Role of fiscal decentralisation in poverty reduction: spatio-temporal evidence from Kenya's devolution framework

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Herein, we address gaps in the fiscal decentralisation literature by analysing the nuanced effects of revenue decentralisation autonomy and intergovernmental transfers on poverty reduction, with a focus on spatial spillovers and feedback effects in Kenya. Findings indicate substantial spatial and demographic differentiation in poverty levels. An inverse correlation between poverty and revenue autonomy is observed, consistent with previous research. The study affirms that empirical results vary based on the measurement of fiscal decentralisation and the choice of model (fixed versus random effects and spatial interactions). Revenue-based indicators (own-source revenue [OSR], equitable share and grants) consistently correlate more strongly with poverty reduction compared with expenditure indicators, which demonstrate marginal significance. While county-specific effect based models elucidate poverty reduction through fiscal tools, random effects based models highlight regional characteristics (economic and demographic). The SLX model emphasises the role of OSR, grants, and their spatial spillover effects on poverty reduction. The spatial panel fixed effects error model underscores the importance of equitable shares and grants in reducing poverty across age groups, with equitable shares far outperforming grants in overall and age-specific poverty reduction. This research highlights the critical role of fiscal decentralisation in poverty reduction through revenue-based indicators, offering insights for targeted policy, improved governance and progress towards sustainable development goals.

Keywords:
fiscal decentralisation,
spatial dependence,
poverty,
regional development,
developing countries

Introduction

The global trends of rising income inequality, poverty rates and regional economic disparities have underscored the urgency of understanding the role of fiscal decentralisation in addressing these pressing challenges. As evidenced by the literature review, a surge in research has focused on unravelling the intricate relation between fiscal decentralisation, poverty alleviation and broader economic development. However, amidst the theoretical debates and empirical studies, there remains a considerable lack of consensus regarding the effectiveness of fiscal decentralisation in reducing poverty and inequality. This ambiguity highlights the critical need for further empirical investigations to inform evidence-based policymaking and address the multi-faceted challenges developing nations face. The theoretical perspectives on decentralisation – ranging from redistribution to efficiency – highlight the complexity of the issue, necessitating nuanced and context-specific analyses. Furthermore, the empirical evidence, as outlined in the literature review, presents conflicting and inconclusive findings, showing the need for deeper exploration into the mechanisms and impacts of fiscal decentralisation.

Considering the diverse perspectives and mixed results in the literature, there is a compelling motivation to delve deeper into the subject matter. Understanding the implications of fiscal decentralisation on poverty, inequality and regional disparities is important for policymakers and for advancing the global agenda of sustainable development. By conducting rigorous empirical research, we can elucidate the nuanced dynamics at play, identify best practices and pave the way for targeted interventions that promote inclusive growth and equitable development. This research seeks to contribute to the existing body of knowledge by examining the impacts of fiscal decentralisation on poverty reduction, particularly in the context of Kenya's recent experience with devolution. Through spatial econometric techniques and a comprehensive analysis of spatial interdependencies among its 47 counties, this study aims to provide actionable insights to inform policy formulation, improve governance practices and ultimately contribute to sustainable development goals. Specifically, the study

a) establishes the clustering and spatial dependence of poverty, fiscal decentralisation and other socio-economic indicators in Kenya's 47 counties and
b) documents the spatial interdependencies and spillovers between poverty (and its demographic age characteristics) and fiscal decentralisation.

The remainder of this paper is organised as follows: first, a brief literature review is setting the stage for the research. Then, the methodology is presented, including the data, spatial visualisation and econometric modelling framework. After that, the results of the non-spatial and spatial models estimated to account for fiscal decentralisation's impact and spatial dependence on poverty are discussed. Finally, the authors draw the conclusions of the paper.

Literature review

The overview of fiscal decentralisation and poverty nexus

Rising income inequality, poverty rates and regional economic gaps are global trends that are acknowledged for marginalising communities and contributing to political unrest in developing nations. Consequently, there has been a surge in research focusing on the effects of fiscal decentralisation on poverty and inequality, with recent studies exploring their link to broader economic growth and development (Ramirez et al. 2017, Rodgers 2022, Yang 2016). The allocation of economic responsibilities, such as reducing poverty and inequality, within multi-level governments has long been a theoretical challenge, with three main perspectives emerging: redistribution, allocation and concurrency. While advocates of redistribution favour a centralised approach, the proponents of efficiency advocate for decentralisation, whereas others propose a combination of both (Hernandez-Trillo 2016). Among these, decentralisation has been a significant policy reform aimed at enhancing governance, public service provision, poverty alleviation and regional equity (Faguet 2014, Nath–Madhoo 2022, Oates 2008, Qian–Weingast 1997, Sanogo 2019). Fiscal decentralisation, one facet of decentralisation alongside political and administrative decentralisation (Martinez-Vazquez et al. 2017), encompasses three key elements: expenditure, revenue and decision-making autonomy. Understanding the implications of fiscal decentralisation is paramount, considering its role in addressing income inequality, poverty and regional disparities.

The empirical evidence regarding the effectiveness of decentralisation remains contentious, conflicting and inconclusive. While some studies suggest that fiscal decentralisation is effective (Cavusoglu–Dincer 2015, Hussain et al. 2021, Sepulveda–Martinez-Vazquez 2011, Siburian 2020, 2022), others argue that fiscal decentralisation is ineffective and, in some cases, exacerbates poverty and inequality (Gavriluta et al. 2020, Hernandez-Trillo 2016, Nguyen 2008). Other studies give inclusive results or conflicting results depending on the inputs and level of measurement (Ahmed–Lodhi 2009, Freinkman–Plekhanov 2010, Yeeles 2015), whereas other authors argue that fiscal decentralisation tools, such as fiscal transfers, have significant effects at the national level but minimal impact on specific spatial inequalities (Yeeles 2015). These intricacies thus warrant research into the effectiveness of fiscal decentralisation and intergovernmental fiscal relations to inform evidence-based policymaking and address the complex challenges of poverty, inequality and regional disparities in developing nations, ensuring that policy interventions are tailored to local contexts and contribute to sustainable development goals.

The success of fiscal decentralisation in tackling poverty and inequality depends on the allocation of expenditure responsibilities, revenue generation and decision-making autonomy across government levels. However, poverty plays a pivotal role in this process, akin to the hen–egg dilemma. Fiscal autonomy, particularly at the subnational level, is mainly driven by revenue generation capacity. However, the ability to raise own-source revenue (OSR) is also influenced by regional factors, such as the quality of regional institutions, household consumption and unemployment rates, which are themselves impacted by poverty levels (Gnangnon 2022, Nguyen et al. 2020). Moreover, spatial disparities exist in both revenue-raising capacity and poverty levels. For instance, Ramirez et al. (2017) analysed Colombia's municipal-level per capita property tax revenues, revealing a significant reduction in multi-dimensional poverty and notable spillover effects. This highlights the need to tailor subnational revenue systems and implement spatially targeted policies to enhance poverty reduction efforts. In sum, fiscal decentralisation can alleviate poverty when local units have financial autonomy, proper budget allocation and accountability mechanisms (Agyemang-Duah et al. 2018). However, this fiscal autonomy should be cognizant of the fiscal capacity of each subnational government.

Empirical studies on the effects of intergovernmental fiscal transfers on poverty reduction and other socio-economic outcomes have yielded mixed results. Though subnational governments have significant autonomy in managing their OSR in modern democracies, they also heavily rely on conditional transfers from the central government owing to the vertical imbalance (Becerra et al. 2023). This highlights fiscal imbalance and complex intergovernmental fiscal relations underpinning administrative decisions and regional dynamics in shaping local fiscal dependence. The ongoing debate in the literature regarding the impact of fiscal dependence necessitates empirical investigations to grasp its nuances across different contexts. For instance, some authors argue that poorly incentivised intergovernmental transfers can result in a 'flypaper effect', where unconditional grants disproportionately increase local spending (Dick-Sagoe et al. 2022, Melo 2002, Wati et al. 2022). Conversely, Yu's (2016) study did not establish evidence of the flypaper effect when spatial dependence and endogeneity problems were accounted for in the modelling. Further research is warranted to understand the nuanced effects of intergovernmental fiscal transfers on poverty reduction and socio-economic outcomes. This ongoing debate highlights the importance of empirical investigations to inform policymaking and improve intergovernmental fiscal relations.

