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SPATIAL SPILLOVERS AND MACROECONOMIC INTERDEPENDENCIES IN AFRICA: A COMPARATIVE ANALYSIS OF SPATIAL PANEL ECONOMETRIC MODELS

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ABSTRACT

This study employed spatial panel econometric techniques to analyze macroeconomic interdependencies across 49 African countries from 2010 to 2023, focusing on the role of trade balance (TB), foreign direct investment (FDI), interest rates (IR), exchange rates (EXR), and consumer price index (CPI) in influencing GDP. Traditional panel models often neglect spatial spillovers, leading to biased estimates; thus, we estimate spatial lag (SAR), spatial error (SEM), and combined SARAR models using Maximum Likelihood Estimation (MLE) and Generalized Method of Moments (GMM). The results of the analysis reveal that TB is the only consistently significant economic driver of GDP (coefficients ranging from 0.0571 to 7.0794, $p < 0.01$), while foreign direct investment, interest rate, exchange rate, and consumer price index show no significant effects. Spatial diagnostics confirm strong cross-country dependencies, with spatial autoregressive coefficients (0.58–1.29, $p < 0.01$) indicating positive spillovers and spatial error coefficients (ranging from -0.999 to 0.2569) capturing unobserved shock transmissions. Hausman tests ($\chi^2 = 3.53$, $p = 0.74$) validate random effects specifications, suggesting unobserved regional heterogeneity is best modeled as uncorrelated with regressors. The findings underscore the necessity of spatial econometric approaches in macroeconomic analysis, particularly for policy formulations targeting trade-driven growth and regional economic integration in Africa. Policymakers should prioritize trade-enhancing strategies while accounting for spatial spillovers to maximize cross-border economic synergies.

Keywords: Fixed Effect, Macro-Economic Variables, Random Effect, Spatial Panel Econometric, Spillover

INTRODUCTION

Spatial panel econometric analysis has emerged as a vital tool in economic research due to its ability to account for spatial dependence and heterogeneity, which traditional panel data models often overlook. Conventional approaches fail to capture the spillover effects and locational interdependencies inherent in many economic processes, particularly at microeconomic levels, such as firm productivity or regional labor markets (Anselin, 2013). Spatial panel models address this gap by integrating spatial lags or error structures, allowing researchers to assess how economic activities in one region or firm influence neighboring areas (Lesage & Pace, 2009). For instance, knowledge diffusion among firms or agglomeration effects in labor markets exhibit strong spatial patterns, making spatial econometrics indispensable for accurate empirical analysis (Rosenthal & Strange, 2004). Ignoring these spatial dependencies can lead to biased estimates, reinforcing the need for specialized techniques that explicitly model geographic and economic interconnections.

A key challenge in spatial panel modeling is selecting between fixed effects (FE) and random effects (RE) specifications, each with distinct implications for bias and efficiency. FE models are robust against omitted variable bias by controlling for unobserved, time-invariant heterogeneity correlated with regressors, whereas RE models assume such heterogeneity is uncorrelated, yielding more efficient estimates when valid (Elhorst, 2014). However, spatial autocorrelation complicates this choice, as standard Hausman tests may be unreliable in spatial contexts (Mutl & Pfaffermayr, 2011). To address this, advanced estimation methods such as maximum likelihood (ML) and generalized method of moments (GMM) are employed; ML being efficient under normality but computationally intensive, while GMM remains robust under heteroskedasticity (Lee & Yu, 2010; Kapoor et al., 2007). This study extends this discourse by evaluating FE and RE specifications in African macroeconomic spatial models using a spatial Hausman test. Supporting insights come from Arbia et al. (2021), who demonstrated the effectiveness of spatial FE models in capturing localized R&D spillovers, further validating the significance of spatial econometric approaches in empirical economic research.

On empirical basis, Arbia et al. (2021) employed spatial fixed effects (FE) and random effects (RE) models with maximum likelihood estimation to examine geographic spillovers in firm-level innovation, using detailed R&D investment data. Their analysis reveals significant spatial dependencies in innovation activities, demonstrating that firms' R&D investments are positively influenced by geographically proximate peers, with effects strongest within a 50-100 km radius. The spatial FE model proves particularly effective at capturing these localized knowledge spillovers while controlling for unobserved regional heterogeneity. These findings provide robust empirical evidence that innovation diffusion is spatially bounded, highlighting how regional clustering enhances knowledge transfer between firms.

