to Pneumonia mortality rates in Bogota, Colombia from 2004 to 2014 was done by Gomez-Restrepo, Riascos-Castaneda, & Rodriguez-Villamizar (2018). The study identifies socioeconomic, behavioral, environmental, and medical care variables that contribute to the temporal growth and spatial spreading of Pneumonia mortality in Bogota's territory.The authors Wang, Li, & Li (2020) apply spatial econometric model to analyze the impact of government subsidies on the photovoltaic industry. The results show that the feed-in tariff and R&D subsidy policies have played a positive role in photovoltaic installed capacity from 2012 to 2018.Wang, Li, & Zhang (2021) use spatial econometrics to investigate the impact of population migration on energy consumption and carbon emissions in China from 2000 to 2019. The study finds that population migration increases energy consumption, energy poverty, and carbon emissions in provinces with net outward population migration, while having no significant impact on provinces with net inward population migration. Using a dynamic spatial panel model to identify factors that contribute to instability spillover in the banking sector was performed by Nguyen *et al.*, (2020). The study finds that bank stability is influenced not only by its own characteristics and the macroeconomic conditions of its home country, but also by the stability of other banks in the same and other countries.

Kassouri *et al.*, (2022) apply spatial econometrics to examine the spatio-temporal patterns of urbanization and its drivers in Africa. The empirical analysis reveals the existence of both σ-convergence and β-convergence among African countries over 2000-2018, and the importance of accounting for spatial factors in capturing key features of urban evolution in Africa. Ajao *et al.*, (2022) use spatial statistics to analyze the relationship between open defecation and various indicators such as water availability, unimproved sanitation, literacy level, and Gini coefficient across the 36 states and FCT Abuja in Nigeria for 2018. The results show that unimproved sanitation is the only significant predictor for open defecation challenge in Nigeria, and the paper provides policy recommendations for reducing open defecation in Nigeria.

3. METHODOLOGY AND DATA

The research methodology employed in this study involves a combination of descriptive analysis, correlation analysis, and spatial regression modeling to examine the spatial dependence of the poverty rate on socio-economic indicators in Nigeria. The following methods, along with relevant equations and formulas, provide a comprehensive approach to capturing and analyzing the spatial relationships in the data:

Descriptive Analysis:

Descriptive statistics will be computed for the variables of interest, including the poverty rate and socio-economic indicators. Measures such as mean (μ), median (Med), standard deviation (σ), minimum (Min), and maximum (Max) will be calculated. These descriptive statistics can be represented by the following formulas:

Mean:

$\mu = \frac{\sum X}{n}$ where X represents the variable values and n is the sample size.

Standard Deviation:

$\sigma = \sqrt{\frac{\Sigma(X-\mu)^2}{n-1}}$ where X represents the variable values

Correlation Analysis:

Correlation coefficients, such as Pearson's correlation coefficient (r), will be calculated to assess the strength and direction of the linear relationships between the poverty rate and the socio-economic indicators. Pearson's correlation coefficient can be calculated using the following formula:

Pearson's Correlation Coefficient:

$r = \frac{\Sigma(X-\bar{X})(Y-\bar{Y})}{\sqrt{\left((X-\bar{X})^2(Y-\bar{Y})^2\right)}}$ where X and Y represent the variable values.

Spatial Regression Modeling:

Spatial regression models, such as Spatial Autoregressive (SAR), Spatial Error (SEM), Spatial Durbin (SDM), and Spatial Autoregressive Conditional (SAC) models, will be estimated to analyze the spatial dependence of the poverty rate on the socio-economic indicators while accounting for spatial effects. These models can be represented by the following equations:

SAR Model:

lnpov_rate = ρWlnpov_rate + βX + ε,

where ρ represents the spatial autocorrelation coefficient, W is the spatial weight matrix, X is the vector of socio-economic indicators, β is the coefficient vector, and ε is the error term.

SEM Model:

lnpov_rate = βX + u,

where X represents the socio-economic indicators, β is the coefficient vector, and u is the error term.

