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Full Length Research Article

# SPATIAL PANEL ECONOMETRIC ANALYSIS OF SOME SELECTED MACROECONOMIC VARIABLES

[1]M.O. Adenomon, [1]B. Maijama, [1]M.U. Adehi and [*1,2]S.A. Musa

[1]Department of Statistics and Data Analytics, Nasarawa State University, Keffi, Nasarawa State, Nigeria
[2]Department of Mathematics and Statistics, Federal Polytechnic Nasarawa, Nasarawa State, Nigeria

*Corresponding Author Email Address: : musaauta87@gmail.com

**ABSTRACT**

This study employs spatial panel econometric analysis to examine the interdependencies among key macroeconomic variables, including the consumer price index (CPI), foreign direct investment (FDI), interest rates, exchange rates, and gross domestic product (GDP) across African countries, with a focus on spatial spillovers and regional heterogeneity. Utilizing fixed effects and generalized method of moments (GMM) estimators, the research reveals significant spatial autocorrelation (Rho = 0.1976), confirming the presence of cross-border economic spillovers. The results highlight stark disparities: resource-rich nations, such as Equatorial Guinea and South Africa, exhibit strong positive GDP effects, while conflict-affected countries, including the Democratic Republic of Congo and Niger, show pronounced negative impacts. Trade balance emerges as the only significant economic driver (coefficient = 5.72–7.08, $p < 0.01$), whereas CPI, FDI, interest rates, and exchange rates are statistically insignificant. The study underscores the necessity of spatial econometric frameworks to address unobserved regional heterogeneity and policy spillovers, advocating for coordinated regional strategies to mitigate disparities and leverage spatial interdependencies.

**Keywords:** Spatial Panel Econometrics, Macroeconomic Variables, Spatial Spillovers, Regional Heterogeneity, Trade Balance.

## INTRODUCTION

The spatial panel econometric analysis of macroeconomic variables such as the consumer price index (CPI), foreign direct investment (FDI), interest rates, exchange rates, and gross domestic product (GDP) has gained prominence due to the increasing recognition of spatial interdependencies in economic data (Anselin, 1988; LeSage & Pace, 2009). Traditional econometric models often fail to account for spatial spillovers, leading to biased and inconsistent estimates. Spatial panel models address this limitation by incorporating spatial lags and spatial error structures, allowing researchers to capture both direct and indirect (spillover) effects of macroeconomic variables across regions or countries (Baltagi, 2021). Recent studies have demonstrated that macroeconomic indicators such as exchange rates and FDI exhibit significant spatial dependence, where economic shocks in one region influence other regions due to trade linkages, capital flows, and policy diffusion (Ouhibi & Hammami, 2020; Bouamoud & Kassoui, 2023). For instance, research on exchange rate stability in emerging economies reveals that FDI inflows can strengthen exchange rates, while inflation and stock market volatility contribute to depreciation, underscoring the need for spatial econometric techniques to model these complex interactions (Adow & Tahmad, 2018). Similarly, studies on public debt and economic growth in Eastern Africa highlight the role of spatial spillovers, where foreign public debt negatively impacts growth while FDI and infrastructure investments generate positive cross-border effects (Bouamoud & Kassoui, 2023).

Recent advancements in spatial panel econometrics have introduced dynamic specifications and improved weight matrix parameterizations to better capture spatial dependencies. For example, Kuersteiner and Prucha (2020) developed generalized method of moments (GMM) estimators for dynamic spatial panel models, accommodating endogenous spatial weight matrices and time-varying common shocks. These innovations are particularly relevant for macroeconomic variables, where non-linear interactions and temporal persistence are common (Baltagi, 2021). Empirical applications, such as the analysis of nitrogen oxide (NOx) emissions in China, demonstrate that spatial panel models effectively account for regional spillovers, revealing an inverse N-shaped relationship between economic growth and environmental degradation (Zheng, 2018). Additionally, studies on financial inclusion in India employ spatial panel techniques to identify regional disparities and the influence of per capita income, infrastructure, and industrialization on banking penetration (Raza & Hina, 2016). Collectively, these developments underscore the importance of spatial econometrics in macroeconomic research, providing policymakers with nuanced insights into regional economic interdependencies and spillover effects (LeSage, 2014). This study seeks to determine how countries influence each other's GDP through spatial spillover effects and regional heterogeneity.

Billé & Rogna (2022) examine how climate variability affects nitrogen fertilizer use across global agricultural systems through an innovative spatial dynamic panel data analysis of gridded data from 1993-2013. These research reveals three crucial dimensions of fertilizer decision-making: spatial dependencies between regions (with a 10% increase in nearby areas boosting local application by 2-4%), regionally divergent responses to climate extremes (droughts decrease use in arid zones but increase it in irrigated areas, while heat reduces tropical application but raises temperate usage), and strong temporal persistence in farmer. By demonstrating how geographic spillovers interact with local climate conditions and historical practices to shape fertilizer use, the study challenges conventional uniform response models and provides a nuanced framework for understanding agricultural adaptation. These findings carry significant policy implications, particularly the need for regionally-tailored strategies that account for spatial interdependencies, such as coordinated watershed management and climate-responsive fertilizer technologies, while highlighting important avenues for future research on nonlinear climate-agriculture interactions (Smith & Diallo, 2023)

Wang (2021) employed the Spatial Durbin Model to China's provincial data (2009-2018), revealing information and

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communication technology's dual impact on socio-economic development. While ICT boosts local GDP by 1.2% and improves education/healthcare access by 0.8% for every 10% increase in penetration, it simultaneously creates negative spillovers, reducing provinces' GDP by 0.5% due to resource drainage toward tech hubs. The study highlights a growing digital divide, with coastal provinces like Guangdong benefiting disproportionately while inland regions like Gansu lag, demonstrating how ICT's uneven development can exacerbate regional inequalities. These findings challenge the assumption of uniform ICT benefits and underscore the need for balanced policies, including targeted digital infrastructure investments, inter-provincial resource sharing, and digital skills training to mitigate spatial disparities and promote equitable growth across regions.