The effectiveness of fiscal decentralisation in reducing poverty also depends on the measurement of fiscal decentralisation and contextual characteristics. For example, Yang (2016) attributes much of China's increasing inequality (1978–2007) to expenditure decentralisation, with revenue decentralisation showing limited impact and decision-making authority yielding mixed results in mitigating inequality. Conversely, Nursini–Tawakkal (2019), examining data from 33 provinces from 2010 to 2016, established that regional government expenditures do not reduce poverty. However, regional government revenues and intergovernmental transfers significantly reduced poverty (Nursini–Tawakkal 2019). Fiscal transfers are crucial in shaping regional income inequality as they can either promote convergence or exacerbate regional disparities (Raiser 1998). Considering the absence of a single universal measure, researchers should strive to develop comprehensive indicators encompassing various dimensions to effectively study fiscal decentralisation.

In assessing the impact of fiscal decentralisation on poverty and economic outcomes, it is crucial to consider spatial dependence. There are spatial interdependence and spillovers of the subnational government's fiscal capacities. Grants and OSR can boost local public provision, motivating neighbouring areas to increase or cut down spending and fostering either vicious or virtuous regional development interdependencies (Vincent–Osei Kwadwo 2022). For example, while previous studies hyped the 'flypaper effect' of unconditional grants, a study of China's county-level education expenditure established the 'anti-flypaper effect' when endogeneity and spatial dependence were accounted for. This highlights that spatial interactions among neighbouring governments influence local OSR generation and spending behaviour.

Kenya's fiscal decentralisation experience

Kenya's fiscal decentralisation evolution is informed by the various regional development policies and strategies to reduce poverty and spatial inequalities in her regions since its political independence from the British Colony in 1963. Kenya's decentralisation evolution oscillated from federal regional governments (1963–1964) to high centralisation (1966–2013) and a devolutionary system from 2013. The historical centralisation epoch exacerbated regional poverty and inequalities despite efforts such as Regional and District Development Planning. Subsequent strategies, including Regional Development Authorities in 1974 and District Focus for Rural Development (established in 1983), faced challenges such as discriminatory development, capture by local elites, overlapping mandates and limited public involvement (Lind 2018). Furthermore, initiatives such as the National Urban Policy (1974–1988) emphasised secondary city development but were hindered by urban bias in infrastructure funding amidst rising fiscal deficits, rapid population growth and sluggish economic growth. Similarly, the establishment of the Constituency Development Fund (CDF) in 2003 and the Local Authority Transfer Fund (LATF) in 2000 highlights the struggle to address regional inequalities and promote balanced economic growth. The LATF aimed to provide funds for development at the local authority level, but it also faced challenges such as uneven revenue distribution. The CDF aimed to provide essential services at the constituency level but also encountered inefficiencies due to coordination challenges and administrative costs.

In 2013, Kenya adopted the devolution of 47 county governments, which entailed democratically elected executive and legislature to mirror the national government. This culminated in a constitution change in 2010 following mounting political and civil society pressure, coupled with public dissatisfaction over growing regional disparities, poverty and marginalisation. The devolution system integrates a bottom–

up determination of regional development priorities and a top–down financing approach to track macroeconomic indicators. The premise is that constitutional decentralisation fosters effective fiscal decentralisation, democracy, good governance and service delivery. The constitution establishes a two-tier government structure comprising a unitary national government and 47 county governments, effectively amalgamating former local governments into county boundaries. County governments can further devolve services by establishing levels and institutions like cities and municipalities to ensure subsidiarity and access to services throughout the republic. Each county's County Public Service Board (CPSB) appoints the respective county government staff. Each county government consists of a County Executive led by an elected governor and a County Assembly responsible for legislation, representation and oversight. To entrench seamless and broker power sharing, the constitution and other enabling legislations establish intergovernmental fiscal institutions (e.g. Commission on Revenue Allocation, the Senate, Council of Governors, Intergovernmental Relations Technical Committee, Intergovernmental Budget and Economic Council) and assign competencies to both government levels. Implementing the devolved system aims to address challenges, such as equitable resource sharing and allocation, functional clarity, improved service delivery efficiency at the county level and improved socio-economic outcomes, such as poverty reduction.

Methodology

This section presents the data and measurements of the critical variables, exploratory spatial data analysis (ESDA) visualisation and confirmatory spatial data analysis (CSDA) results.

Data

For comparability, this study employs 2019–2021 administrative datasets collected from various state agencies in Kenya, including the Kenya Bureau of Statistics, the National Treasury, the Office of Controller of Budget and the Commission on Revenue Allocation. Poverty data are typically measured using household surveys. However, these surveys have not been annual and, in some cases, were collected intermittently and with a considerable time lag (in some cases 10 years), which limits research and policymaking by using outdated data. Nevertheless, this research applies the available (2019–2021) Kenya Continuous Household Survey Programme data [1]. It is comparable to other datasets collected in the same period such as the fiscal, demographic and other economic indicators [2]. Fiscal data were collected from administrative data and various reports of the Office of the Controller of Budget. We use MS Excel and the R software packages for data management, visualisation and analysis. Table 1 presents the description of variables and data sources.

Table 1

Variable description and sources of data

#	Variable	Description	Data source
		Dependent variables	
1	TotalPov	total (overall poverty)	KNBS [3]
2	ChildPov	child poverty (0–17 years)	KNBS
3	YouthPov	youth poverty (18–35 years)	KNBS
4	AdultPov	adult poverty (36–59 years)	KNBS
5	RetireePov	retiree poverty (60–69 years)	KNBS
6	SeniorPov	senior citizens' poverty (70+ years)	KNBS
		Fiscal decentralisation variables	
7	equit_pc	equitable share per capita (revenue raised nationally is shared 1) vertically between the national and county governments and 2) horizontally among county governments using a defined formula)	OCOB [4]
8	OSR_pc	own-source revenue per capita	OCOB
9	grants_pc	conditional and unconditional grants per capita	OCOB
10	Capex_pc	capital (development) expenditure per capita	OCOB
11	Opex_pc	operations (recurrent) expenditure per capita	OCOB
12	DeceRevPc	revenue decentralisation – autonomy ([actual OSRpc/total revenue pc] *100)	
13	DepeRatio	fiscal grants dependency (actual OSR/[total revenue – actual OSR] *100)	
		control variables-regional characteristics	
14	GCPpc	economic–gross county product per capita (2016)	KNBS [5]
15	transrate	demographic–secondary school transition rate	KNBS [6]

Poverty

Poverty and inequality are multi-faceted social issues that vary in definitions, measurements, depth, breadth and duration (Kwadzo 2015). Poverty typically refers to a state or condition in which individuals or communities lack the resources and capabilities to meet their basic needs for a decent standard of living. This often includes food and non-food necessities, such as food, shelter, clothing, education and healthcare. Poverty can be measured in various ways, including income levels, access to basic services and overall quality of life. Various approaches to understanding poverty exist in the literature underpinned by the 'monetary, capability, social exclusion, and participatory' milieu (Laderchi et al. 2003). This study will not delve into the measurement debate but will adopt the validated regional statistics as published by the Kenya National Bureau of Statistics, where poverty was measured in tandem with the decomposable poverty measures (Foster et al. 1984), wherefore

$$p(\propto) = \frac{1}{N}\sum_{i=1}^{N} \left(\frac{z-yi}{n}\right)^{\alpha} I(yi < z)\ldots\ldots \quad (1)$$

where P denotes the poverty level; N, size of the population; y_i, ith individual welfare level; z, poverty line; α, poverty sensitivity indicator; and I(.), indicator constraint function taking the value 1 when the condition is satisfied and 0 when not satisfied. Please see the report for more information on the computation of the regional poverty values.