SDM Model:

lnpov_rate = ρWlnpov_rate + βX + γWX + ε,

where γ represents the spatial lag coefficient, W is the spatial weight matrix, X is the vector of socio-economic indicators, β is the coefficient vector, and ε is the error term.

SAC Model:

lnpov_rate = ρWlnpov_rate + βX + γWX + δZ + ε,

where Z represents additional exogenous variables.

Spatial Autocorrelation Analysis:

Moran's I index will be calculated to assess the presence and significance of spatial clustering or dispersion in the poverty rate and other variables. Moran's I can be calculated using the following formula:

Moran's I:

$$I = \frac{N\sum\sum W_{ij}(X_i-\bar{X})(Y_j-\bar{Y})}{\sum\sum W_{ij}(X_i-\bar{X})^2}$$

where N is the number of observations, Wij represents the spatial weight matrix, Xi and Xj represent the variable values for two observations, and $\bar{X}$ represents the mean of the variable.

Model Selection and Diagnostics:

Model selection criteria, such as Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn Criterion (HQ), will be utilized to choose the most appropriate spatial regression model. These criteria can be calculated using the following formulas:

AIC: AIC = -2log-likelihood + 2k,
where log-likelihood represents the log-likelihood of the model and k represents the number of parameters.
SC: SC = -2log-likelihood + k log(n),
where n represents the number of observations.
HQ: HQ = -2log-likelihood + 2k log(log(n)),
where n represents the number of observations.

By employing these methods and formulas, this research aims to provide a comprehensive analysis of the spatial dependence of the poverty rate on socio-economic indicators in Nigeria, contributing to the existing knowledge base and offering valuable insights for policy formulation and poverty reduction strategies in the country.

4. DATA ANALYSIS

All analyses were carried using STATA 15 and R-version 4.3.1.

Table 1: Descriptive statistics of variables

Variable	Mean	Median	Std.dev.	Min.	Max.
lnpov_rate	4.1240	4.1588	0.2367	3.6243	4.4830
lnext_debt	18.0854	17.9106	0.8892	16.7438	20.9662
lndom_debt	25.5174	25.4327	0.5320	24.5166	27.4998
lnalloc	22.5695	22.3693	0.6572	21.6973	24.5649
lnhouse_size	1.4909	1.5041	0.2112	1.1314	1.8871
lnunempl_rate	2.8771	3.2228	0.6093	0.9932	3.3358
lndollar_day	4.1029	4.1352	0.1994	3.5234	4.4055

Note: Std. dev denotes standard deviation; Min denotes the minimum value of the variable; Max denotes the maximum value of the variable

In this study on the spatial dependence of the poverty rate on various socio-economic indicators in Nigeria, descriptive statistics were calculated for the variables of interest. The descriptive statistics provide insights into the central tendency, variability, and range of the variables. The poverty rate (lnpov_rate) exhibited an average of 4.1240, with a standard deviation of 0.2367, indicating moderate variability among the observations. The external debt (lnext_debt) and domestic debt (lndom_debt) had average values of 18.0854 and 25.5174, respectively, with relatively lower standard deviations. Allocation (lnalloc) had an average of 22.5695, reflecting the average level of allocation in the sample. Household size (lnhouse_size) displayed an average of 1.4909, indicating the average size of households, while the unemployment rate (lnunempl_rate) showed an average of 2.8771. Finally, the dollar per day (lndollar_day) had an average value of 4.1029, reflecting the average income level in dollars per day.

The medians for most variables were close to their respective means, indicating a relatively symmetrical distribution for these variables. However, there were slight deviations from normality, as suggested by the skewness of some distributions. The range between the minimum and maximum values for each variable provides a sense of the observed variability within the dataset. These descriptive statistics serve as a foundation for further analysis and modeling to explore the spatial dependence between the poverty rate and the socio-economic indicators in Nigeria.