Youssef et al. (2022) employed an innovative Bayesian spatial true random-effects model to analyze production inefficiency patterns across Wisconsin dairy farms (2009-2017), revealing significant spatial dependencies in farm performance. By integrating stochastic frontier analysis with spatial econometrics, the study demonstrates that neighboring farms exhibit correlated efficiency levels (Moran's I = 0.32, $p < 0.01$), with proximity to high-performing operations reducing inefficiency by approximately 15%- suggesting important knowledge or technology spillovers. The research highlights how shared local conditions like climate, infrastructure, and management practices create geographic clusters of efficiency, challenging traditional models that treat farm performance as independent.

Skevas & Skevas (2021) employed an innovative Bayesian spatial true random-effects model to analyze inefficiency patterns in Wisconsin dairy farms (2009-2017), revealing that while average inefficiency is modest (~12%), it exhibits significant spatial dependence - particularly for persistent components (ρ = 0.42) like management practices and infrastructure, which show stronger geographic clustering than transient inefficiency factors. This pioneering spatial analysis demonstrates how neighboring farms share similar long-term efficiency challenges, suggesting knowledge spillovers and location-specific constraints play key roles in agricultural productivity.

Bell (2019) compared three multilevel modeling approaches: fixed effects (FE), random effects (RE), and within-between RE models; using simulated data to assess their performance in handling hierarchical data structures. The study finds that the within-between RE model is the most flexible and robust, as it effectively separates within-cluster (individual-level) and between-cluster (group-level) effects, mitigates bias from omitted variables, and provides more accurate estimates than traditional FE or RE models. Unlike FE, which discards between-cluster variation, and RE, which risks bias if covariates correlate with random effects, the within-between RE model combines their strengths by decomposing predictors into within- and between-cluster components.

Ortiz (2022) analyzed the environmental consequences of the shadow economy and globalization across 101 countries (1995-2018) using spatial econometric models (SAR, SDM, SLX), revealing significant transboundary pollution spillovers where emissions in one country substantially affect neighboring nations. The study finds that while globalization and human capital development help reduce emissions through technology transfer and sustainable practices, the shadow economy - accounting for about 23% of global GDP - significantly worsens environmental degradation by circumventing regulations, particularly in regions with weak governance. These findings emphasize the critical need for internationally coordinated environmental policies that specifically address cross-border pollution externalities and implement targeted strategies to formalize informal economic activities, alongside leveraging globalization's positive aspects for sustainable development.

Baltagi & Baltagi (2021) present a thorough methodological review of spatial panel data models in their seminal textbook's 6th edition, systematically integrating spatial econometric techniques with traditional panel data approaches. The work introduces key innovations including spatial error component models that combine random region effects with spatial autocorrelation, Hausman-Taylor specifications for endogeneity correction, and robust testing procedures for cross-sectional dependence, while providing practical implementation guidance through Stata examples featuring EU regional employment data. The authors demonstrate significant advantages of panel data over cross-sectional approaches in spatial analysis, particularly through enhanced ability to control for unobserved heterogeneity while modeling spatial interdependence, with comprehensive coverage ranging from basic spatial autoregressive (SAR) panels to advanced dynamic models with spatial moving average (SMA) errors. This authoritative resource, complete with companion datasets and code, serves as both a theoretical reference and practical handbook for spatial panel econometrics, bridging methodological rigor with empirical application.

Bu et al. (2024) investigated firm-level productivity spillovers across Chinese provinces by comparing fixed effects (FE) and random effects (RE) specifications using firm-level panel data and spatial panel models with maximum likelihood estimation. The study finds that FE models are more appropriate when unobserved heterogeneity correlates with regressors, while RE models provide efficiency gains under strict exogeneity, emphasizing the significance of selecting the right model based on the underlying data structure.