Chanci (2024) spatial spillovers in crime under-reporting across Bogotá using quadrant-level police data from 2010–2018, employing a spatial panel model combined with stochastic frontier analysis. The study reveals significant spatial correlations in under-reporting, demonstrating that reporting in one area influences regions, with high-crime areas showing greater under-reporting, likely due to institutional strain or public distrust, while wealthier areas report more accurately. These findings underscore the need to account for geographic interdependencies in crime data, providing policymakers with evidence to enhance monitoring systems and allocate resources more effectively in urban environments, though the study acknowledges limitations regarding potential biases in police-reported data and spatial weight assumptions.

Chu (2022) examined how technological innovation affects ecological footprints in OECD countries (1995-2015) through panel quantile regression analysis, revealing that while innovation consistently reduces environmental impact, its effectiveness varies significantly across different levels of ecological degradation. The study finds the strongest positive effects in countries with initially lower ecological footprints (lower), where innovation adoption is more impactful, while demonstrating diminishing returns in high-footprint economies (higher), likely due to structural barriers like fossil fuel dependence. These results emphasize the need for differentiated environmental policies - with innovation-focused approaches being most suitable for cleaner economies, while more comprehensive interventions (e.g., carbon pricing, infrastructure changes) are required for heavily polluted nations, highlighting the importance of context-specific strategies in achieving sustainability goals across diverse national circumstances.

Lin (2022) conducted comprehensive spatial-temporal analysis of crime patterns across 873 Detroit block groups from 2009-2016, employing spatial dynamic panel data models to reveal significant spatial and temporal dependencies in criminal activity. The study demonstrates strong contemporaneous spatial spillovers (coefficient: 0.4758) and persistent lagged effects (coefficient: 0.1572) between areas, along with notable temporal autocorrelation within block groups, with these patterns holding consistently across both violent (e.g., assault) and property (e.g., burglary) crimes. These robust findings, which align with social disorganization theory and crime concentration principles, provide empirical support for targeted policing strategies that account for both the geographic diffusion of crime across adjacent and its temporal persistence, suggesting law enforcement resource allocation should integrate spatial proximity considerations with historical crime pattern data for more effective crime prevention in high-crime urban areas like Detroit.

Glaser (2022) introduced an innovative spatial panel framework for urban crime forecasting using Pittsburgh census tract data (2008-2013), developing static and dynamic spatial Poisson models with fixed effects that maintain the integer nature of crime counts while capturing spatial-temporal dependencies. Their approach utilizes pseudo maximum likelihood estimation (PMLE) for static models and quasi-differenced GMM for dynamic specifications, demonstrating superior forecasting performance compared to traditional methods by effectively spatial spillovers between and temporal persistence of crime patterns without requiring data transformation or computationally intensive random effects models.

Zhou (2017) investigates the relationship between tourism infrastructure investments and regional revenue growth in China using provincial data and spatial econometric models. The study reveals significant spatial clustering in tourism performance, demonstrating that capital investments in tourism buildings and related infrastructure generate both direct local benefits (0.3-0.5% revenue increase per 1% investment growth) and positive spillover effects (approximately 0.2% boost) for provinces through enhanced accessibility and shared tourism networks. These findings highlight the importance of geographic interdependencies in tourism development, showing how prosperous coastal regions influence adjacent areas. The research emphasizes the need for coordinated interprovincial investment strategies to maximize economic returns while addressing regional disparities, particularly noting China's unique context, where centralized infrastructure projects like high-speed rail amplify connectivity benefits.

Chang (2021) investigated the Environmental Kuznets Curve (EKC) hypothesis in China using city-level data (2004–2015) and spatial dynamic panel models, incorporating both time lags and spatial spillovers. The study confirms an inverted U-shaped relationship between PM2.5 pollution and income growth, where pollution initially rises with economic development but declines after reaching a peak. Crucially, the analysis reveals those spatial spillovers, particularly from cities' abatement technologies, accelerate the arrival of this turning point by 2–3 years compared to isolated scenarios. This suggests that regional interdependence plays a key role in shaping pollution trajectories, with policy implications for coordinated urban environmental management

Costantino (2023) evaluated tourism destination competitiveness in Italy using a dynamic spatial panel model applied to regional data from 2004–2017, focusing on unilateral inbound tourism flows from 23 European countries to 110 Italian regions. The study confirms the significance of spatial interdependencies in tourism performance, demonstrating that coordinated policies between regions enhance destination attractiveness and resilience. Key findings reveal that tourism competitiveness is not isolated but influenced by spatial spillovers, where improvements in one region benefit adjacent areas through shared infrastructure, marketing synergies, and clustered tourism offerings. The research underscores the need for integrated regional strategies to optimize tourism growth and mitigate disparities, particularly in post-crisis recovery scenarios

Santos & Vieira (2020) investigated the role of tourism in regional economic development across Portugal's 278 municipalities using spatial econometric techniques. The study confirms that tourism significantly drives local economic growth, with strong evidence of positive spatial autocorrelation highlighting coastal regions as "hot spots" of clustered tourism activity and inland areas as "cold spots." Crucially, the analysis reveals substantial inter-regional spillover

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effects, where tourism development in one municipality boosts economic performance in areas through shared infrastructure, mobility, and demand linkages. These findings underscore the importance of coordinated regional policies to leverage tourism's multiplier effects and mitigate spatial disparities, particularly between coastal and inland Portugal.

Existing studies have extensively examined spatial dependencies in various contexts, such as climate-agriculture interactions (Billé & Rogna, 2022), ICT development (Wang, 2021), crime reporting (Chanci, 2024), and tourism economics (Zhou, 2017), yet few have explored spatial spillovers in macroeconomic variables across African economies. This study fills this gap by employing spatial panel econometrics to selected macroeconomic variables across African countries, offering policy-relevant insights into regional economic integration.