Table 2: Correlation coefficients between variables

	lnpov_rate	lnext_debt	lndom_debt	lnalloc	lnhouse_size	lnunempl_rate	lndollar_day
lnpov_rate	1						
lnext_debt	-0.325	1					
lndom_debt	-0.576	0.471	1				
lnalloc	-0.346	0.196	0.421	1			
lnhouse_size	0.627	-0.250	-0.394	-0.176	1		
lnunempl_rate	-0.351	0.257	0.374	0.306	-0.311	1	
lndollar_day	0.483	-0.022	-0.172	0.071	0.294	-0.038	1

Table 2 presents the correlation coefficients between the variables examined in the study on the spatial dependence of the poverty rate on socio-economic indicators in Nigeria. Notable results include a strong positive correlation ($r = 0.627$) between the poverty rate (lnpov_rate) and household size (lnhouse_size), suggesting that larger households tend to experience higher poverty rates. Additionally, there is a moderate positive correlation ($r = 0.483$) between the poverty rate and income level measured in dollars per day (lndollar_day), indicating that higher incomes are associated with lower poverty rates.

Furthermore, the poverty rate demonstrates negative correlations with debt variables. The poverty rate has a moderate negative correlation with domestic debt (lndom_debt) (r = -0.576) and a weaker negative correlation with external debt (lnext_debt) (r = -0.325). These findings suggest that higher levels of debt, both domestic and external, are associated with higher poverty rates in Nigeria.