Measurement of fiscal decentralisation

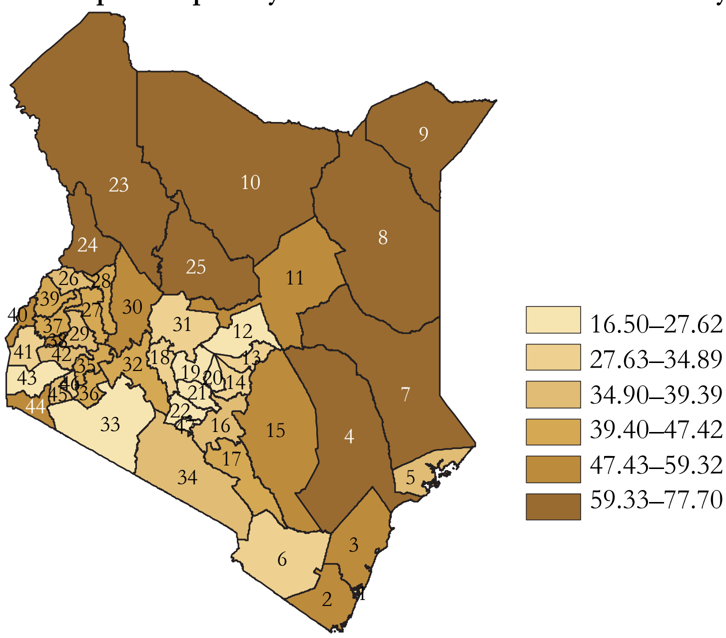
The ongoing discussion on measuring fiscal decentralisation persists in economics and political science research. The key indicators often include locally generated revenues, decision-making autonomy, utilisation of national grants at the local level and the scale and quantity of local administrative units (Martinez-Vazquez et al. 2017). In line with the previous literature, we measured revenue decentralisation using OSR and proxy municipal autonomy (Sanogo 2019).

The fiscal decentralisation variables were measured from revenue (OSR, equitable share and grants) and expenditure (capital and operations expenditures). We included economic (gross county product per capita) and demographic (secondary school transition rates) controls.

County population and land size disparities were noted, as shown in Appendix Table A1. We normalised to account for these disparities in the regression model by measuring the relevant variables per capita and linearised them using logarithms. The total poverty distribution is depicted in Figure 1.

Figure 1

Choropleth map of the poverty distribution in the Countries of Kenya, 2021



Note: see Appendix Table A1 for county codes and county names.

Overall, poverty, measured based on household consumption, is spatially distributed with huge disparities. Nairobi, Kenya's commercial and capital city, has the lowest poverty rate (16.7) and other counties in central Kenya such as Kirinyaga, Kiambu, Narok, Meru and Nyeri. The counties with the highest poverty rates are in the Arid and Semi-Arid lands (ASAL) in northern Kenya, such as Marsabit, Wajir, West Pokot, Samburu, Garissa, Tana River, Mandera, and Turkana.

ESDA

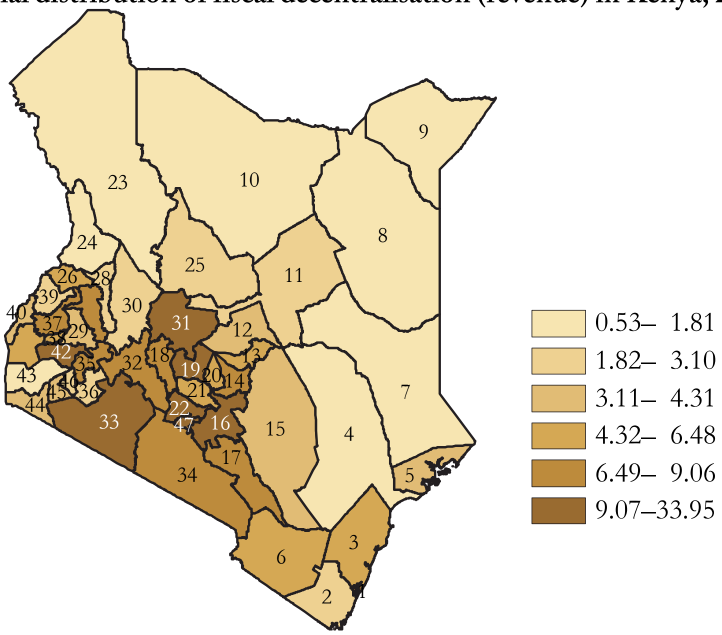
The choropleth maps are used to visualise the geospatial clustering or observations.

Geospatial clustering of poverty and fiscal decentralisation

Figure 2 depicts fiscal decentralisation (revenue autonomy) per capita (b) as spatially distributed. Compared to Figure 1, on the spatial distribution of poverty, the wealthier counties (16.5–27.63 poverty rates) agglomerate around the central region. These counties also have smaller land sizes per square kilometre than counties with the highest poverty rates. The counties with high poverty levels (59.33–77.7) are in the north and east, with large land sizes. Conversely, fiscal decentralisation (revenue) per capita is lowest (0.53–1.81) in the poorest counties and relatively high in the wealthier counties (9.06–33.95). This implies an inverse relationship between poverty and fiscal decentralisation. The clusters form similarly to the poverty rates. In general, poverty rates are higher than fiscal decentralisation per capita.

Figure 2

Spatial distribution of fiscal decentralisation (revenue) in Kenya, 2021



Demographic distribution of poverty in Kenya

We accounted for the demographic distribution of poverty by using age. We divided the population into five clusters, including children (0–17 years), youth (18–35 years), adults (36–59 years), retirees (60–69 years) and senior citizens/the aged (70+ years). As will be demonstrated, these age groups are impacted differently by applying government fiscal policies, particularly fiscal decentralisation. The necessity of age-specific fiscal policies is clear, as the poverty levels of these groups also differ spatially and in magnitudes, and they spread depending on the counties of residence.

Figure 3

Spatial distribution of poverty by age categories in Kenya, 2021

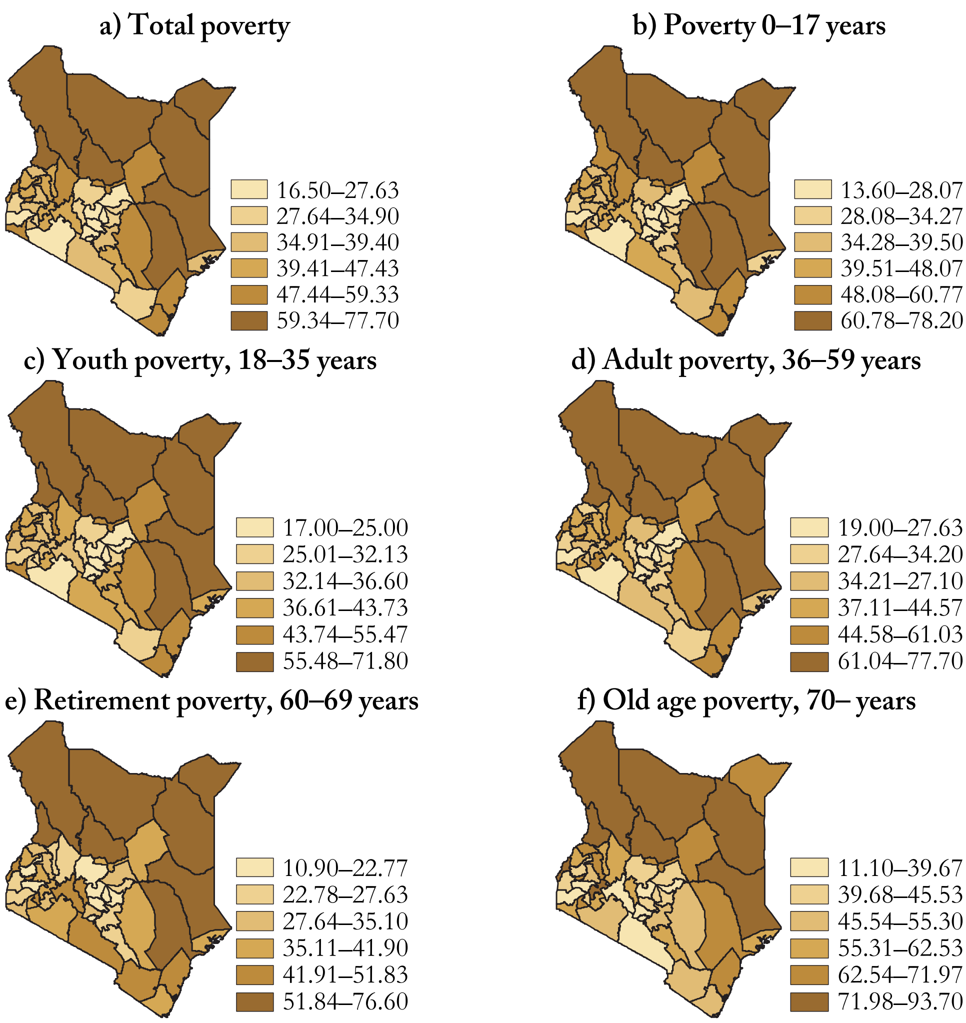


Figure 3 presents Kenya's spatial distribution of poverty according to age and demographic characteristics. Though the clustering and divergence follow a similar pattern as total poverty, some pertinent issues come into play. For example, whereas the range of poverty in retirement is 10.9%–76.6%, that of the elderly (old age) ranges from 11.1%–93.7%, an indicator of the deplorable condition of the elderly. In addition, the intensity of poverty may differ with age group in a given county; for example, county number 9 (Mandera) records less intensity in old age poverty compared with the other age groups.