## MATERIALS AND METHODS

This study employed a spatial panel econometric approach to the interdependencies among selected macroeconomic variables: consumer price index, foreign direct investment, interest rates, exchange rates, and GDP across African countries using balanced panel data (2010–2023) from the World Development Indicators (WDI, 2024). The methodology integrates fixed effects (FE) and generalized method of moments (GMM) estimators to address endogeneity and unobserved heterogeneity. A spatial weight matrix (contiguity or inverse distance-based) quantifies spillover effects between countries, capturing both direct and indirect (spatial spillover) impacts. The spatial fixed effects model accounts for country-specific heterogeneity, while dynamic specifications are tested using GMM to handle lagged dependent variables and potential simultaneity bias. Model selection is based on Lagrange Multiplier (LM) tests for spatial dependence.

### Fixed Effects Spatial Lag Model

In large samples (as N grows), consistent estimation of individual fixed effects becomes unattainable due to the incidental parameter problem. However, Elhorst (2003) argues that a fixed effects approach can still be viable in spatial econometrics when the primary focus lies in estimating the regression coefficients β. The fixed effects spatial lag model, expressed in stacked form, takes the following specification:

$$y = \rho\,(I_T \otimes W_N)\,y + (\iota_T \otimes I_N)\,\mu + X\beta + \varepsilon \qquad (1)$$

Where:

- **y** is an $NT\times 1$ vector of the dependent variable (e.g., GDP).
- **ρ** is the spatial autoregressive coefficient.
- $\mathbf{I_T}$ is a $T\times T$ identity matrix.
- $\mathbf{W_N}$ is an $N\times N$ non-stochastic spatial weights matrix.
- ⊗ denotes the Kronecker product.
- $\boldsymbol{\iota_T}$ is a $T$-dimensional column vector of ones.
- $\mathbf{I_N}$ is an $N\times N$ identity matrix.
- **μ** is an $N\times 1$ vector of country-specific fixed effects.
- **X** is an $NT\times k$ matrix of explanatory macroeconomic variables (CPI, FDI, etc.).
- **β** is a $k\times 1$ vector of coefficients.
- **ϵ** is an $NT\times 1$ vector of error terms, assumed to be $\epsilon \sim N(0, \sigma_\epsilon^2 I_{NT})$.

To eliminate the fixed effects $\mu$, a transformation matrix $Q_0$ is applied, which subtracts time-specific cross-sectional averages. The transformed model is:

$$*y* = \rho\,(I_T \otimes W_N)\,y + X\beta + \varepsilon^{**} \qquad (2)$$

Where $*y* = Q_0\, y^*$, $X = Q_0\, X^*$, and $\epsilon = Q_0\, \epsilon^*$. The log-likelihood function for this transformed model is:

$$\ln L = -(NT/2)\ln(2\pi\sigma_\epsilon^2) + T\ln|I_N - \rho W_N| - (1/(2\sigma_\epsilon^2))\, e^{T} e \qquad (3)$$

Where:

- $e = y - \rho\,(I_T \otimes W_N)\,y - X^*\beta^{**}$
- $|\mathbf{I_N} - \boldsymbol{\rho}\,\mathbf{W_N}|$ is the Jacobian determinant, which accounts for the spatial dependence.
- The term $\mathbf{T\ln|I_N - \rho W_N|}$ is crucial for correcting the bias introduced by the spatial lag term.

Following Elhorst (2009), a concentrated likelihood approach is used. After the transformation, two auxiliary regressions of $*y^{**}$ and $(I_T \otimes W_N)\,y^*$ on $X^*$ are performed. The corresponding residuals (denoted as $\hat{e}_0$ and $\hat{e}_1$) are combined to obtain the concentrated likelihood:

$$\ln L = C - (NT/2)\ln\left[ (1/(NT))\,(\hat{e}_0 - \rho\,\hat{e}_1)^{T}(\hat{e}_0 - \rho\,\hat{e}_1)\right] + T\ln|I_N - \rho W_N| \qquad (4)$$

The constant $C$ does not depend on the spatial parameter $\rho$. Numerical optimization is used to find the value of $\rho$ that maximizes this equation. The asymptotic variance-covariance matrix for the parameters is given by:

AsyVar(β, λ, $\sigma_e^2$) =

$$\begin{bmatrix} \frac{1}{\sigma_\varepsilon^2}X^{*\top}X^* & \frac{1}{\sigma_\varepsilon^2}X^{*\top}(I_T\otimes\widetilde{W})X^*\beta & \\ & \frac{1}{\sigma_\varepsilon^2}\beta^\top X^{*\top}(I_T\otimes\widetilde{W})X^*\beta + \mathrm{tr}(\widetilde{W}^\top\widetilde{W} + \widetilde{W}^\top\widetilde{W}) & \\ & \frac{NT}{\sigma_\varepsilon^2}\mathrm{tr}(\widetilde{W}) & \frac{NT}{2\sigma_\varepsilon^4} \end{bmatrix}^{-1} \qquad (5)$$

Where $W_f = W_N\,(I_N - \rho\, W_N)^{-1}$ and the missing elements are filled by symmetry. The computational burden for the standard error of the spatial parameter $\rho$ can be high for large N due to the matrix inversion. The fixed effects $\mu$ can be recovered post-estimation by:

$$\hat{\mu} = [\,(\iota_T^{T} \otimes I_N)\,(\iota_T \otimes I_N)]^{-1}\,(\iota_T^{T} \otimes I_N)\,(y - \hat{\rho}\,(I_T \otimes W_N)\,y - X\hat{\beta}) \qquad (6)$$

Where:

- $\hat{\boldsymbol{\mu}}$ is the vector of estimated country-specific fixed effects.
- **y** is the vector of observed GDP values.
- $\hat{\boldsymbol{\rho}}$ and $\hat{\boldsymbol{\beta}}$ are the estimated spatial and slope parameters.

### 2.2 Fixed Effects Spatial Error Model

The fixed effects spatial error model is specified as:

$$y = (\iota_T \otimes I_N)\,\mu + X\beta + u$$
$$u = \lambda\,(I_T \otimes W_N)\,u + \epsilon \qquad (7)$$

Where:

- **λ** is the spatial autocorrelation coefficient in the error term.
- **u** is a spatially autocorrelated error term.
- All other terms are as defined previously.