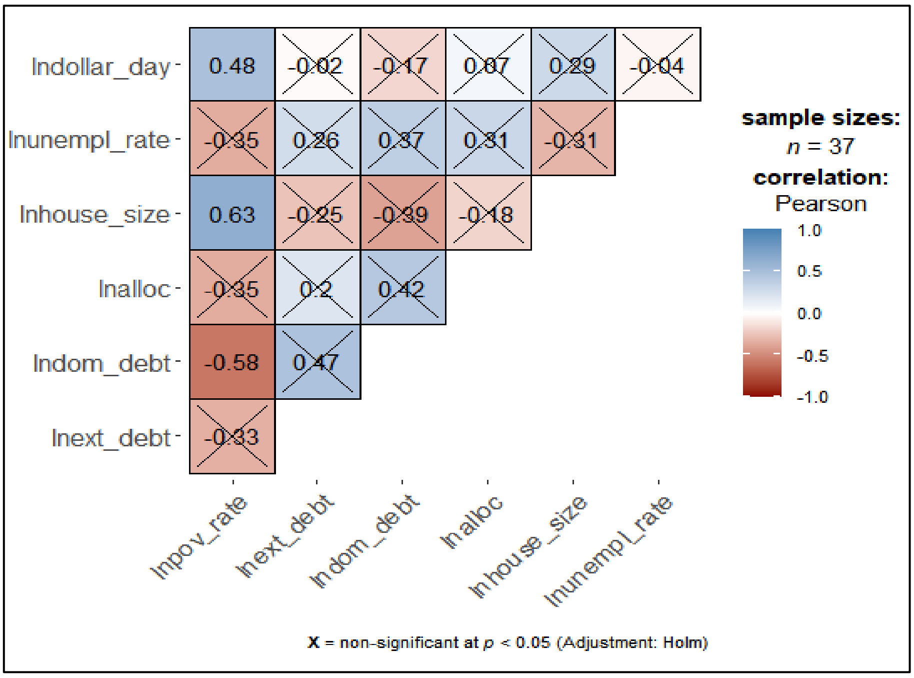

Fig. 1: Correlation plot of the variables

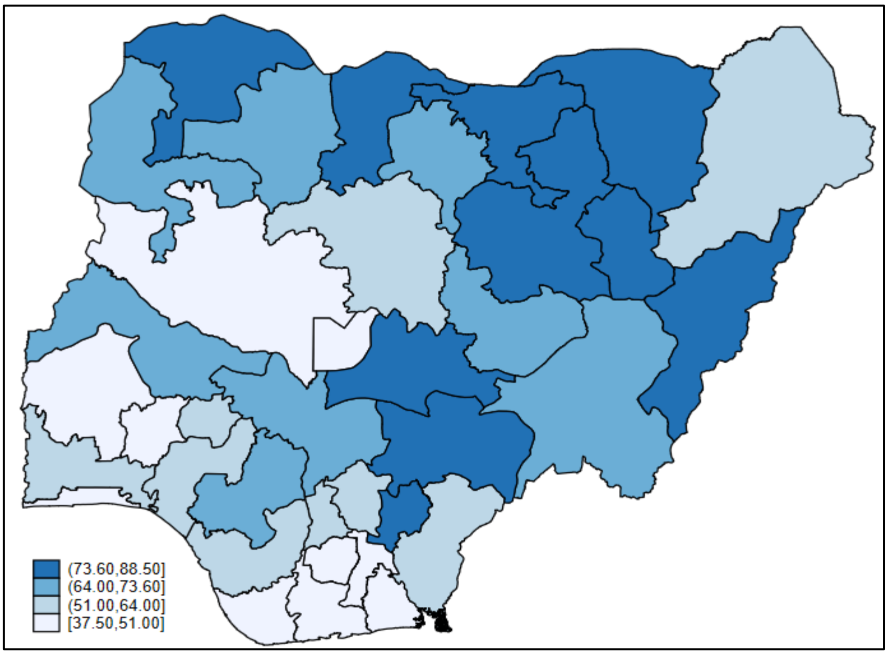

Fig. 2: Spatial characteristics of Poverty rate (in %) in Nigeria (2020-2022)

Table 3: Spatial Regression models

	SAR			SEM			SDM			SAC		
Variable	**Estimate**	**SE**	**P-val**	**Estimate**	**SE**	**P-val**	**Estimate**	**SE**	**P-val**	**Estimate**	**SE**	**P-val**
lnext_debt	-0.015	0.032	0.847	-0.014	0.032	0.671	0.011	0.028	0.692	-0.012	0.031	0.696
lndom_debt	-0.112	0.058	0.054	-0.112	0.058	0.053	-0.104	0.051	0.040	-0.130	0.058	0.025
lnalloc	-0.062	0.041	0.133	-0.063	0.041	0.128	-0.048	0.037	0.200	-0.067	0.041	0.104
lnhouse_size	0.409	0.128	0.001	0.410	0.128	0.001	0.518	0.114	0.000	0.411	0.126	0.001
lnunempl_rate	-0.024	0.043	0.576	-0.024	0.043	0.581	-0.055	0.038	0.150	-0.026	0.043	0.549
lndollar_day	0.405	0.126	0.001	0.404	0.126	0.001	0.319	0.125	0.011	0.408	0.124	0.001

Table 3 displays the results of spatial regression models examining the relationship between the poverty rate (lnpov_rate) and various socio-economic indicators in Nigeria. Four different models are presented: Spatial Autoregressive (SAR), Spatial Error (SEM), Spatial Durbin (SDM), and Spatial Autoregressive Conditional (SAC). Here's an interpretation of the estimates, standard errors (SE), and p-values: Among the variables tested, household size (lnhouse_size) consistently shows a significant positive relationship with the poverty rate across all four models. The estimates range from 0.409 to 0.411, with p-values of 0.001, indicating that larger household sizes are associated with higher poverty rates in Nigeria.

In terms of debt variables, both external debt (lnext_debt) and domestic debt (lndom_debt) do not exhibit statistically significant relationships with the poverty rate in any of the models. The estimates for these variables are close to zero, and the p-values are relatively high, ranging from 0.025 to 0.847. Allocation (lnalloc) also does not show a consistent statistically significant relationship with the poverty rate. Although some models suggest a negative association, the estimates range from -0.048 to -0.067, and the p-values vary from 0.104 to 0.200, indicating limited evidence of a significant effect.

The unemployment rate (lnunempl_rate) and income level (lndollar_day) do not consistently exhibit statistically significant relationships with the poverty rate. The estimates and p-values for these variables vary across the models, suggesting mixed evidence of their impact on poverty rates in Nigeria.