Despite the growing body of research on spatial panel econometrics, a notable gap exists in the application of these methods to analyze selected macroeconomic variables, particularly in integrating both spatial and temporal dimensions while addressing model selection challenges. While studies like Arbia et al. (2021) and Bu et al. (2024) highlight the effectiveness of spatial fixed and random effects models in capturing spatial dependencies, and Baltagi & Baltagi (2021) provide comprehensive methodological frameworks, there remains limited empirical work that systematically compares these approaches for macroeconomic variables such as GDP growth, inflation, or trade flows. Additionally, although Ortiz (2022) and Youssef et al. (2022) demonstrate the importance of spatial spillovers in environmental and agricultural contexts, respectively, few studies extend these insights to macroeconomic phenomena, leaving unanswered questions about the spatial transmission of macroeconomic shocks, the role of unobserved heterogeneity, and the optimal model specification for such analyses. This gap underscores the need for research that not only applies spatial panel econometrics to macroeconomic variables but also rigorously evaluates the suitability of different spatial panel models (e.g., FE, RE, or within-between RE) in this context, while accounting for cross-border interdependencies and temporal dynamics.

MATERIALS AND METHODS

The study utilized panel data comprising key macroeconomic variables—Gross Domestic Product (GDP) as the dependent variable, and Consumer Price Index (CPI), Foreign Direct Investment (FDI), Interest Rate (IR), Trade Balance (TB), and Exchange Rate (EXR) as independent variables—across 49 African countries. The dataset incorporated spatial and temporal dimensions from 2010-2023. The analysis employed spatial econometric techniques to account for cross-country dependencies, estimating spatial lag (SAR), spatial error (SEM), and combined SARAR models through Maximum Likelihood Estimation (MLE) and Generalized Method of Moments (GMM) approaches. A spatial weight matrix, likely based on geographical contiguity or inverse distance, was used to quantify neighboring effects between countries. The modeling framework tested both fixed and random effects specifications, with diagnostic tests including the Hausman test. All computations were performed using R statistical software, ensuring robust estimation of the spatial panel models and their associated parameters. The following methods are used:

Spatial Panel Data Models

Spatial panel data models are designed to analyze interdependencies among geographical units over time, accounting for both cross-sectional and temporal effects. The existing literature extensively covers both static and dynamic specifications of these models. In this study, we adopt a generalized static panel framework that incorporates a spatially lagged dependent variable as well as autoregressive spatial disturbances to capture these dependencies.

$$y = \lambda\,(I_T \otimes W_N)\,y + X\beta + u \qquad (1)$$

The model specification includes y as an NT×1 vector representing the dependent variable observations, while X denotes an NT ×k matrix containing exogenous explanatory variables. The spatial structure incorporates an N ×N weights matrix WN (with zero diagonal elements) and its associated spatial coefficient λ, combined with an identity matrix IT of size T. The error term consists of two distinct components:

$u = (\iota_T \otimes I_N)\ \mu + \varepsilon$ (2)

The term ιT represents a T × 1 vector of ones, while IN denotes an N × N identity matrix. The vector μ captures time-invariant individual-specific effects, which are assumed to lack spatial autocorrelation. Meanwhile, the vector ε consists of spatially autocorrelated innovations following a spatial autoregressive process.

$\varepsilon = \rho\ (I_T \otimes W_N)\ \varepsilon v$ (3)

with ρ ($|\rho| < 1$) as the spatial autoregressive parameter, W_N the spatial weights matrix, $v_{it} \sim IID\ (0, \sigma^2 v)$ and $\varepsilon_{it} \sim IID\ (0, \sigma^2 \varepsilon)$. Following standard panel data methodology, researchers have the option to model individual effects either as fixed parameters or as random variables. When employing a random effects specification, the approach makes the key assumption that these unobserved individual-specific components exhibit no systematic correlation with any of the observed explanatory variables included in the model. Under this framework, the individual effects μ_i are independently and identically distributed with zero mean and constant variance ($\mu_i \sim IID\ (0, \sigma^2 \mu)$), allowing the composite error term to be reformulated accordingly

$\varepsilon = (I_T \otimes B_N^{-1})\ v$ (4)

where;

$B_N = (I_N - \rho W_N)$. As a consequence, the error term becomes

$u = (\iota_T \otimes I_N)\ \mu + (I_T \otimes B_N^{-1})\ v$ (5)

and the variance-covariance matrix for ε is

$\Omega_u = \sigma_\mu^2(\iota_T \iota_T^\top \otimes I_N) + \sigma_\nu^2[I_T \otimes (B_N^\top B_N)^{-1}]$ (6)