CSDA

Using a balanced spatial panel dataset (2019–2021) from Kenya, we analysed the relationship between fiscal decentralisation poverty indicators using a scatterplot and a basic panel analysis model. The indicators for fiscal decentralisation were normalised at the per capita levels, including OSR, equitable share, conditional and unconditional grants, capital expenditure (Capex) and operations expenditure (Opex). The poverty indicators include total poverty, child poverty (0–17 years), youth poverty (18–35 years), adult poverty (36–49 years), retiree poverty (50–60 years) and senior citizen poverty (70+ years). Most indicators show a normal distribution, with a few having moderate right or left skews from their tails. The correlations and statistical significance among the poverty indicators are extremely high. There is also a significant correlation between poverty and fiscal decentralisation indicators, although the significance varies among age categories. As poverty is the focus of this research, the analysis will consider each age category in separate regressions to elucidate the nuanced dynamics of fiscal decentralisation on poverty.

To ascertain the non-spatial relationship between fiscal decentralisation and poverty, we estimated the conventional panel data analysis models: fixed effects estimator and random effects estimator. Research demonstrates that while pooled OLS and random effects estimators can yield identical treatment effect point estimates under certain assumptions, the fixed effects estimator typically provides different point estimates. Moreover, these estimators differ in their estimated standard errors and variance–covariance matrices, with fixed effects and random effects models accounting differently for unobserved heterogeneity (Oaxaca–Dickinson 2016). We conducted the Hausman test to select the appropriate non-spatial model (Baltagi–Liu 2016). A fixed effects model (equation 2) assumes that individual-specific characteristics are invariant in time and correlated with the independent variables, whereas a random effects model (equation 3) assumes that the individual-specific effects are random and uncorrelated with the independent variables. The equations are as follows:

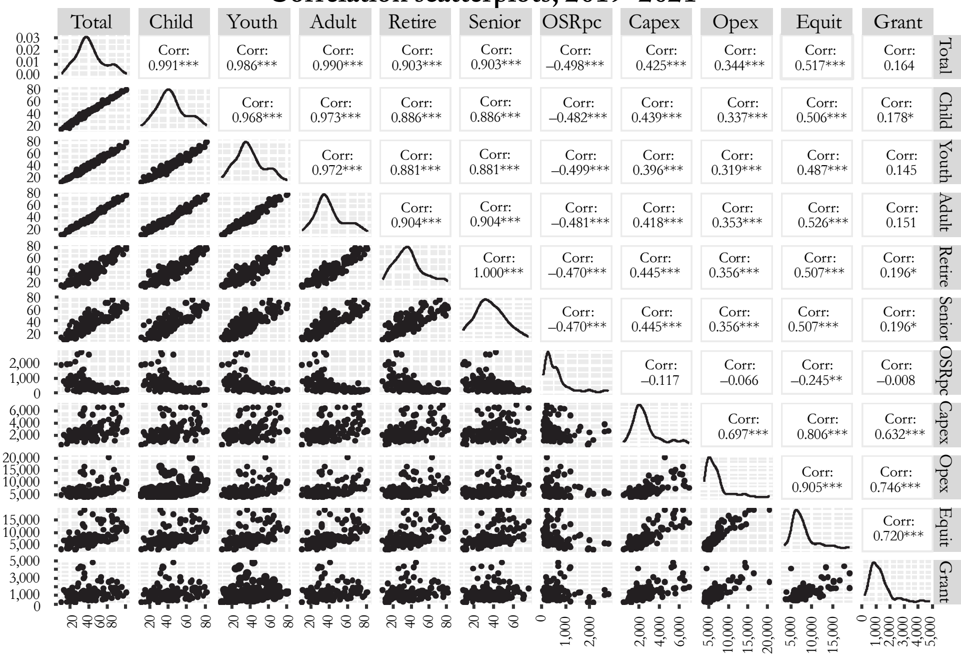
$$y_{it} = \alpha_i + \beta X_{it} + \epsilon_{it}; i = 1 \dots N, t = 1 \dots T, \dots \dots \quad (2)$$

$$y_{it} = \alpha + \beta X_{it} + u_i + \epsilon_{it}; i = 1 \dots N, t = 1 \dots T, \dots \dots \quad (3)$$

where y_{it} denotes the dependent variable for entity county (i) at a time (t); α, an intercept (subscript i if fixed effect); β, a vector of independent variable coefficients; Xit, the matrix of independent variables for an entity (i) at a time (t); ϵ_{it}, the error term of an entity (i) at a time (t); and u_i, the entity-specific random effect.

Figure 4

Correlation scatterplots, 2019–2021



Spatial panel econometric specification, choice and modelling

Spatial econometrics analysis and modelling have continued to gain traction since the recognition of Tobler's First Law of Geography stating that 'everything is related to everything else, but near things are more related than distant things' (Sui 2004). In response to the realisation that conventional econometrics analysis tools, such as the standard OLS models, do not account for spatial dependence, a myriad of econometricians have proposed and nurtured a strand of econometrics analysis that incorporates spatial interactions in regional science (Anselin 1988, Anselin et al. 1996, Elhorst 2003).

In spatial econometric modelling, the general nesting spatial (GNS) model offers the point of departure as it captures the three basic types of spatial interaction effects: spatial lags of the dependent variable (endogenous), independent variables (exogenous) and spatial error terms (Halleck Vega–Elhorst 2015). It can be seen as an extension or combination of several models, including the spatial lag model, spatial error model (SEM) and spatial Durbin model (SDM). The spatial lag model, also called the spatial autoregressive model, assumes that spatial dependence arises from the influence of neighbouring observations on each other. It accounts for the possibility that the value of a variable in one location is influenced by the values of the same variable in neighbouring locations (Anselin et al. 1996, Anselin–Arribas-Bel 2013). The SEM assumes that spatial dependence arises from unobserved factors or omitted variables that are spatially correlated (Anselin–Arribas-Bel 2013). It accounts for the possibility that the error terms of observations in the local and neighbouring locations correlate. However, SLM and SEM's spillovers and feedback effects are global, where a change in a particular location is indiscriminately transmitted to all other locations. The SDM, consequently, models spatial dependence by incorporating both the SLM and SEM, including their spatial lags. The GNS is given in equation 4.

$$y_{it} = \rho \sum_j W_{ij} y_{jt} + \alpha + \beta X_{it} + \theta \sum_j W_{ij} X_{jt} + u_{it};\ u_{it} = \lambda \sum_j W_{ij} u_{jt} + \eta_i + \lambda_t + \varepsilon_{it} \quad (4)$$

where y_{it} denotes the N × 1 vector of observation of the dependent variable for County (i = 1…47) at time t; X, the N × K matrix of explanatory variables; β, the K × 1 vector of coefficients; ε, the vector of the error term ($\varepsilon \sim N(0, \delta^2, I_n)$); and W, the matrix of N × N spatial weight matrix relating the spatial dependence structure. ϱ is the spatial autoregressive parameter measuring the strength of spatial dependence; λ, the spatial error parameter; and β and θ, the response coefficient vectors.