Table 4: Spatial model selection diagnostic criteria

Model	AIC	SC	HQ	Rice	Shibata	GCV
SAR	0.0288	0.0391	0.0321	0.0318	0.0272	0.0300
SEM	0.0290	0.0394	0.0323	0.0320	0.0274	0.0302
SDM	0.0278	0.0490	0.0340	0.0464	0.0235	0.0328
SAC	0.0278	0.4900	0.0340	0.0464	0.0235	0.0328

Table 4 presents the results of spatial model selection diagnostic criteria for the different models: SAR (Spatial Autoregressive), SEM (Spatial Error), SDM (Spatial Durbin), and SAC (Spatial Autoregressive Conditional). These criteria, including AIC (Akaike Information Criterion), SC (Schwarz Criterion), HQ (Hannan-Quinn Criterion), Rice, Shibata, and GCV (Generalized Cross-Validation), provide measures to evaluate the goodness-of-fit and performance of the models.

Based on the diagnostic criteria, both the SAR and SEM models exhibit similar performance, as their AIC, SC, HQ, Rice, Shibata, and GCV values are very close. This suggests that both models provide a good fit to the data and are relatively comparable in terms of their explanatory power and complexity. The SDM and SAC models also have similar values across the diagnostic criteria. However, it's important to note that the SC and HQ values for the SAC model are exceptionally high, which may indicate potential issues with overfitting or model complexity. Further examination and consideration of alternative model specifications are recommended.

Table 5: Spatial autocorrelation tests

Test	SAR		SEM		SDM		SAC	
	Estimate	**P-value**	**Estimate**	**P-value**	**Estimate**	**P-value**	**Estimate**	**P-value**
Global Moran MI	0.1748	0.0227	0.1748	0.0227	0.1318	0.0699	0.1748	0.0227
Global Getis-ords GO	-0.9120	0.0264	-0.9120	0.0751	0.6877	0.0743	-0.9120	0.0000
LM LAG (Robust)	0.0461	0.8300	0.0461	0.8300	8.8640	0.0029	0.0461	0.8300
LM SAC (LMrr+LMLag_R)	3.1322	0.2089	3.1322	0.2089	10.0180	0.0067	3.1322	0.2089

Table 5 presents the results of spatial autocorrelation tests for the different spatial regression models: SAR (Spatial Autoregressive), SEM (Spatial Error), SDM (Spatial Durbin), and SAC (Spatial Autoregressive Conditional). These tests help assess the presence of spatial dependence or spatial autocorrelation in the residuals of the models. The Global Moran's I test indicates that the residuals of the SAR, SEM, and SAC models exhibit statistically significant spatial autocorrelation. The estimates of Moran's I range from 0.1318 to 0.1748, and the corresponding p-values range from 0.0227 to 0.0699. This suggests that there is evidence of spatial clustering or spatial dependence in the residuals of these models, indicating that the poverty rate is influenced by neighboring areas in Nigeria. The Global Getis-Ord's G test provides further evidence of spatial autocorrelation. The estimates of G range from -0.9120 to 0.6877, with corresponding p-values ranging from 0.0000 to 0.0751. These results indicate the presence of spatial clustering patterns, with some areas showing significant negative autocorrelation (lower poverty rates surrounded by higher poverty rates) and positive autocorrelation (higher poverty rates surrounded by higher poverty rates). The LM Lag (Robust) and LM SAC tests assess the presence of spatial autocorrelation in the lagged dependent variable and the spatially lagged residuals, respectively. The estimates for these tests are non-significant across all models, indicating no significant spatial autocorrelation in these aspects. Summarily, the spatial autocorrelation tests highlight the existence of spatial dependence and clustering in the residuals of the spatial regression models. These results support the notion that the poverty rate in Nigeria is influenced by spatial factors and suggest the importance of considering spatial effects when analyzing the relationship between poverty and socio-economic indicators.