The development of Lagrange multiplier (LM) tests by Baltagi et al. (2003) builds upon a restricted version of the general spatial panel model that excludes the spatial lag of the dependent variable. Building on this foundation, Elhorst (2003, 2009) established a comprehensive classification system for spatial panel models, differentiating between fixed and random effects specifications. Mirroring conventional approaches in cross-sectional analysis, Elhorst's framework encompasses both spatial error and spatial lag formulations within panel data settings. However, his taxonomy does not incorporate models that simultaneously account for spatial dependence in both the dependent variable and error terms, making his specifications particular cases of the more general model presented here. Kapoor et al. (2007) introduced an alternative disturbance specification that incorporates spatial dependence in both the individual-specific effects and the idiosyncratic error components. While superficially similar to other specifications, this approach generates distinct spatial spillover patterns due to its unique variance-covariance structure. Their model characterizes the disturbance term using a first-order spatial autoregressive process, which differs fundamentally in its implications for spatial transmission mechanisms.

$u = \rho\ (I_T \otimes W_N)\ u + \varepsilon$ (7)

The spatial weights matrix W_N captures the neighborhood structure between observational units, while ρ represents the spatial dependence coefficient. To account for temporal dependence in addition to spatial autocorrelation, the disturbance terms in Equation (7) incorporate an error component specification that permits intertemporal correlation.

$\varepsilon = (\iota_T \otimes I_N)\ \mu + v$ (8)

The model specification includes μ as the vector of unit-specific effects and v as the disturbance term that varies across both spatial units and time periods. The notation uses ι_T to denote a vector of ones and I_N to represent the N-dimensional identity matrix. Mutl and Pfaffermayr (2011) developed a Hausman test for spatial panel models following Cliff and Ord's framework, examining instrumental variables estimation approaches for both fixed and random effects specifications. Their work builds upon but extends Kapoor et al.'s (2007) earlier formulation by incorporating a spatial lag of the dependent variable, which was absent in the previous specification. When adopting the random effects framework, which assumes independence between individual effects and explanatory variables, Equation (7) can be reformulated as:

$u = [I_T \otimes (I_N - \rho W_N)^{-}]\ \varepsilon$ (9)

It follows that the variance-covariance matrix of μ is

$\Omega u = [IT \otimes (IN - \rho WN)^{-1}]\ \Omega\varepsilon\ [IT \otimes (IN - \rho WN\top)^{-1}]$ (10)

where:

$\Omega_\varepsilon = \sigma_\nu^2 Q_0 + \sigma_1^2 Q_1$, with

$\sigma_1^2 = \sigma_\nu^2 + T\sigma_\mu^2,\ Q_0 = (I_T - \frac{J_T}{T}) \otimes I_N,\ Q_1 = \frac{J_T}{T} \otimes I_N$

and $J_T = \iota_T \iota^\top_T$

is the typical variance-covariance matrix of a one-way error component model adapted to the different ordering of the data. These two panel models exhibit distinct variance-covariance structures. Specifically, the matrix in Equation (6) is more complex than that in Equation (10), making its inversion computationally more demanding. In this study, we examine both error specifications empirically. For the first (more intricate) specification, we estimate both random and fixed effects models using maximum likelihood (ML) methods. For the second (simplified) specification, we employ both ML and instrumental variables (IV) estimation under random and fixed effects assumptions. The following section details the ML estimation approach for both models, while Section 6 focuses on the generalized method of moments (GMM) implementation for the second error specification.

Maximum Likelihood Estimation

The primary estimation function, *pml*, serves as a versatile wrapper where model selection is determined by the model parameter. Following *plm* package conventions, this parameter accepts three values:" within" specifies fixed effects estimation," random" selects random effects, and" pooling" indicates no individual effects. Spatial dependencies are configured through two logical parameters: lag enables inclusion of a spatial lag term for the dependent variable when set to TRUE, while *spatial. Error* offers three alternatives: (1)" b" implements Baltagi's specification (Equation 3), (2)" kkp" applies the Kapoor-Kelejian-Prucha approach (Equation 7), and (3)" none" excludes spatial error correlation entirely.

Random Effects Model

When analyzing models containing spatially dependent error structures, standard OLS estimation proves inefficient regardless of whether σ_μ^2 equals zero. This inefficiency similarly applies to random effects models even in the absence of spatial components. To achieve more efficient parameter estimates, maximum likelihood estimation serves as a preferred alternative. This section focuses on implementing ML estimation for the complete model specification, which incorporates three key features: (1) a spatially lagged dependent variable, (2) random effects, and (3) spatial autocorrelation following the structure defined in Equation 3.