Although other econometric models, such as the spatial Durbin error model and spatial lag of X (SLX), have been used together with the SDM and GNS to account for direct and indirect effects, the SLX is recommended in the literature for its flexibility and simplicity in accounting for spatial dependence and parameterised spatial weights (W) (Halleck Vega–Elhorst 2015, Rüttenauer 2022). It captures the spatially lagged independent variable, as depicted in equation 5.

$$y_{it} = \alpha + \beta X_{it} + \theta \sum_j W_{ij} X_{jt} + \eta_i + \lambda_t + \varepsilon_{it} \quad (5)$$

where θ denotes the spatial effects of the explanatory variables.

We conducted the SLX. Considering that the spatial units under consideration are extremely heterogeneous in size, the SLX model was parameterised using a row-normalised binary contiguity matrix based on the Queen contiguity matrix.

While the SLX model has specific advantages, such as its relative simplicity and the ability to model spatial spillover effects of the explanatory variables explicitly, it also has several drawbacks. It does not account for endogenous spatial interactions among the dependent variables, which can lead to biased estimates. Consequently, it only incorporates the spatial lag of the explanatory variables but does not include a spatial lag of the dependent variable. This can be limiting in cases where the dependent variable in one region is influenced by the dependent variables in neighbouring regions. Furthermore, the SLX model does not address spatial dependence in the error terms, which can lead to inefficient estimates and biased standard errors, making inference problematic.

Owing to the limitations of the SLX and role of spatial interactions when employing fiscal policy tools to alleviate poverty, we estimated a spatial panel fixed effects error model (SPEM-FE) individual effects. In our study context, spatial spillovers and regional interactions are central to the analysis. We considered the SPEM-FE appropriate for our spatial modelling context due to the potential spatial dependence in the errors and entity-specific unobserved heterogeneity. The SPEM-FE is specified as follows.

$$y_{it} = \alpha_i + \beta X_{it} + u_{it};\ u_{it} = \lambda \sum_j W_{ij} u_{jt} + \eta_i + \lambda_t + \varepsilon_{it} \qquad (6)$$

where y_{it} denotes the dependent variable for entity i at time t; α_i, the fixed effects for each county; Xit, the matrix of K × N explanatory variables; β, the vector of coefficients for the explanatory variables; u_{it}, the spatially autocorrelated error term; λ, the spatial autoregressive parameter in the error term; W, the spatial weight matrix; η_i, captures individual fixed effects; and ε_{it}, the idiosyncratic error term.

Test for spatial autocorrelation

We tested for spatial autocorrelation using the Moran test. The Moran I test is a standard tool used in spatial statistics and spatial econometrics to detect spatial autocorrelation, which is the correlation of a variable with itself through space (Kelejian–Prucha 2001). The statistic ranges from –1 to 1. Positive values indicate positive spatial autocorrelation (similar values clustered together), negative values indicate negative spatial autocorrelation (dissimilar values clustered together) and values around zero indicate no spatial autocorrelation. The *P*-values indicate the probability of observing Moran I statistic (or one more extreme) under the null hypothesis of spatial randomness. Lower *P*-values suggest more robust evidence against the null hypothesis.

$$I = \frac{N}{W} \frac{\sum_{t=1}^{N} \sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} (y_{it} - \bar{y})(y_{jt} - \bar{y})}{\sum_{t=1}^{T} \sum_{i=1}^{N} (y_{it} - \bar{y})^2} \qquad (7)$$

where $W = \sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij}$ is the sum of all elements in the spatial weight matrix W; $\sum_{t=1}^{T}$, the summation of the periods; $\sum_{i=1}^{N} \sum_{j=1}^{N}$, the summation of the spatial entities; w_{ij}, the spatial relationship between entities i and j; $(y_{it} - \bar{y})$, the deviation of y_{ij} from the mean; and $(y_{jt} - \bar{y})$, the deviation of y_{jt} from the mean.

To run the Moran I test, we first estimated the SDM as our focus was local spatial autocorrelation (influence of neighbouring regions) using the 'spml function'(Millo–Piras 2012). The SDM accounts for spatial lags in dependent and independent variables, capturing the direct and indirect spillovers and other complex spatial relationships (Anselin 2021). Leveraging on pre-set Kenya counties' geographical boundaries, we specified contiguity-based spatial weights because, as already seen from the choropleth maps, the counties are irregular and significantly differ in size. The Queen's spatial weight matrix outperforms other specifications in spatial econometrics as it captures a broader and realistic set of spatial relationships, is flexible in handling irregular spatial units and is robust in various empirical settings (Sobari et al. 2023).

We extracted the residuals and accounted for the panel structure by expanding the spatial weight matrix. Given T (3 years) periods and N (47 counties) cross-sectional units, we expanded spatial weight matrix W to cover all the panels using the Kronecker product. Using the expanded spatial weight matrix, we performed the Moran I test on the residuals. The results are presented in Table 1.

$$W_{exp} = I_T \otimes W_{sp}$$

W_{exp} denotes the expanded weight matrix; I_T, an identity matrix of size T × T; and W_{sp}, the spatial weight matrix for the cross-sectional units.

Results and discussion

This section provides a comprehensive discussion of the results of the estimated econometric models. To provide a comprehensive view, it first presents the results of the non-spatial model before presenting the spatial econometric models.

The Moran I results

The Moran I test results (Table 2) indicate that total poverty, child poverty, youth poverty, adult poverty, retiree poverty and senior citizen poverty have significant positive spatial autocorrelation in the residuals. This implies that poverty levels tend to cluster geographically. However, the intensity of clustering differs across demographic groups, where total, child, youth and adult poverties have very strong spatial autocorrelation and retiree and senior citizen poverties indicate moderate spatial autocorrelation.

Table 2

Moran I test results

Type of poverty	Moran I statistic	Standard deviation	*P*-value	Interpretation
Total poverty	0.2956	5.5895	2.2E−08	strong positive spatial autocorrelation; high/low poverty clusters together
Child poverty	0.2307	4.3944	4.467E−13	significant positive spatial autocorrelation; spatial clustering of child poverty
Youth poverty	0.3588	6.7566	2.2E−16	strong positive spatial autocorrelation; high clustering of youth poverty
Adult poverty	0.2503	4.7553	9.91E−07	significant positive spatial autocorrelation; spatial clustering of adult poverty
Retiree poverty	0.1392	2.7006	0.009965	moderate positive spatial autocorrelation; some spatial clustering of retiree poverty
Senior citizen poverty	0.3708	6.9672	1.616E−12	significant positive spatial autocorrelation; spatial clustering of adult poverty

The results show positive Moran I statistics and extremely low *P*-values, indicating strong evidence against the null hypothesis of spatial randomness. This implies the presence of significant positive spatial autocorrelation, which estimates spatial models as statistically justified.

Results of non-spatial fixed model

We estimated fixed effects and random effects models. The two models depicted sharp contrasts in how the predictors of fiscal decentralisation drive and inhibit poverty alleviation in totality and across demographic age categories. The results of the random effects models presented in Appendix Table A2 indicate that OSR, grants, GCP per capita and secondary school transition rate significantly reduce poverty. Furthermore, the significance levels vary when the model is applied to the various age categories. Other fiscal decentralisation measures (revenue and expenditure) gain or lose significance in poverty alleviation. Alternatively, the fixed effects model emphasises the equitable share as the most significant driver in overall poverty alleviation across the poverty levels measured.