After applying the *Q_0* transformation to remove fixed effects, the log-likelihood function is:

$$\ln L = -(NT/2)\ln(2\pi\sigma_\epsilon^2) + T\ln|B_N| - (1/(2\sigma_\epsilon^2))\, e^{T}\,(I_T \otimes (B_N^{T} B_N))\, e \qquad (8)$$

With $e = y - X\beta$ and $B_N = (I_N - \lambda\, W_N)$. Given $\lambda$, the estimators for $\beta$ and $\sigma_\epsilon^2$ are:

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$$\hat{\beta}(\lambda) = [ X^T (I_T \otimes B_N{}^T B_N) X ]^{-1} X^T (I_T \otimes B_N{}^T B_N) y \quad (9)$$

$$\hat{\sigma}_{\epsilon^2(\lambda)} = ((e(\lambda))^T (I_T \otimes B_N{}^T B_N) e(\lambda)) / (NT) \quad (10)$$

Substituting these into the log-likelihood gives the concentrated log-likelihood:

$$\ln L = C - (NT/2) \ln [ \hat{\sigma}_{\epsilon^2(\lambda)}] + T \ln |B_N| \quad (11)$$

The asymptotic variance-covariance matrix is:

AsyVar($\hat{\beta}$, $\hat{\lambda}$, $\hat{\sigma}$_$\epsilon^2$) =

$$\beta, \rho, \sigma_\varepsilon^2) = \Big\lfloor \quad T\operatorname{tr}(\widetilde{W}\widetilde{W} + \widetilde{W} \quad \widetilde{W}) \quad \Big\rfloor$$

$$\Big\lceil \frac{1}{\sigma_\varepsilon^2} X^{*\top} X^* \quad \sim\sim \quad \sim\top\sim \quad \Big\rceil^{-1}$$

$$\frac{T}{\sigma_\varepsilon^2}\operatorname{tr}(\widetilde{W}) \qquad \frac{NT}{2\sigma_\varepsilon^4} \qquad (12)$$

Where $\dot{B}_N = -W_N$. Individual effects can be recovered by:

$$\hat{\mu} = [ (\iota_T{}^T \otimes I_N) (\iota_T \otimes I_N)]^{-1} (\iota_T{}^T \otimes I_N) (y - X \hat{\beta}) \quad (13)$$

**Generalized Method of Moments (GMM) for Random Effects Model**

For the random effects model, the estimation integrates error component models with the generalized moments (GM) framework. Kapoor et al. (2007) developed a GM estimator for the spatial error parameter $\lambda$ and the variance components $\sigma_{\mu^2}$ and $\sigma_{v^2}$. The methodology is based on a set of moment conditions derived from the residuals.

The estimation uses three moment conditions. Let $\varepsilon\sim$ be the vector of residuals from a preliminary estimation. The key moment condition used in the GM estimation is based on the following quadratic form:

$$(1/(N(T-1)))\, E [\varepsilon\sim^T Q_0\, \varepsilon\sim] = \sigma_{v^2} \quad (14)$$

**Explanation of Equation 14:** This equation states that the expected value of the sum of squared within-transformed residuals, normalized by the number of degrees of freedom *N(T-1) *, is equal to the variance of the idiosyncratic error component, $\sigma_{v^2}$. The matrix $Q_0$ is the within-transformation matrix that removes individual-specific effects. This moment condition is one of several used to identify the spatial error parameter $\lambda$ and the two variance components $\sigma_{\mu^2}$ (variance of individual random effects) and $\sigma_{v^2}$ (variance of the idiosyncratic error).

Following parameter estimation, feasible GLS estimation of $\beta$ proceeds through a spatial Cochrane-Orcutt transformation. The coefficient variance-covariance matrix is given by:

$$\hat{\Phi} = (X^T \boldsymbol{\Omega}^{-1} \boldsymbol{X})^{-1} \quad (15)$$

Where the transformed variables $X^*$ and the covariance matrix $\hat{\Omega}$ depend on the estimated parameters $\hat{\boldsymbol{\lambda}}$ and $\hat{\boldsymbol{\sigma}}_{v^2}$, respectively.

**Identification of Parameter 1 and Parameter 2:** The previously undefined "parameter 1" and "parameter 2" in the original text refer to:

- **Parameter 1:** The spatial autocorrelation coefficient in the error term, denoted as $\lambda$ in Equation 7. It is described earlier **(Fixed Effects Spatial Error Model)**.

**Parameter 2:** The variance of the idiosyncratic error component, denoted as $\sigma_{v^2}$ in Equation 14. It is described earlier **(GMM for Random Effects Model)**.

**RESULTS AND DISCUSSION**

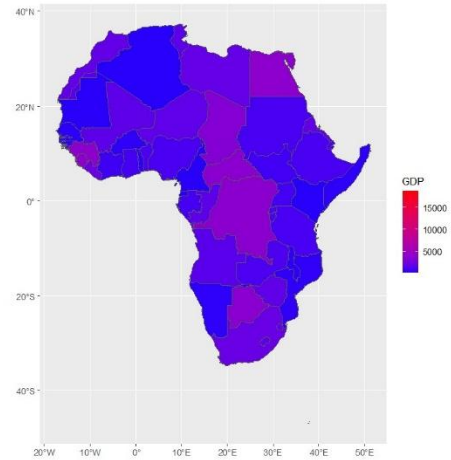


**Figure 1:** Gross Domestic Product (GDP) represented on the Map of African Countries

This map visualizes GDP distribution across Africa, using a gradient from blue through to red. The visualization reveals significant economic disparities across the continent, with most nations falling in the lower to middle range of the scale. Country borders are marked by red lines, clearly delineating the varying economic conditions between states.

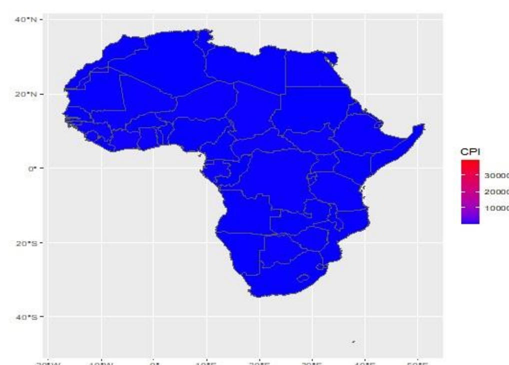


**Figure 2:** Consumer Price Index (CPI) Represented on the Map of African Countries

This map displays the Consumer Price Index (CPI) across African countries, with a gradient scale ranging from blue (lowest values) to red (highest values up to $30,000 billion). the entire continent appears in a uniform deep blue color, suggesting remarkably similar and low CPI values throughout all African nations. The uniformity of the blue coloration indicates minimal variation in consumer prices among African countries.