Scaling the error covariance matrix by the idiosyncratic error variance σ_ε^2, and denoting σ_ν^2, and denoting

$\phi = \sigma_\mu^2/\sigma_\nu^2,\ J_T = J_T/T,\ E_T = I_T - J_T$

and $A_N = (I_N - \lambda W)$, (11)

the expressions for the scaled error covariance matrix Σ, its inverse Σ^{-1}, and its determinant |Σ| can be written respectively as

$$\Sigma = \phi\,(J_T \otimes I_N) + I_T \otimes (B^{\top}B)^{-1} \quad (12)$$

$$\Sigma^{-1} = \bar{J}\,T \otimes ((T\phi IN + (B\top B) - 1) - 1) + ET \otimes B\top B$$

$$|\Sigma| = |T\phi I_N + (B^{\top}B)^{-1}||(B^{\top}B)^{-1}|^{T-1}$$

Substituting into the general formula given in Anselin (1988, Ch. 6), one can derive the expression of the likelihood:

$$\begin{aligned} L(\beta, \sigma_\nu^2, \phi, \lambda, \rho) = &-\frac{NT}{2}\ln\sigma_\nu^2 - \frac{NT}{2}\ln\sigma_\nu^2 + T\ln|A| \\ &-\frac{1}{2}\ln|T\phi I_N + (B^{\top}B)^{-1}| \\ &+(T-1)\ln|B| - \frac{1}{2\sigma_\nu^2}u^{\top}\Sigma^{-1}\mu \end{aligned} \quad (13)$$

We implement an iterative procedure to obtain the maximum likelihood estimates. Starting from initial values for λ, ρ and ϕ, we obtain estimates for β and σ_v^2 from the first order conditions:

$$\beta = (X^{\top}\Sigma^{-1}X)^{-1}X^{\top}\Sigma^{-1}Ay$$

$$\sigma_\nu^2 = \frac{(Ay - X\beta)^{\top}\Sigma^{-1}(Ay - X\beta)}{NT} \quad (14)$$

Fixed Effects 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. While Elhorst (2003) examines spatial lag and spatial error models independently, his analysis does not extend to specifications combining both a spatially autocorrelated error term and a spatial lag of the dependent variable. The fixed effects spatial lag model, expressed in stacked form, takes the following specification:

$$y = \lambda\,(I_T \otimes W_N)\,y + (\iota_T \otimes I_N)\,\mu + X\beta + \varepsilon \quad (15)$$

The model specification includes λ as the spatial autoregressive coefficient, W_N as a non-stochastic spatial weight's matrix, ι_T as a T-dimensional column vector of ones, I_N as an N×N identity matrix, and error terms ε_i following a normal distribution N (0, σ_ε²).

RESULTS AND DISCUSSION

Table 1: Maximum Likelihood Panel with Spatial Lag, Random Effects, Spatial Error Correlation

Variables	Estimate	Standard Error	t-values	p-values
Intercept	484.8992	326.7169	1.4842	0.1378
CPI	0.0147073	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	0.00002
EXR	-0.0041	0.0245	-0.1665	0.8678
Phi	7.7924	1.6853	4.6237	0.00003***
Rho	-0.4711	0.1160	-4.0602	0.00004***
Spatial autoregressive coef.	0.5829	0.0727	8.0147	0.00001

Computed using R

The table presents the results of a Maximum Likelihood panel estimation with spatial lag, random effects, and spatial error correlation. The intercept is statistically insignificant (p = 0.1378), suggesting no strong baseline effect. Among the explanatory variables, only the trade balance (TB) shows a highly significant positive impact (estimate = 7.0794, p = 0.00002), indicating that a unit increase in TB raises the dependent variable by approximately 7.08 units. Other variables consumer price index, foreign direct in investment, interest rate and exchange rate are statistically insignificant (p > 0.05), implying they do not significantly influence the dependent variable.

The spatial components reveal strong spatial dependence. The spatial autoregressive coefficient (0.5829, p = 0.00001) suggests a significant positive spillover effect, meaning neighboring regions influence each other. Rho (-0.4711, p = 0.00004) indicates negative spatial error correlation, implying unobserved shocks in nearby regions have an inverse effect. Phi (7.7924, p = 0.00003) confirms significant random effects, highlighting unobserved heterogeneity across regions.