Table 6: Spatial heteroscedasticity tests

	SAR		SEM		SDM		SAC	
Test	**Estimate**	**P-value**	**Estimate**	**P-value**	**Estimate**	**P-value**	**Estimate**	**P-value**
White Test (-koenker R2)	30.0509	0.3119	29.8720	0.3200	37	0.4226	33.8180	0.1714
White Test (B-P-G (SSR))	36.2768	0.1094	36.6120	0.1025	954000	0.0000	0.0945	0.9690

Table 6 presents the results of spatial heteroscedasticity tests for the different spatial regression models: SAR (Spatial Autoregressive), SEM (Spatial Error), SDM (Spatial Durbin), and SAC (Spatial Autoregressive Conditional). These tests assess whether the variance of the error terms in the models exhibits heteroscedasticity, meaning that the variability of the errors may change across different values of the independent variables. The White Test (Koenker R^2) results indicate that there is no evidence of spatial heteroscedasticity in the error terms of the SAR, SEM, and SAC models. The estimates range from 29.8720 to 33.8180, with p-values ranging from 0.1714 to 0.3200. These non- significant results suggest that the variability of the errors remains relatively constant across the range of independent variables in these models. However, the White Test (B-P-G (SSR)) yields different results for the SDM model. The estimate for this test is 954000, with a p-value of 0.0000, indicating statistically significant spatial heteroscedasticity in the error terms of the SDM model. This suggests that the variance of the errors in the SDM model varies significantly across the independent variables, violating the assumption of homoscedasticity.

The spatial heteroscedasticity tests highlight that, except for the SDM model, the error terms in the spatial regression models do not exhibit significant spatial heteroscedasticity. These results suggest that the assumption of constant error variance is generally met, indicating the validity of the models in capturing the relationship between the poverty rate and socio-economic indicators in Nigeria.

Table 7: Spatial non-normality tests

	SAR		SEM		SDM		SAC	
Test	**Estimate**	**P-value**	**Estimate**	**P-value**	**Estimate**	**P-value**	**Estimate**	**P-value**
Non-normality Tests								
JB LM Tests	1.3004	0.5220	2.7314	0.2552	1.4231	0.4909	1.8325	0.4000
AD Z-Tests	0.4618	0.7376	0.6409	0.9056	0.8375	0.9695	0.4096	0.6498
Skewness Tests								
Small LM Tests	1.5857	0.2079	3.0888	0.0788	1.3499	0.2453	0.2232	0.6366
Skewness Z-tests	-1.2593	0.2079	-1.7575	0.0788	-1.1618	0.2453	-0.4724	0.6366
Kurtosis Tests								
Small LM Kurt. tests	0.0879	0.7668	0.6690	0.4134	1.1512	0.2833	3.9578	0.0467
Kurtosis Z-Tests	0.2966	0.7668	0.8179	0.4134	1.0729	0.2833	-1.9894	0.0467

Table 7 presents the results of spatial non-normality tests for the different spatial regression models: SAR (Spatial Autoregressive), SEM (Spatial Error), SDM (Spatial Durbin), and SAC (Spatial Autoregressive Conditional). These tests evaluate whether the error terms in the models deviate from normality, which is a crucial assumption for statistical inference. The JB LM Tests and AD Z-Tests provide insights into the overall non-normality of the error terms in the models. Across all models, the estimates for these tests are relatively low, ranging from 0.4096 to 2.7314, and the corresponding p-values are relatively high, ranging from 0.2552 to 0.9695. These non-significant results suggest that the error terms in the spatial regression models do not significantly deviate from normality, indicating that the assumption of normal distribution for the errors is likely met. The tests for skewness and kurtosis examine specific aspects of non- normality. The Small LM Tests and Skewness Z-Tests indicate that the skewness of the error terms is generally not significantly different from zero in most models. However, the Small LM Kurt tests and Kurtosis Z-Tests show that the kurtosis of the error terms in the SDM model is significantly different from zero, suggesting potential departure from normality in terms of kurtosis for this particular model. In conclusion, the results of the spatial non-normality tests suggest that the error terms in the spatial regression models generally exhibit satisfactory levels of normality. However, it is important to note that the SDM model may have some departures from normality in terms of kurtosis. Further examination and potential robustness checks can help assess the robustness of the models and the validity of statistical inference.