Table 3

Non-spatial fixed effects model

Variable	Total	Child	Youth	Adult	Retiree	Senior citizens
log(OSR_pc)	0.5265 (2.2764)	0.0426 (2.3257)	−0.2311 (2.6490)	0.6947 (2.4167)	0.1485 (3.4885)	0.5279 (4.6899)
log(equit_pc)	−36.3047*** (7.9055)	−39.5285*** (8.0765)	−46.7966*** (9.1991)	−32.6774*** (8.3924)	−48.3206*** (12.1147)	10.0971 (16.2869)
log(grants_pc)	−4.4387* (1.7180)	−3.1133 (1.7551)	−5.1653* (1.9991)	−4.8801** (1.8238)	−4.0117 (2.6327)	−6.4700 (3.5394)
log(Capex_pc)	3.3060 (2.1264)	5.1967* (2.1724)	2.5388 (2.4743)	3.0388 (2.2573)	2.6587 (3.2585)	−2.7724 (4.3808)
log(Opex_pc)	1.3515 (6.2164)	1.4511 (6.3509)	−0.1659 (7.2337)	3.1227 (6.5993)	−7.0787 (9.5264)	15.2028 (12.8072)
log(GCPpc)	31.9723 (18.9609)	27.3749 (19.3711)	30.3060 (22.0637)	33.0063 (20.1288)	19.3894 (29.0567)	100.6747* (39.0635)
log(transrate)	12.6271* (5.1388)	5.7303 (5.2500)	17.9290** (5.9798)	15.3782** (5.4554)	12.6443 (7.8750)	40.3680*** (10.5871)

Note: *p < 0.10, **p < 0. 05, and *** p< 0.01. The standard errors are in parenthesis.

The Hausman test ($P < 0.001$) showed that fixed effects models were the most appropriate non-spatial models. They effectively account for individual heterogeneity in the data. Table 3 presents the fixed effects model results. Although the models are consistent in that fiscal transfer-based revenue measures such as equitable share and grants are the most significant in poverty reduction, the significance intensity varies among the age categories. OSR and expenditure-based fiscal decentralisation indicators were insignificant. Moreover, capital expenditure and secondary school transition seemed to aggravate poverty in some categories, albeit at a 10% significance level. The results conflict with the allocative efficiency tenets of fiscal federalism theory and thus justify further investigations into the dynamics of fiscal decentralisation in poverty alleviation (Nath–Madhoo 2022, Oates 2008). Furthermore, these models did not account for spatial dependence, and it will be intriguing to determine the role of spatial dependence in poverty alleviation when fiscal tools are applied. In the following subsection, we will test spatial autocorrelation and spatial models to elucidate these dynamics.

Spatial econometric model results

This section will discuss the results of two spatial panel models: the SLX and SPEM-FE.

SLX model

As a point of departure, we analysed six different SLX models to understand the factors influencing poverty across various demographic groups: total, child, youth, adult, retiree and senior citizen poverties. We also sought to account for the effects of direct and indirect spatial interactions (spillover and feedback). The results are reported in Table 4.

The models are consistent in that OSR (revenue decentralisation) and targeted grants (conditional and unconditional) are the most significant fiscal decentralisation measures for alleviating poverty. In addition, the lags of OSR and grants are significant, albeit at reduced significance, implying local spillovers and feedback effects. Surprisingly, the equitable share is insignificant, even at the lagged level in these models.

On the expenditure side of fiscal decentralisation, capital expenditure had mixed results. Regarding direct effects, it was 10% significant in the child, retiree and senior citizen models but not the other models. Moreover, the lag.log (Capex) is negative and significant, which implies that development expenditure in the neighbouring counties had the potential to reduce poverty in the local county. Meanwhile, operations expenditures were insignificant in poverty alleviation in local and neighbouring counties.

The regional economic and demographic characteristics measured by GCP per capita and secondary school transition rate are negative and significant, highlighting them as vital strategies for reducing poverty across all demographic groups of the local and neighbouring counties.

As expected, the spatial autocorrelation ('rho') is generally small and negative across the models, suggesting that the impact of the independent variables in nearby regions leads to dissimilar poverty rates to some extent. While some spatial lagged predictors are significant, the overall spatial autocorrelation is relatively low.

Table 4

Regression output results of the effects of fiscal decentralisation on poverty in Kenya by age

SLX final output fiscal decentralisation and poverty in Kenya						
	dependent variable:					
	total	children	youth	adult	retiree	senior
	slx1	slx2	slx3	slx4	slx5	slx6
	–1	–2	–3	–4	–5	–6
log(OSR_pc)	−5.541***	−5.226***	−5.937***	−5.199***	−6.172***	−4.549**
	(1.544)	(1.594)	(1.578)	(1.578)	(1.873)	(2.291)
log(equit_pc)	9.914	4.940	7.893	10.551	−1.253	44.101***
	(7.460)	(7.711)	(7.604)	(7.625)	(9.066)	(11.100)
log(grants_pc)	−4.718**	−3.308	−4.968**	−6.416***	−4.541*	−7.062**
	(2.044)	(2.114)	(2.079)	(2.088)	(2.480)	(3.044)
log(Capex_pc)	3.182	4.828*	3.676	2.603	6.363*	−5.706
	(2.705)	(2.799)	(2.743)	(2.755)	(3.261)	(4.004)
log(Opex_pc)	0.732	1.188	1.829	2.033	3.148	−12.020
	(6.197)	(6.400)	(6.312)	(6.341)	(7.564)	(9.222)
log(GCPpc)	−11.496***	−12.414***	−10.647***	−12.331***	−13.119***	−4.006
	(3.125)	(3.223)	(3.196)	(3.194)	(3.779)	(4.630)
log(transrate)	−2.812***	−3.142***	−2.524**	−3.081***	−5.063***	−0.711
	(0.997)	(1.028)	(1.017)	(1.019)	(1.212)	(1.480)
lag.log(OSR_pc)	−8.434**	−7.023*	−10.374***	−7.881**	−6.284	−6.622
	(3.732)	(3.845)	(3.812)	(3.805)	(4.535)	(5.487)
lag.log(equit_pc)	12.524	12.803	15.062	10.927	−2.602	12.972
	(15.862)	(16.385)	(16.157)	(16.220)	(19.292)	(24.115)
lag.log(grants_pc)	8.234*	9.589**	6.391	7.580*	6.485	12.651*
	(4.453)	(4.601)	(4.539)	(4.561)	(5.413)	(6.633)
lag.log(Capex_pc)	−15.242**	−16.642***	−11.680*	−13.417**	−11.473	−20.382**
	(6.043)	(6.255)	(6.165)	(6.175)	(7.358)	(9.042)
lag.log(Opex_pc)	13.235	9.509	11.273	16.014	29.046*	13.844
	(13.075)	(13.510)	(13.331)	(13.383)	(15.951)	(19.456)
lag.log(GCPpc)	14.265*	11.634	20.778***	15.663*	10.343	13.584
	(7.926)	(8.201)	(8.038)	(8.092)	(9.550)	(11.503)
lag.log(transrate)	4.481*	3.411	5.832**	4.749*	5.361*	4.421
	(2.385)	(2.471)	(2.423)	(2.440)	(2.922)	(3.524)
Constant	−135.897	−73.471	−181.194*	−168.493	−93.816	−299.003*
	(104.114)	(107.791)	(106.082)	(106.370)	(126.630)	(155.910)
Observations	141	141	141	141	141	141
Log likelihood	−507.891	−512.432	−510.288	−510.608	−534.542	−563.736
Sigma2	77.684	82.978	80.670	81.187	114.849	172.160
Akaike information criterion	1,049.782	1,058.864	1,054.577	1,055.217	1,103.084	1,161.472
Wald test (df = 1)	4.154**	3.666*	3.037*	2.454	0.203	2.960*
LR test (df = 1)	3.592*	3.122*	2.768*	2.222	0.187	2.628

Note: *p **p ***p < 0.01.

Spatial panel fixed effects error model (SPEM-FE) individual effects

The results of six models of the SPEM-FE are shown in Table 5. These six models estimate the relationship between overall poverty (overall and poverty across various age categories) and independent variables (fiscal decentralisation and regional characteristics) across different counties and fiscal years in Kenya while accounting for spatial autocorrelation in the error terms. The spatial autocorrelation is captured by the spatial error parameter (lambda). The models use fixed effects to control unobserved heterogeneity across counties. The results indicate an extremely significant spatial error parameter (0.723147, $P < 0.001$), implying that the errors in one county correlate with the errors in neighbouring counties.

Regarding fiscal decentralisation, it is noted that transfer-based fiscal tools such as equitable share and grants (conditional and unconditional) are the only negative and significant variables in several models, indicating their importance in explaining the variation in poverty alleviation. However, the strength of significance varies across the age categories. While the equitable share is insignificant in predicting overall poverty, a 1% increase in equitable share reduces poverty among vulnerable groups – children, retirees and senior citizens – by 25%, 41% and 41%, respectively. It is intriguing to note that a 1% increase in conditional and unconditional grants reduces the overall youth and adult poverty by 2.31%, 2.32% and 2.94%, respectively. This implies that whereas the equitable share impacts the vulnerable groups the most, grants, consequently, effectively reduce poverty among the active (working) population.