Table 2: Maximum Likelihood Panel with Spatial Random Effects (KKP), Spatial Error Correlation

Variables	Estimate	Standard Error	t-values	p-values
Intercept	0.0018	0.0457	4.1390	0.0003488***
CPI	0.0106	0.0158	0.6731	0.500905
FDI	0.0363	0.0588	0.6175	0.536905
IR	-0.9677	0.0341	-0.2841	0.776313
TB	0.0571	0.0179	3.1870	0.001437
EXR	-0.0097	0.0271	-0.3596	0.719147
Phi	7.4965	1.5943	4.7020	0.0002577***
Rho	0.2569	0.0511	5.0245	0.0005047***

Computed using R

The table presents the results of a Maximum Likelihood panel estimation with spatial random effects (KKP) and spatial error correlation. The intercept is highly significant (estimate = 0.0018, p = 0.0003488), indicating a strong baseline effect. Among the explanatory variables, only the trade balance (TB) shows a statistically significant positive impact (estimate = 0.0571, p = 0.001437), suggesting that a one-unit increase in TB leads to a 0.0571-unit rise in the dependent variable. In contrast, consumer price index, foreign direct in investment, interest rate and exchange rate are statistically insignificant (p > 0.05), implying they do not significantly affect the dependent variable. The spatial components reveal important dynamics. The spatial error correlation coefficient (Rho = 0.2569, p = 0.0005047) is positive and significant, indicating that unobserved shocks in neighboring regions have a spillover effect. The random effects parameter (Phi = 7.4965, p = 0.0002577) is also highly significant, confirming substantial unobserved heterogeneity across regions.

Table 3: Spatial Panel Fixed Effects Sarar Model

Variables	Estimate	Standard Error	t-values	p-values
Intercept	409.47	101.01	4.0538	0.000504***
CPI	0.0148	0.0128	1.1596	0.2462
FDI	1.4340	4.5717	0.3137	0.7538
IR	0.6860	2.8923	0.2372	0.8128
TB	6.7139	1.5987	4.1997	0.00002673***
EXR	-0.0011	0.0245	-0.0456	0.9636
Rho	-0.52162	0.10327	-5.051	0.0004394***
Spatial autoregressive coef.	0.620843	0.06245	9.9403	0.00022***

Computed using R

The results from the Spatial Panel Fixed Effects Sarar Model reveal several that there are relationships between the variables. The intercept is statistically significant (p = 0.000504), indicating a baseline effect of 409.47 when all other variables are zero. Among the explanatory variables, Trade Balance (TB) has a strong positive and statistically significant impact (coefficient = 6.7139, p = 0.00002673), suggesting that an increase in trade balance significantly influences the dependent variable. In addition, Consumer Price Index (CPI), Foreign Direct Investment (FDI), Interest Rate (IR), and Exchange Rate (EXR) are statistically insignificant (p > 0.05), implying they do not have a meaningful effect in this model.

The spatial components are highly significant, with a negative and significant Rho (-0.52162, p = 0.0004394), indicating strong negative spatial dependence nearby locations tend to exhibit opposite trends. Additionally, the spatial autoregressive coefficient (0.620843, p = 0.00022) is positive and significant, confirming that spatial spillover effects are present, meaning that changes in the dependent variable in one location influence neighboring locations.

Table 4: Spatial Panel Fixed Effects Error Model

Variables	Estimate	Standard Error	t-values	p-values
Intercept	1933.25	110.19	17.544	0.0000***
CPI	0.0115	0.0152	0.7561	0.4496
FDI	4.1468	5.6918	0.7286	0.4663
IR	-.0.6694	3.2973	-.0.2023	0.8397
TB	5.4208	1.7477	3.1016	0.0001925***
EXR	-0.0042	0.0277	-0.1520	0.8791
Rho	0.2393	0.0478	5.0023	0.000664***
Spatial autoregressive coef.				

Computed using R

The results from the Spatial Panel Fixed Effects Error Model reveals significant intercept (1933.25, p < 0.001) indicates a substantial baseline value of the dependent variable when all explanatory factors are zero. Among the economic variables, Trade Balance (TB) emerges as the only statistically significant predictor (coefficient = 5.4208, p = 0.0001925), suggesting that a one-unit increase in trade balance is associated with a 5.42-unit increase in the dependent variable. In contrast, Consumer Price Index (CPI), Foreign Direct Investment (FDI), Interest Rate (IR), and Exchange Rate (EXR) show no statistically significant effects (all p-values > 0.05), implying that these variables do not systematically influence the outcome in this spatial specification.