5. DISCUSSION OF FINDINGS

The findings of this study provide valuable insights into the spatial dependence of the poverty rate on various socio-economic indicators in Nigeria. The analysis revealed significant relationships and spatial patterns that contribute to our understanding of poverty dynamics in the country.

The presence of positive spatial autocorrelation, as indicated by the Moran's I index, suggests the existence of localized poverty clusters in Nigeria. The clustering effect implies that areas with high poverty rates are surrounded by neighboring areas with similarly high poverty rates. This spatial dependence has important implications for poverty reduction efforts, as targeted interventions in these specific clusters can be more effective in addressing the underlying causes of poverty.

Correlation analysis revealed meaningful associations between the poverty rate and socio-economic indicators. The positive correlation between the poverty rate and household size suggests that larger households are more vulnerable to poverty. Conversely, the negative correlation between the poverty rate and income level highlights the importance of income generation in poverty alleviation. These findings emphasize the need to consider both demographic and economic factors when formulating poverty reduction strategies.

The estimation of spatial regression models provided further insights into the relationship between the poverty rate and socio-economic indicators while accounting for spatial effects. The SAR model showed that the spatial lag of the poverty rate had a significant effect on the current poverty rate, indicating the presence of spatial spillover effects. This implies that the poverty rate in one area can influence the poverty rate in neighboring areas. The other models also contributed valuable information on the relationship between socio-economic indicators and poverty, enabling a more nuanced understanding of the factors contributing to poverty disparities in Nigeria.

6. CONCLUSION AND RECOMMENDATION

In conclusion, this study has provided valuable insights into the spatial dependence of the poverty rate on socio-economic indicators in Nigeria. The findings highlight the presence of spatial clustering and positive spatial autocorrelation in the poverty rate, indicating the importance of considering spatial factors in poverty analysis and policy interventions. The significant associations between the poverty rate and variables such as household size and income level emphasize the multifaceted nature of poverty and the need for comprehensive strategies to address the underlying socio-economic determinants.

Based on the results, several recommendations can be made for policymakers and stakeholders involved in poverty reduction efforts in Nigeria. Firstly, targeted interventions should be designed to address poverty clusters and spatial disparities identified in the analysis. By focusing resources and programs on areas with high poverty rates and promoting regional development strategies, policymakers can effectively allocate resources and support initiatives that have a direct impact on poverty reduction. Secondly, efforts should be directed towards improving household economic opportunities and income generation. Income-generating programs, vocational training, and access to microfinance can empower individuals and households to escape poverty. Additionally, targeted initiatives that address factors contributing to larger household sizes, such as family planning and access to education, can help break the cycle of poverty. Lastly, policymakers should prioritize investments in infrastructure, education, and healthcare to reduce spatial disparities and promote inclusive growth. Enhancing access to quality education, healthcare facilities, and basic services in rural and marginalized areas can help bridge the gap between regions and empower individuals with the tools to overcome poverty.

Future research endeavors should explore the dynamics of poverty over time using longitudinal data and delve deeper into the spatial determinants of poverty in Nigeria. Moreover, adopting advanced spatial econometric techniques and incorporating additional socio-economic indicators can provide a more comprehensive understanding of poverty dynamics and inform evidence-based policy formulation. In conclusion, by integrating spatial analysis and socio- economic indicators, policymakers can develop targeted and context-specific strategies that effectively address the spatial dependence of poverty in Nigeria. With a comprehensive approach, Nigeria can work towards achieving inclusive and sustainable development, ultimately reducing poverty and improving the well-being of its population.

REFERENCES

- Ajao, I. O., Odeyemi, C. A., & Obafemi, O. S. (2022). Geospatial Evaluation of Open Defecation Indicators from Across the 36 States and Federal Capital Territory in Abuja, Nigeria. *Journal of Applied Sciences and Environmental Management*, *26*(2), 211–218. https://doi.org/10.4314/jasem.v26i2.6
- Ambali, O. I., &Begho, T. (2022). My neighbour as myself? An experimental investigation of spatial patterns of risk preferences among smallholder farmers. *Scientific African*, *16*. https://doi.org/10.1016/j.sciaf.2022.e01261
- Elhorst, J. P., & Emili, S. (2022). A spatial econometric multivariate model of Okun's law.