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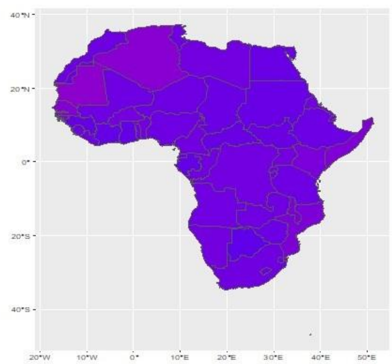


**Figure 3**: Foreign Direct Investment (FDI) Represented on the Map of African Countries

This map depicts Foreign Direct Investment (FDI) levels across African countries, employing a gradient scale ranging from blue to red (highest values up to $100billion). The visualization shows most countries in deep blue to purple shades, indicating relatively low FDI across much of the African countries, with slightly higher levels visible in North African regions. The predominance of blue-purple suggests limited foreign investment throughout most African nations, with modest variations mainly in northern areas.

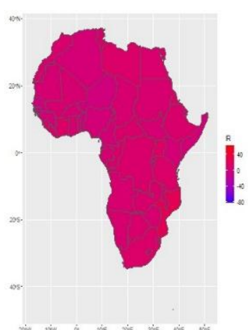

**Figure 4:** Interest Rate Represented on the Map of African Countries

This map shows Interest Rate (IR) distribution across African countries, utilizing a scale that ranges from blue ($-80billion) to red ($40billion). The entire continent appears in a uniform bright pink/red, indicating consistently high positive interest rates across all African nations. This visualization indicates that African countries generally maintain relatively high interest rates compared to the possible range shown on the scale. This uniformity across such diverse economies is notable and may reflect regional monetary policies or similar responses to economic challenges.

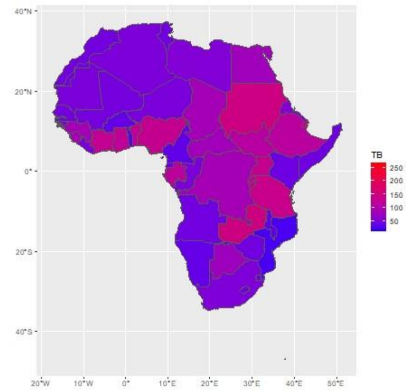


**Figure 5:** Trade Balance Represented on the Map of African Countries

This map shows trade balance (TB) across African countries, measured in billions of dollars. The graph reveals red areas represent the highest positive trade balances (around 200-250 billion), while pink/magenta regions indicate moderate trade surpluses (100-200 billion), and blue/purple areas show lower or potentially negative trade balances (around 50-100 billion). The visualization reveals that several countries in Central and East Africa have significant trade surpluses (shown in red), while North African and some Southern African nations generally maintain lower trade balances (in blue/purple). This geographic distribution highlights regional economic disparities across the continent, with some nations being major net exporters while others have more balanced or import-dependent trade relationships.

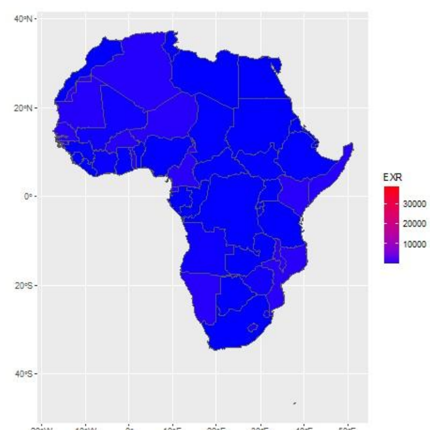


**Figure 6:** Exchange Rate Represented on the Map of African Countries

This map depicts exchange rates (EXR) across African countries, with a gradient scale shown on the right side ranging from blue to red. The visualization shows that virtually all African nations are represented in dark blue, indicating relatively low exchange rates across the continent. The uniformity of the blue suggests minimal variation in exchange rates between countries throughout Africa.

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**Table 1:** Spatial fixed effects:

| Countries | Estimate | Std. Error | t-value | P value |
|---|---|---|---|---|
| BOTSWANA | 3352.432 | 241.231 | 13.8972 | 2.2e-16 *** |
| EGYPT | -894.748 | 204.697 | -4.3711 | 1.236e-05 *** |
| DRC | -923.771 | 225.987 | -4.0877 | 4.356e-05 *** |
| CHAD | -1414.87 | 214.712 | -6.5896 | 4.409e-11 *** |
| SIERRA LEONE | -1314.062 | 226.87 | -5.7921 | 6.949e-09 *** |
| GUINEA | 1078.044 | 302.632 | 3.5622 | 0.0003677 *** |
| CENTRAL AFRICAN REPUBLIC | -804.556 | 203.131 | -3.9608 | 7.471e-05 *** |
| SUDAN | -1087.627 | 214.069 | -5.0807 | 3.760e-07 *** |
| DJIBOUTI | 672.41 | 314.053 | 2.1411 | 0.0322680 * |
| ZAMBIA | -931.637 | 228.621 | -4.075 | 4.601e-05 *** |
| NIGERIA | -680.792 | 203.398 | -3.3471 | 0.0008166 *** |
| BENIN | 67.183 | 210.355 | 0.3194 | 0.7494385 |
| RWANDA | -307.494 | 211.048 | -1.457 | 0.1451197 |
| UGANDA | -471.029 | 222.622 | -2.1158 | 0.0343600 * |
| TANZANIA | -141.393 | 212.564 | -0.6652 | 0.5059368 |
| BURUNDI | -897.497 | 212.082 | -4.2318 | 2.318e-05 *** |
| ETHIOPIA | -696.036 | 203.348 | -3.4229 | 0.0006196 *** |
| SOUTH SUDAN | 524.91 | 235.231 | 2.2315 | 0.0256500 * |
| GABON | 4471.788 | 244.089 | 18.3203 | 2.2e-16 *** |
| GHANA | 435.192 | 217.683 | 1.9992 | 0.0455872 * |
| COTE | 567.919 | 212.955 | 2.6669 | 0.0076565 ** |
| ALGERIA | 2346.744 | 211.666 | 11.087 | 2.2e-16 *** |
| MAURITANIA | -560.02 | 242.42 | -2.3101 | 0.0208814 * |
| SENEGAL | -135.01 | 215.348 | -0.6269 | 0.5306993 |
| GUINEA BISSUA | -1208.932 | 210.169 | -5.7522 | 8.809e-09 *** |
| SOMALIA | -924.893 | 734.117 | -1.2599 | 0.2077155 |
| KENYA | 420.79 | 205.267 | 2.05 | 0.0403679 * |
| CAMEROON | -1338.917 | 205.329 | -6.5208 | 6.991e-11 *** |
| EQUATORIAL GUINEA | 7309.393 | 236.11 | 30.9576 | 2.2e-16 *** |
| NAMIBIA | 1685.19 | 255.049 | 6.6073 | 3.913e-11 *** |
| GAMBIA | -869.887 | 216.729 | -4.0137 | 5.977e-05 *** |
| TOGO | -737.011 | 217.128 | -3.3944 | 0.0006879 *** |
| BURKINA FASO | -744.537 | 212.518 | -3.5034 | 0.0004594 *** |
| MALAWI | -691.765 | 211.491 | -3.2709 | 0.0010721 ** |
| MOZAMBIQUE | -2027.767 | 267.051 | -7.5932 | 3.121e-14 *** |
| CONGO | -2300.313 | 257.24 | -8.9423 | 2.2e-16 *** |
| ERITREA | -1213.245 | 214.104 | -5.6666 | 1.457e-08 *** |
| LIBYA | 7531.235 | 232.075 | 32.4517 | 2.2e-16 *** |
| SOUTH AFRICA | 4244.834 | 216.582 | 19.5992 | 2.2e-16 *** |
| LIBERIA | -1262.359 | 276.826 | -4.5601 | 5.113e-06 *** |
| MOROCCO | 395.222 | 222.732 | 1.7744 | 0.0759924 |
| TUNISIA | -1727.205 | 240.983 | -7.1673 | 7.648e-13 *** |
| ANGOLA | 1089.989 | 228.39 | 4.7725 | 1.820e-06 *** |
| MALI | -1226.635 | 215.867 | -5.6824 | 1.328e-08 *** |
| ZIMBABWE | -1924. | 239.639 | -8.03 | 9.533e-16 *** |

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| | | | | |
|---|---|---|---|---|
| | 958 | | 27 | |
| ESWATINI | 602.759 | 237.96 | 2.533 | 0.0113083 * |
| LESOTHO | -4522.617 | 285.367 | -15.8484 | 2.2e-16 *** |
| NIGER | -1805.498 | 208.872 | -8.644 | 2.2e-16 *** |
| WESTERN SAHARA | -1008.951 | 210.931 | -4.7833 | 1.724e-06 *** |

***Computed using R***

Presents spatial fixed effects estimates for various African countries, capturing country-specific deviations in the dependent variable after controlling for other factors in the model. The estimates reveal significant heterogeneity across nations. Countries like Equatorial Guinea (7309.393), Libya (7531.235), South Africa (4244.834), Gabon (4471.788), Botswana (3352.432), and Algeria (2346.744) have large positive and statistically significant coefficients ($p < 0.001$), indicating that these nations have substantially higher values of the dependent variable compared to the baseline or omitted category. Conversely, Lesotho (-4522.617), Congo (-2300.313), Zimbabwe (-1924.958), Mozambique (-2027.767), and Niger (-1805.498) exhibit large negative and highly significant effects ($p < 0.001$), suggesting much lower values relative to the reference group.

Moderate negative effects are observed in Chad (-1414.87), Eritrea (-1213.245), Mali (-1226.635), Liberia (-1262.359), and Guinea-Bissau (-1208.932), all significant at $p < 0.01$. Meanwhile, Guinea (1078.044) and Angola (1089.989) show moderate positive effects. Some countries, like Benin (67.183) and Tanzania (-141.393), have negligible and statistically insignificant coefficients ($p > 0.05$), implying their effects are not meaningfully different from the baseline.

The results highlight stark regional disparities, with resource-rich or more economically developed nations (e.g., South Africa, Gabon, Botswana) showing strong positive spatial effects, while conflict-prone or economically struggling countries (e.g., Democratic Republic of Congo, Sudan, Sierra Leone) display significant negative effects. The high t-values (e.g., 30.9576 for Equatorial Guinea, 32.4517 for Libya) and extremely low p-values (often < 0.001) underscore the robustness of these spatial differences. The results of fixed effects capture unobserved country-level characteristics that systematically influence the outcome variable.