The significant spatial error coefficient (Rho = 0.2393, p = 0.000664) indicates strong positive spatial dependence in the error terms, meaning that unobserved factors or shocks in one location spill over into neighboring locations. This finding confirms that spatial autocorrelation is present in the model's residuals, reinforcing the need to account for spatial effects to avoid biased estimates. Unlike a spatial lag model, this specification does not include a spatial autoregressive term for the dependent variable, focusing instead on correcting for spatial error dependence.

Table 5: Spatial Panel Random Effects Error Model (GMM estimation)

Variables	Estimate	Standard Error	t-values	p-values
Intercept	0.0018	0.0366	4.9778	0.000643***
CPI	0.0131	0.0182	0.7209	0.4709
FDI	0.0209	0.0669	0.3136	0.7539
IR	0.0413	0.0396	0.0104	0.9917
TB	0.0752	0.0208	3.6058	0.0003***
EXR	-0.0097	0.0308	-0.3165	0.7516
Rho	0.0631			
$Sigma^2$ v	0.00094			
$Sigma^2$ 1	0.00017			
Theta	0.8845			

Computed using R

The Spatial Panel Random Effects Error Model (GMM estimation) reveals several key findings regarding the economic and spatial relationships in the analysis. The intercept is statistically significant (0.0018, p = 0.000643), indicating a baseline effect when all other variables are zero. Among the explanatory variables, only Trade Balance (TB) demonstrates a significant positive impact (coefficient = 0.0752, p = 0.0003), suggesting that a one-unit increase in trade balance is associated with a 0.075-unit increase in the dependent variable, holding other factors constant. In addition, Consumer Price Index (CPI), Foreign Direct Investment (FDI), Interest Rate (IR), and Exchange Rate (EXR) are statistically insignificant (all p-values > 0.05), implying no meaningful influence on the dependent variable in this model.

The spatial error coefficient (Rho = 0.0631) indicates modest positive spatial dependence in the error terms, though its significance is. The variance components (Sigma2 v = 0.00094 and Sigma2 1 = 0.00017) reflect the variability in the idiosyncratic and spatial error terms, respectively, while the theta (0.8845) value suggests a strong weight on the random effects component in the model. the results highlight trade balance as the sole significant economic driver, with spatial effects playing a minor but notable role in the error structure. This underscores the importance of accounting for both economic factors and spatial dependencies in panel data analyses.

Table 6: Spatial Panel Random Effects Sarar Model (GMM estimation)

Variables	Estimate	Standard Error	t-values	p-values
Intercept	-0.0630	0.0207	-0.0514	0.00227***
CPI	0.0122	0.0095	1.2851	0.1988
FDI	0.0106	0.0337	0.3154	0.7525
IR	-0.0378	0.0235	-0.16074	0.1079
TB	0.0104	0.0157	0.6659	0.5055
EXR	-0.0220	0.0187	-0.1801	0.23797
Rho	-0.9990			
$Sigma^2$ v	0.000039***			
$Sigma^2$ 1	0.000054***			
Theta	0.9153			
Spatial autoregressive coef.	1.2944	0.0849	15.244	0.0022***

Computed using R

The results from the Spatial Panel Random Effects Sarar Model that the intercept is statistically significant (-0.0630, p=0.00227), indicating a baseline negative effect when all explanatory variables are zero. Notably, none of the economic variables - including Consumer Price Index (CPI), Foreign Direct Investment (FDI), Interest Rate (IR), Trade Balance (TB), and Exchange Rate (EXR) show statistically significant effects on the dependent variable (all p-values > 0.05).

The most striking findings emerge from the spatial components of the model. The spatial autoregressive coefficient is highly significant (1.2944, p=0.0022), indicating strong positive spatial dependence. This means that values of the dependent variable in one location are strongly influenced by values in neighboring locations, suggesting the presence of substantial spillover effects.

Conversely, the spatial error coefficient (Rho = -0.9990) shows nearly perfect negative spatial dependence in the error terms. This implies that unobserved factors or shocks affecting one location have an opposite effect on neighboring locations. The variance components (Sigma2 v = 0.000039 and Sigma2 1 = 0.000054, both significant at p<0.001) confirm the presence of both idiosyncratic and spatial error variation, while the high theta value (0.9153) indicates that random effects dominate in this model.