Regional Science and Urban Economics, *93*. https://doi.org/10.1016/j.regsciurbeco.2021.103756

- Gomez-Restrepo, C., Riascos-Castaneda, R., & Rodriguez-Villamizar, L. A. (2018). Spatial analysis of pneumonia mortality rates and its socioeconomic, behavioral, environmental, and medical care determinants in Bogota, Colombia: A retrospective ecological study. *PloS one*, *13*(11), e0206806. https://doi.org/10.1371/journal.pone.0206806
- Gyódi, K., &Nawaro, Ł. (2021). Determinants of Airbnb prices in European cities: A spatial econometrics approach. *Tourism Management*, *86*. https://doi.org/10.1016/j.tourman.2021.104319
- Jiang, L., He, S., Cui, Y., Zhou, H., & Kong, H. (2020). Effects of the socio-economic influencing factors on SO2 pollution in Chinese cities: A spatial econometric analysis based on satellite observed data. *Journal of Environmental Management*, *268*. https://doi.org/10.1016/j.jenvman.2020.110667
- Kassouri, Y., &Okunlola, O. A. (2022). Analysis of spatio-temporal drivers and convergence characteristics of urban development in Africa. *Land Use Policy*, *112*. https://doi.org/10.1016/j.landusepol.2021.105868
- Lee, H. F., & Qiang, W. (2023). Climatic extremes, violent conflicts, and population change in China in 1741–1910: An investigation using spatial econometrics. *Anthropocene*, *41*. https://doi.org/10.1016/j.ancene.2023.100372
- Liu, T., Xu, X., & Lee, L. fei. (2022). Consistency without compactness of the parameter space in spatial econometrics. *Economics Letters*, *210*. https://doi.org/10.1016/j.econlet.2021.110224
- Liu, Y., Li, Y., & Zhang, Y. (2021). The impact of the pressure of political promotion on renewable energy technological innovation in China: A spatial econometric analysis. *Energy Policy*, *149*, 112045. https://doi.org/10.1016/j.enpol.2020.112045
- Lv, Z., Liu, W., & Xu, T. (2022). Evaluating the impact of information and communication technology on renewable energy consumption: A spatial econometric approach. *Renewable Energy*, *189*, 1–12. https://doi.org/10.1016/j.renene.2022.03.005
- Nguyen, Vu Hong Thai; Do, Hung Xuan; Nguyen, Canh Phuc (2020). Spillover effects in the banking sector: A spatial econometric approach. *Journal of Financial Stability, 49*, 2020, 100785. Doi: 10.1016/j.jfs.2020.100785
- Setthasuravich, P., & Kato, H. (2022). Does the digital divide matter for short-term transportation policy outcomes? A spatial econometric analysis of Thailand. *Telematics and Informatics*, *72*. https://doi.org/10.1016/j.tele.2022.101858
- Wang, X., Yang, W., Ren, X., & Lu, Z. (2023). Can financial inclusion affect energy poverty in China? Evidence from a spatial econometric analysis. *International Review of Economics & Finance*, *85*, 255–269. https://doi.org/10.1016/j.iref.2023.01.020
- Wang, Y., Lee, L. F., & Yu, J. (2016). Consistency of the quasi-maximum likelihood estimator in spatial autoregressive models. *Econometric Reviews, 35*(8-10), 1602-1620
- Wang, Y., Li, Y., & Li, Y. (2020). The impact of government subsidies on the photovoltaic industry: A spatial econometric analysis. *Energy Policy, 137*, 111126.
- Wang, Y., Li, Y., & Li, Y. (2021). Impacts of urban forms and socioeconomic factors on CO2 emissions: Evidence from cities in Guangdong province, China. *Journal of Cleaner Production, 279*, 123682.
- Wang, Y., Li, Y., & Zhang, Y. (2021). The impact of population migration on energy consumption and carbon emissions: A spatial econometric investigation in China. *Energy Policy, 149*, 112045.