Table 5

Spatial panel fixed effects error model (SPEM-FE) outputs

Coefficients	Total	Child	Youth	Adult	Retiree	Senior citizen
lambda	0.7231*** (0.0636)	0.5296*** (0.0890)	0.7002*** (0.0671)	0.7094*** (0.0657)	0.2248 (0.1163)	0.5487*** (0.0868)
log(OSR_pc)	0.0034 (1.2470)	−0.3766 (1.5513)	−0.7752 (1.4874)	0.3629 (1.3003)	−0.5429 (2.6290)	0.2662 (3.1253)
log(equit_pc)	−12.5034 (8.3645)	−25.7005** (8.4002)	−18.0798 (9.7330)	−16.9722* (8.5944)	−41.7530*** (10.6781)	−20.2541 (0.2411)
log(grants_pc)	−2.3115* (1.1305)	−2.3187 (1.3575)	−2.9424* (1.3442)	−2.4380* (1.1766)	−3.7051 (2.1185)	−1.7735 (2.7461)
log(Capex_pc)	−0.4192 (1.2308)	1.8763 (1.5265)	−1.1365 (1.4686)	0.4702 (1.2837)	2.6144 (2.5228)	−4.44206 (3.0771)
log(Opex_pc)	4.9346 (3.7219)	6.1622 (4.5342)	5.3870 (4.4299)	5.8964 (3.8760)	−9.1999 (7.3862)	13.4462 (9.1557)
log(GCPpc)	12.9013 (11.7989)	14.4966 (13.9638)	9.2420 (13.9864)	8.6126 (12.2574)	20.8434 (22.4002)	66.6033* (28.258)
log(transrate)	−4.1846 (3.2849)	−5.6832 (3.9740)	1.6058 (3.9089)	−0.3269 (3.4205)	7.4175 (6.2826)	13.3771 (8.0339)

Note: *p < 0.10, **p < 0. 05, and *** p< 0.01. The standard errors are in parenthesis.

The other fiscal decentralisation variables, such as the OSR, capital and recurrent expenditure and regional characteristics (economic and demographic), were not significantly correlated with poverty alleviation in the SPEM-FE models, as shown in Table 5.

Discussion

This study has comprehensively analysed the role of fiscal decentralisation in poverty alleviation, determining whether spatial spillovers and feedback effects matter in line with the postulates of Tobler's First Law of Geography. Using balanced fiscal, economic, demographic, poverty and spatial datasets from Kenya for 2019–2021, we have demonstrated that poverty is spatially and demographically differentiated. The ESDA choropleth maps have indicated spatial clustering and intriguing patterns. When poverty is spatially compared with fiscal policy interventions, such as revenue autonomy (Figure 2), it is apparent that there is an inverse correlation between the two. This syncs with previous research that generally found that subnational revenue decentralisation and autonomy correlate with poverty reduction (Sanogo 2019). Furthermore, the ESDA shows that the severity of poverty is not only spatially dependent but also varies by age category. This highlights the importance of identifying the poor and their spatial characteristics in intergovernmental relations strategies, such as fiscal decentralisation, to alleviate poverty (Bird et al. 1995, Mutiarani–Siswantoro 2020).

Previous research on the effects of fiscal decentralisation and poverty yielded mixed results (Karim–Khan 2020, Sepulveda–Martinez-Vazquez 2011, Shahzad–Yasmin 2016). This research sheds some light on the conundrum of what drives different results regarding the effectiveness of fiscal decentralisation and intergovernmental fiscal relations in addressing the complex challenges of poverty. This research shows that mixed results can arise from various factors, including the data and measurement of fiscal decentralisation, choice of fixed or random effects, selection of spatial models and whether global or local spatial interactions are considered. Extant literature highlights the lack of a single universally agreed measurement of fiscal decentralisation (Martinez-Vazquez et al. 2017). However, in line with previous empirical practice, we selected fiscal decentralisation from revenue (OSR, equitable share and grants) and expenditure (Rodden 2002). The results across all models, including non-spatial and spatial panel models, with fixed and random effects, consistently demonstrated that revenue-based indicators exhibited significant statistical relationships, whereas expenditure indicators did not exhibit consistent significance to poverty alleviation. The statistical significance of these indicators varies between fixed and random effects models. Random effects models highlight the significance of regional characteristics (economic and demographic), whereas fixed effects models consistently attribute significance to revenue-based indicators.

The results also vary depending on whether spatial interactions are included in the model, suggesting that spatial dependence significantly affects the analysis. This suggests that for comprehensive policy recommendations, it is crucial to consider spatial spillovers and feedback effects, including the scale of these effects (global versus local). For example, the SLX model has shown that a percentage increase in OSR will reduce overall poverty by 5.54%. Consequently, it would directly reduce poverty in the local county for child (5.23%), youth (5.93%), adult (5.20%), retiree (6.17%) and senior citizen (4.55%) poverties. From the local spillover and feedback effects, the model shows that a percentage increase in the OSR in the neighbouring county will reduce overall poverty in the local county by 8.43%, whereby child poverty will be reduced by 7.02%, youth by 10.37% and adult by 7.88%.

The robustly estimated SPEM-FE provides invaluable insights into the interplay between fiscal decentralisation in Kenya's devolutionary framework and poverty alleviation. The models' significant lambda ($P < 0.001$) indicates strong spatial dependency in the error terms. The SARAR model (see in Appendix Table A3) corroborates the significant spatial autocorrelation in overall poverty and among the age categories. The models show that equitable shares and grants play a pivotal role in overall and age category-specific poverty alleviation. This interplay has been supported by previous research in Ethiopia, which found that the effective application of grants reduces poverty (Khan et al. 2017). Moreover, the equitable share, mainly an unconditional transfer from the national government, has the highest significance and impact in the overall and age-specific poverty. For example, a 1% increase in equitable share reduces adult poverty by 16.97% and retiree poverty by 41.76%. In comparison, a 1% increase in grants reduces adult poverty by 2.44% and retiree poverty by 3.71%. This supports the fiscal federalism theory that revenue and spending autonomy significantly reduce poverty (Agyemang-Duah et al. 2018). The OSR, capital expenditure and operations expenditure are insignificant. This can be attributed to several factors, including the huge revenue potential gap in the counties of Kenya [7]. Furthermore, the national government still makes significant regional development expenditures through specialised agencies, such as the Regional Development Authorities and the National Government Constituencies Development Fund, which, though performing devolved functions, make the assessment of their contribution to poverty reduction through this fiscal dataset challenging.

Conclusion

This study analysed the role of fiscal decentralisation in poverty alleviation in Kenya from 2019 to 2021, focusing on spatial spillovers and feedback effects. Our findings indicate that poverty is spatially and demographically differentiated, with significant spatial clustering. Furthermore, the EDSA and CSDA exhibit an inverse correlation between poverty and revenue autonomy, consistent with previous research. By empowering subnational governments with greater revenue autonomy, regions can implement targeted initiatives for poverty alleviation across the population demographics. Fostering fiscal decentralisation alongside a nuanced understanding of regional dynamics can promote more sustainable and inclusive pathways towards poverty reduction and equitable development.