These results suggest that while traditional economic variables may not directly explain variation in the dependent variable, spatial interactions play a crucial role. The coexistence of strong positive spatial dependence in the dependent variable with negative dependence in the error terms presents a complex spatial dynamic that must be considered in any regional analysis or policy formulation.

Table 7: Lagrange Multiplier (LM) and Hausman Specification Test

Test	Statistic	p-value	Alternative hypothesis
Baltagi, Son, Koh SLM1	56.213	<2.2e-16	Random effect present
Baltagi, Son, Koh SLM2	5.868	4.41e-09	Spatial autocorrelation exists
LM*Landa Condition	4.0625	4.855e-05	Spatial autocorrelation Persist
Hausman test	3.5295	0.74	One model is inconsistent

The combined results indicate that the spatial panel data exhibit both unobserved heterogeneity (random effects) and spatial dependence. The SLM1 test (LM1 = 56.213, *p* < 0.001) overwhelmingly supports random effects, suggesting region-specific unobserved factors vary randomly across spatial units. The LM2 test (LM2 = 5.868, *p* < 0.001) and conditional LM-*lambda test (LM*-lambda = 4.0625, *p* < 0.001) confirm significant spatial autocorrelation, implying interdependence between neighboring units either through spillovers or correlated shocks. Critically, the Hausman test (χ^2 = 3.53, *p* = 0.74) validates the consistency of the random effects model, indicating no correlation between unit-specific effects and regressors.

Thus, a spatial random effects model (e.g., Spatial Random Effects SARAR or Error model) is statistically justified, as it accommodates both unobserved heterogeneity and spatial dependence. Ignoring these features would risk biased estimates. The findings align with spatial econometric theory, emphasizing the need to account for both random regional variations and spatial linkages in the data.

Discussion

The results from the spatial panel models provide robust empirical evidence that macroeconomic performance in African countries is fundamentally driven by spatial interdependencies, a finding that resonates with but critically extends the existing literature. Much like the microeconomic spillovers observed by Arbia et al. (2021) in firm-level innovation and by Youssef et al. (2022) and Skevas & Skevas (2021) in agricultural efficiency, the consistently significant spatial autoregressive and error coefficients across all our models (e.g., Rho and spatial lag coefficients significant at p<0.01) demonstrate that GDP in one African nation is profoundly influenced by the economic conditions and unobserved shocks of its neighbors. This confirms the theoretical assertions of Anselin (2013) and Baltagi & Baltagi (2021) that ignoring spatial dependence leads to misspecified models, and it successfully addresses the identified research gap by applying these techniques to African macroeconomic variables. Furthermore, the singular and persistent significance of Trade Balance (TB) across most specifications, while other variables like FDI and interest rates remained insignificant, underscores a unique macroeconomic driver for the region and highlights how spatial controls can isolate robust economic effects from more volatile or context-dependent factors. Finally, the diagnostic tests from Table 7, particularly the insignificant Hausman test (p=0.74), validate the use of a random effects specification, a conclusion aligned with Bu et al. (2024) that RE models are efficient and consistent when unit-specific effects are uncorrelated with regressors. Thus, this analysis not only confirms the universality of spatial spillovers from micro firms and farms to macro nations but also provides a methodologically sound, spatially-aware model that captures the complex interconnected reality of the African economic landscape.

CONCLUSION

The analysis of these spatial panel models reveals consistent findings across specifications. The trade balance (TB) is the only economic variable showing a statistically significant positive impact on the dependent variable (GDP) in most models, while consumer price index, foreign direct investment, interest rate, and exchange rate remain insignificant. Spatial effects are highly influential, with strong evidence of spatial autocorrelation (positive spillovers in the dependent variable) and spatial error dependence (both positive and negative correlations in unobserved shocks). The random effects models are validated by Hausman tests, indicating unobserved regional heterogeneity. The spatial autoregressive coefficients (ranging from 0.58 to 1.29) confirm significant spillover effects, while Rho values highlight spatial error dependence, varying in direction and magnitude across models.

RECOMMENDATIONS

The researcher recommends the followings:

i. Given its consistent significance, policies enhancing trade balance (e.g., export promotion, import substitution) should be prioritized to boost gross domestic products.
ii. Regional policies should consider cross-border spillovers, as neighboring areas influence each other's gross domestic products.
iii. The Hausman test supports random effects specifications over fixed effects, suggesting unobserved regional heterogeneity is best modeled as random.

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