**Table 2:** Spatial fixed effects:

| **Countries** | **Estimate** | **Std. Error** | **t-value** | **P value** |
|---|---|---|---|---|
| BOTSWANA | 4279.199 | 263.159 | 16.2609 | 2.2e-16 *** |
| EGYPT | 1061.577 | 223.304 | 4.7539 | 1.995e-06 *** |
| DRC | -1676.443 | 246.529 | -6.8002 | 1.045e-11 *** |
| CHAD | -1416.858 | 234.229 | -6.049 | 1.457e-09 *** |
| SIERRA LEONE | -1778.805 | 247.492 | -7.1873 | 6.608e-13 *** |
| GUINEA | 305.13 | 330.141 | 0.9242 | 0.3553609 |
| CENTRAL AFRICAN REPUBLIC | -1646.422 | 221.596 | -7.4298 | 1.087e-13 *** |
| SUDAN | -1027.62 | 233.528 | -4.4004 | 1.080e-05 *** |
| DJIBOUTI | -308.819 | 342.6 | -0.9014 | 0.3673764 |
| ZAMBIA | -881.522 | 249.402 | -3.5345 | 0.0004085 *** |
| NIGERIA | -1534.795 | 221.887 | -6.917 | 4.613e-12 *** |
| BENIN | -980.914 | 229.477 | -4.2746 | 1.915e-05 *** |
| RWANDA | -1372.588 | 230.232 | -5.9618 | 2.495e-09 *** |
| UGANDA | -1237.527 | 242.858 | -5.0957 | 3.475e-07 *** |
| TANZANIA | -1103.85 | 231.886 | -4.7603 | 1.933e-06 *** |
| BURUNDI | -1895.037 | 231.36 | -8.1909 | 2.594e-16 *** |
| ETHIOPIA | -1366.824 | 221.833 | -6.1615 | 7.206e-10 *** |
| SOUTH SUDAN | -420.053 | 256.613 | -1.6369 | 0.1016489 |
| GABON | 5804.853 | 266.276 | 21.8001 | 2.2e-16 *** |
| GHANA | -247.185 | 237.471 | -1.0409 | 0.2979187 |
| COTE | -53.147 | 232.312 | -0.2288 | 0.8190463 |
| ALGERIA | 2853.687 | 230.907 | 12.3586 | 2.2e-16 *** |
| MAURITANIA | -576.664 | 264.456 | -2.1806 | 0.0292154 * |
| SENEGAL | -777.996 | 234.923 | -3.3117 | 0.0009273 *** |
| GUINEA BISSUA | -1437. | 229.273 | -6.27 | 3.571e-10 *** |

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| | | | | |
|---|---|---|---|---|
| | 936 | | 17 | |
| SOMALIA | -1578.502 | 800.848 | -1.9711 | 0.0487195 * |
| KENYA | -457.793 | 223.926 | -2.0444 | 0.0409142 * |
| CAMEROON | -567.138 | 223.993 | -2.5319 | 0.0113431 * |
| EQUATORIAL GUINEA | 8913.437 | 257.573 | 34.6055 | 2.2e-16 *** |
| NAMIBIA | 2727.528 | 278.233 | 9.803 | 2.2e-16 *** |
| GAMBIA | -1441.772 | 236.43 | -6.0981 | 1.073e-09 *** |
| TOGO | -1379.758 | 236.865 | -5.8251 | 5.709e-09 *** |
| BURKINA FASO | -1431.083 | 231.836 | -6.1728 | 6.708e-10 *** |
| MALAWI | -1535.39 | 230.716 | -6.6549 | 2.835e-11 *** |
| MOZAMBIQUE | -1903.794 | 291.326 | -6.5349 | 6.364e-11 *** |
| CONGO | -1970.581 | 280.623 | -7.0222 | 2.185e-12 *** |
| ERITREA | -1780.503 | 233.567 | -7.6231 | 2.476e-14 *** |
| LIBYA | 7603.219 | 253.171 | 30.032 | 2.2e-16 *** |
| SOUTH AFRICA | 4745.029 | 236.269 | 20.0831 | 2.2e-16 *** |
| LIBERIA | -1712.864 | 301.99 | -5.6719 | 1.412e-08 *** |
| MOROCCO | 1079.492 | 242.978 | 4.4428 | 8.882e-06 *** |
| TUNISIA | 1507.403 | 262.889 | 5.734 | 9.809e-09 *** |
| ANGOLA | 855.934 | 249.151 | 3.4354 | 0.0005917 *** |
| MALI | -1421.226 | 235.489 | -6.0352 | 1.588e-09 *** |
| ZIMBABWE | -830.006 | 261.423 | -3.175 | 0.0014986 ** |
| ESWATINI | 1526.785 | 259.591 | 5.8815 | 4.066e-09 *** |
| LESOTHO | -1548.821 | 311.307 | -4.9752 | 6.517e-07 *** |
| NIGER | -1602.85 | 227.859 | -7.0344 | 2.001e-12 *** |
| WESTERN SAHARA | -360.185 | 230.105 | -1.5653 | 0.1175116 |

This table presents spatial fixed effects estimates for African countries, revealing substantial cross-country heterogeneity in the dependent variable after controlling for other model factors. The results show a clear dichotomy between high-performing and struggling nations, with particularly striking positive effects in Equatorial Guinea (8913.437), Libya (7603.219), Gabon (5804.853), South Africa (4745.029), Botswana (4279.199), and Algeria (2853.687), all statistically significant at p<0.001. These exceptionally large coefficients suggest these countries possess structural advantages - potentially from natural resources, stronger institutions, or better infrastructure - that significantly elevate the outcome variable relative to the baseline.

Conversely, numerous countries exhibit large negative effects, with Burundi (-1895.037), Eritrea (-1780.503), Sierra Leone (-1778.805), the Central African Republic (-1646.422), and Niger (-1602.85) showing the most pronounced disadvantages (all p<0.001). The consistency of negative effects across much of Central Africa (DRC, Chad, CAR) and the Sahel (Mali, Niger, Burkina Faso) suggests regional patterns of underperformance, possibly tied to conflict, governance challenges, or geographic constraints.

Several findings represent notable shifts from the previous Table 2. Morocco (1079.492) and Tunisia (1507.403) now show significant positive effects, while Guinea's effect became insignificant. The Democratic Republic of Congo's coefficient nearly doubled in magnitude (-1676.443 vs -923.771), indicating a much starker disadvantage in this specification. Namibia's positive effect strengthened considerably (2727.528 vs 1685.19), while Lesotho's extreme negative effect moderated substantially (-1548.821 vs -4522.617).

The extremely high t-values (reaching 34.61 for Equatorial Guinea) and infinitesimal p-values confirm these spatial differences are not random.