Empirical results on the effects of fiscal decentralisation on poverty alleviation vary depending on how fiscal decentralisation is measured, whether fixed or random effects are considered and if spatial interactions are included in the model. Unlike expenditure indicators, revenue-based indicators (OSR, equitable share and grants) consistently showed significant relationships with poverty reduction. The SLX model demonstrated that a 1% increase in OSR reduces overall poverty by 5.54%, with reductions across various age groups. In addition, local spillover effects revealed that a 1% increase in OSR in neighbouring counties reduces overall poverty by 8.43%. The SPEM-FE highlighted the importance of equitable shares and grants in alleviating poverty across different age groups. For example, a 1% increase in equitable share reduces adult poverty by 16.97% and retiree poverty by 41.76%, whereas a 1% increase in grants reduces adult poverty by 2.44% and retiree poverty by 3.71%. This research shows that fiscal decentralisation is crucial for poverty reduction, mainly through revenue-based indicators. However, the effectiveness of capital and operations expenditure remains inconclusive, likely due to regional revenue disparities and significant national government expenditures

This research contributes to the knowledge of fiscal federalism by examining the effects of fiscal decentralisation on poverty reduction in the context of the Global South. The results of this study thus hold global relevance, particularly in developing countries. Understanding the nuanced regional dynamics provides actionable insights for targeted policy formulation, improves governance practices and ultimately contributes to sustainable development goals (Mutiarani–Siswantoro 2020). The results of the models indicate significant spatial autocorrelation. Future studies can explore what other regional characteristics drive, inhibit or moderate the application of fiscal policy tools for poverty alleviation.

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Appendix

Table A1

Kenya county codes and geographical information, 2021

Codes	County	Area_sq_km	Population	Poverty total 2021
1	Mombasa	219.9	1,256,006	31.8
2	Kwale	8,253.66	900,872	50.5
3	Kilifi	12,553.27	1,518,160	49.2
4	Tana River	37,903.62	334,765	67.8
5	Lamu	6,283.02	158,960	35.1
6	Taita Taveta	17,152.01	355,073	33.9
7	Garissa	44,753.2	883,144	68.3
8	Wajir	56,773.81	826,133	66.3
9	Mandera	25,942.15	911,265	71.9
10	Marsabit	70,944.27	491,483	65.9
11	Isiolo	25,349.19	301,382	53.9
12	Meru	7,013.95	1,585,608	26.3
13	Tharaka-Nithi	2,564.36	407,529	28.1
14	Embu	2,820.67	635,160	28.7
15	Kitui	30,429.61	1,200,627	55.2
16	Machakos	6,037.27	1,457,065	35.6
17	Makueni	8,176.67	1,019,118	39.7
18	Nyandarua	3,285.76	669,950	32.0
19	Nyeri	3,324.98	818,202	26.4
20	Kirinyaga	1,478.31	642,463	19.3
21	Murunga	2,522.77	1,088,456	26.7
22	Kiambu	2,538.7	2,551,620	20.5
23	Turkana	68,233.08	971,900	77.7
24	West Pokot	9,123.28	646,190	61.4
25	Samburu	21,089.69	329,638	66.2
26	Trans Nzoia	2,495.17	1,029,856	36.3
27	Uasin Gishu	3,398.61	1,207,797	40.4
28	Elgeyo-Marakwet	3,032.06	481,359	47.3
29	Nandi	2,849.4	920,906	35.7
30	Baringo	10,984.62	702,256	47.5
31	Laikipia	9,507.64	539,414	34.8
32	Nakuru	7,504.91	2,250,502	39.4
33	Narok	17,931.68	1,213,213	21.9
34	Kajiado	21,871.18	1,208,593	39.2
35	Kericho	2,436.09	929,777	39.8
36	Bomet	2,507.08	914,280	45.4
37	Kakamega	3,016.62	1,932,305	39.6
38	Vihiga	563.76	615,206	48.8
39	Bungoma	3,023.94	1,729,265	43.9
40	Busia	1,699.78	931,984	58.3
41	Siaya	2,529.74	1,021,774	34.2
42	Kisumu	2,085.43	1,206,931	36.3
43	Homa Bay	3,152.53	1,185,135	26.6
44	Migori	2,613.48	1,176,159	48.0
45	Kisii	1,323.28	1,319,443	37.2
46	Nyamira	897.32	649,528	34.7
47	Nairobi City	703.87	4,593,757	16.5

Table A2

Non-spatial random effects model

Variable	Total	Child	Youth	Adult	Retiree	Senior
(Intercept)	149.8026 (55.94)**	184.0179 (55.72)***	168.2736 (58.56)**	123.5259 (57.07)*	202.6496 (65.66)**	202.6496 (65.66)**
log(OSR_pc)	−3.5260 (1.91)	−3.5155 (1.90)	−4.6305 (2.09)*	−3.3931 (1.97)	−5.0393 (2.41)*	−5.0393 (2.41)*
log(equit_pc)	−8.0439 (6.03)	−13.6158 (5.97)*	−10.6441 (6.84)	−5.4279 (6.28)	−11.1605 (8.25)	−11.1605 (8.25)
log(grants_pc)	−3.8381 (1.6422)*	−2.3145 (1.6253)	−3.8881 (1.8860)*	−4.7550 (1.7185)**	−2.3185 (2.2898)	−2.3185 (2.2898)
log(Capex_pc)	4.1715 (2.0713)*	6.2578 (2.0497)**	4.2703 (2.3796)	3.5835 (2.1681)	5.8654 (2.8861)*	5.8654 (2.8861)*
log(Opex_pc)	9.3934 (5.6587)	8.8651 (5.6035)	9.9587 (6.4326)	10.5473 (5.9076)	4.9588 (7.7155)	4.9588 (7.7155)
log(GCPpc)	−18.5846 (4.57)***	−19.0624 (4.56)***	−17.7300 (4.71)***	−18.3385 (4.64)***	−17.7264 (5.24)***	−17.7264 (5.24)***
log(transrate)	−3.8247 (1.65)*	−4.5611 (1.64)**	−3.9378 (1.66)*	−3.6740 (1.66)*	−6.3283 (1.82)***	−6.3283 (1.82)***

Note: *p < 0.10, **p < 0. 05, and *** p< 0.01. The standard errors are in parenthesis.

The random effects model emphasises that regional economic conditions and demographic characteristics are the main drivers of poverty reduction. Grants also play a pivotal role but with lesser effect compared with the regional characteristics.

Table A3

SARAR model

Spatial panel random effects ML model (spatial error and spatial lag weight matrix)

Parameter	Total	Child	Youth	Adult	Retiree	Senior citizen
phi	5.383 (1.732) ***	3.633 (1.184) **	3.221 (1.083) **	5.276 (1.691) ***	1.135 (0.405) **	1.135 (0.405) **
lambda	0.842 (0.070) ***	0.706 (0.180) ***	0.837 (0.069) ***	0.855 (0.063) ***	0.734 (0.102) ***	0.734 (0.102) ***
rho	−0.296 (0.189)	−0.181 (0.278)	−0.282 (0.192)	−0.355 (0.177) *	−0.417 (0.184) *	−0.417 (0.184) *
intercept	91.501 (57.629)	114.531 (60.305)	74.930 (57.274)	107.111 (58.389)	86.606 (64.709)	86.606 (64.709)
log(OSR_pc)	−1.845 (1.239)	−2.711 (1.495)	−2.829 (1.377)	−1.487 (1.254)	−4.551 (1.915) *	−4.551 (1.915) *
log(equit_pc)	3.736 (6.316)	−1.616 (6.976)	6.140 (6.734)	1.079 (6.413)	13.331 (9.026)	13.331 (9.026)
log(grants_pc)	−1.566 (1.263) *	−1.408 (1.540)	−2.087 (1.463)	−1.597 (1.283)	−1.885 (2.241)	−1.885 (2.241)
log(Capex_pc)	−0.073 (1.377)	2.054 (1.716)	−0.997 (1.600)	0.460 (1.396)	2.321 (2.509)	2.321 (2.509)
log(Opex_pc)	5.171 (3.914)	6.480 (4.772)	4.865 (4.482)	6.334 (3.971)	−6.808 (6.709)	−6.808 (6.709)
log(GCPpc)	−16.613 (3.882) ***	−16.747 (4.151) ***	−14.982 (3.857) ***	−17.991 (3.925) ***	−10.932 (4.494) **	−10.932 (4.494) **
log(transrate)	−3.828 (1.454) **	−4.183 (1.536) **	−2.940 (1.422) **	−4.018 (1.470) **	−4.878 (1.577) **	−4.878 (1.577) **

Note: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. The standard errors are in parenthesis.

The SARAR model affirms significant spatial autocorrelation in the overall poverty and among the age categories. However, the spatial lag is not as dominant. The model thus highlights that the most significant drivers of poverty reduction are the regional economic and demographic characteristics, including the quality of human capital development.

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