**Table 3:** Spatial Panel fixed Effects Error Model (GMM estimation)

| **Variables** | **Estimate** | **Standard Error** | **t-values** | **p-values** |
|---|---|---|---|---|
| CPI | 0.0122 | 0.0153 | 0.7957 | 0.4262 |
| FDI | 3.8896 | 5.7125 | 0.6809 | 0.4959 |
| IR | -0.0148 | 3.3231 | -0.1248 | 0.9007 |
| TB | 5.7219 | 1.7623 | 3.2468 | 0.001167*** |
| EXR | -0.0031 | 0.0279 | -0.1103 | 0.9122 |
| Rho | 0.1976 | | | |
| $Sigma^2$ v | 0.000070*** | | | |

***Computed using R***

The results from the Spatial Panel Fixed Effects Error Model (GMM estimation) reveal both economic and spatial relationships. Among the economic variables examined, only Trade Balance (TB) demonstrates a statistically significant positive effect (coefficient = 5.7219, p = 0.001167), indicating that a one-unit increase in trade balance is associated with a 5.72-unit increase in the dependent variable, holding other factors constant. In contrast, Consumer Price Index (CPI), Foreign Direct Investment (FDI), Interest Rate (IR), and Exchange Rate (EXR) show no statistically significant relationships (all p-values > 0.05), suggesting these variables do not meaningfully influence the outcome in this model.

The significant spatial error coefficient (Rho = 0.1976) indicates moderate positive spatial dependence in the error terms, meaning that unobserved shocks or omitted variables in one location spill over into other locations. This finding confirms the presence of spatial autocorrelation in the model's residuals, reinforcing the need to account for spatial effects to avoid biased estimates. Additionally, the highly significant variance component (Sigma2 v = 0.000070, p < 0.001) reflects substantial variability in the idiosyncratic error term, further highlighting the importance of controlling for unobserved heterogeneity.

**Table 4:** Linear Hypothesis Testing

| **Variables** | **Estimate** | **Standard Error** | **t-values** | **p-values** |
|---|---|---|---|---|
| Intercept | 484.8992 | 324.7169 | 1.4842 | 0.1378 |
| CPI | 0.0147 | 0.0135 | 1.0900 | 0.2757 |
| FDI | 1.0536 | 4.8489 | 0.2173 | 0.8280 |
| IR | 0.5839 | 3.0543 | 0.1912 | 0.8484 |
| TB | 7.0794 | 1.6476 | 4.2967 | 0.000173*** |
| EXR | -0.0041 | 0.0245 | -0.1665 | 0.8678 |

The results from Table 4: Linear Hypothesis Testing reveal the relationships between the explanatory variables and the dependent variable. The intercept (484.8992) is statistically insignificant (p = 0.1378), indicating no substantial baseline effect when all predictors are zero. Among the independent variables, only Trade Balance (TB) demonstrates a strong, statistically significant positive relationship (coefficient = 7.0794, p = 0.000173), suggesting that a one-unit increase in trade balance is associated with a 7.08-unit increase in the dependent variable, holding other factors constant.

The spatial fixed effects estimate in Tables 1 and 2 reveals significant heterogeneity in economic performance across African countries, aligning with existing literature on spatial dependencies (Billé & Rogna, 2022; Wang, 2021). Resource-rich nations such as Equatorial Guinea, Libya, and Gabon exhibit strong positive spatial effects, likely due to natural resource endowments and higher economic integration, consistent with Zhou (2017), who found that infrastructure investments generate positive spillovers. Conversely, conflict-prone and economically struggling countries like the Democratic Republic of Congo, Sierra Leone, and Niger display large negative effects, suggesting structural disadvantages that hinder development. These findings reinforce the importance of spatial spillovers in economic performance, as seen in studies on crime (Lin et al., 2022) and tourism (Santos & Vieira, 2020), where geographic proximity influences outcomes. The significant Rho (0.1976) in Table 3 further confirms spatial dependence, indicating that unobserved shocks in one country affect neighboring economies, necessitating regional policy coordination. The GMM estimation in Table 3 highlights that trade balance (TB) is the only significant macroeconomic driver, echoing findings from Chang et al. (2021), where spatial spillovers accelerated pollution reductions. The insignificance of FDI, CPI, and exchange rates contrasts with Wang (2021), where ICT had localized benefits but negative spillovers, suggesting that macroeconomic impacts in Africa may be more region-specific. The linear hypothesis test (Table 4) reaffirms the trade balance's robustness, supporting the need for policies that enhance intra-regional trade, similar to Costantino (2023)'s emphasis on coordinated tourism strategies. Overall, the results underscore the necessity of spatially-aware policies in Africa, where economic disparities and interdependencies require tailored interventions, as seen in studies on climate adaptation (Billé & Rogna, 2022) and crime prevention (Glaser, 2022).

## Conclusion

The spatial fixed effects analysis reveals significant disparities across African countries, with resource-rich and economically stable nations (e.g., Equatorial Guinea, Libya, Gabon, South Africa, Botswana, Algeria) exhibiting strong positive effects on the dependent variable (GDP), while conflict-prone and economically weaker countries (e.g., Democratic Republic of Congo, Chad, Burundi, Niger, Eritrea) show large negative effects. Trade balance (TB) is the only consistently significant economic variable (coefficient = 5.72–7.08, p < 0.01), while consumer price index, foreign direct investment, interest rate, and exchange rate remain insignificant. Spatial error models confirm moderate positive autocorrelation (Rho = 0.1976), indicating spillovers in unobserved shocks. The highly significant country-specific fixed effects (p < 0.001) highlight unobserved regional heterogeneity, reinforcing the need for spatial econometric approaches.

## Recommendations:

The researcher recommends that:

i. Support high-performing economies (e.g., South Africa, Botswana) to sustain growth.
ii. Address structural weaknesses in struggling nations (e.g., the Democratic Republic of Congo, Niger) through governance reforms, infrastructure investment, and conflict resolution.
iii. Account for spillover effects in policymaking, as neighboring countries influence each other's economic outcomes.
iv. Use spatial error models to correct for autocorrelation in residuals.
v. Encourage regional economic integration to leverage positive spatial spillovers.

**Availability of Data:**
The data will be made available upon request
**Competing Interest:**
The authors declare that they have no competing interests

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**Author's contributions:**
All the authors (S.A. Musa, M. O. Adenomon, B. Maijama, & M. U. Adehi designed the study and wrote the manuscript, while M. O. Adenomon did the analysis

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