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Budget Inertia and Cross-County Spillovers: A Dynamic Spatial Panel Analysis of Development Expenditure in Kenya's County Governments

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Abstract

Despite the devolution of fiscal responsibilities to Kenya's county governments, the extent to which development expenditure exhibits budget inertia and persists across fiscal years remains insufficiently understood. Existing analyses may overlook the spatial interdependence of county-level fiscal decisions, particularly the extent to which development spending in one county influences expenditure patterns in neighbouring counties. This limits understanding of whether observed expenditure persistence reflects institutional and budgetary rigidities, strategic fiscal responses, or spillover effects across county boundaries. Furthermore, the dynamic and spatial mechanisms through which these effects interact over time remain inadequately established. Consequently, a dynamic spatial panel analysis is necessary to quantify budget inertia, identify cross-county spillovers, and establish their implications for the efficiency and coordination of development expenditure in Kenya's devolved system of public finance. A static spatial model can tell us that counties which spend more on development tend to sit next to one another, but it cannot say whether a county carries its own spending forward from one year to the next, or how an increase in the equitable share plays out over time rather than on impact. This study takes up those questions for Kenya's 47 county governments over fiscal years 2014/15 through 2024/25, using a balanced panel of 517 county-year observations. All monetary variables are converted to constant 2014/15 shillings with a Kenya consumer price index deflator, and the analysis moves from the static spatial autoregressive model used in earlier work to a dynamic spatial panel that adds a one-year lag of development spending. The preferred specification is a dynamic spatial autoregressive model with county fixed effects, estimated by quasi-maximum likelihood and reported with cluster-robust standard errors. Development spending shows clear budget inertia: roughly fifteen percent of a county's capital spending carries over from the previous year ($\tau = 0.152$, $p = .015$). Counties also continue to move together across borders in the same year ($\rho = 0.237$, $p < .001$), but there is little sign that they respond to what their neighbors spent a year earlier. Separating each driver into its short-run and long-run effect shows that the equitable-share pass-through builds over time, from 0.99 on impact to 1.24 in the long run, while the wage-bill crowd-out deepens from −0.44 to −0.54 and the election-year slowdown from −0.19 to −0.24. The findings strengthen the case for faster and steadier equitable-share disbursement, a binding wage-bill ceiling, and a structured plan to clear pending bills.

Keywords: *budget inertia, development expenditure, dynamic spatial panel, fiscal federalism, Kenya counties, short-run and long-run effects*

1. Introduction

1.1. Background

Kenya's move to devolved government in 2013 handed 47 newly created county governments a wide set of functions, among them agriculture, health, early childhood education, and local infrastructure, together with a constitutional guarantee that at least 15% of the most recently audited national revenue would be shared among them as an equitable share (Constitution of Kenya, 2010). Development expenditure, the capital and project spending counties undertake as opposed to recurrent spending on wages and operations, is the part of the budget that devolution was meant to turn into better roads, clinics, water systems and improved agricultural infrastructure. A decade in, that spending varies sharply from one county to the next, and in many counties the share of the budget that reaches development has stayed below the 30% floor set in the Public Finance Management Act of 2012.

The classic argument for devolution is that public goods are supplied more efficiently by the level of government closest to the people who use them, because that level knows local preferences better (Oates, 1972). That logic assumes jurisdictions act independently, which is hard to defend in Kenya, where neighboring counties share labor markets, road networks, supply chains, and political history. A road, market, or water system built in one county spills across its border, and a drought or a commodity-price swing hits whole clusters of counties at once. When outcomes in one unit depend on outcomes in its neighbors, a model that treats counties as independent gives biased and inefficient estimates (Anselin, 1988; Elhorst, 2014). A recent static spatial analysis of these same counties confirmed exactly this pattern, reporting a positive spatial autoregressive parameter in county development spending (Benedict et al., 2026).

A static spatial model, however, answers only half of the question. It can show that neighboring counties move together within a year, but it is silent on time. It cannot say whether a county's capital spending is sticky, carrying forward from one budget to the next, nor whether a county reacts to what its neighbors spent in the previous year, nor, most importantly for policy, how an increase in the equitable share works its way through the system over several

fiscal years rather than landing all at once. Those are dynamic questions, and they require a model that carries both space and time.

This paper supplies that model. It builds a balanced panel of all 47 counties observed annually from fiscal year 2014/15 to 2024/25, converts every monetary variable to constant 2014/15 shillings, and estimates a dynamic spatial panel that adds a one-year lag of development spending to the spatial autoregressive structure. The payoff is threefold. The paper measures budget inertia directly; it separates contemporaneous spatial co-movement from any delayed reaction to neighbors; and it decomposes each fiscal driver into its short-run impact and its long-run, spillover-inclusive total. Because the lagged dependent variable also absorbs the serial correlation that troubles static panels, the dynamic specification turns out to satisfy more of the standard diagnostic assumptions than its static predecessor.

1.2. Statement of the Problem

County development spending in Kenya is spatially uneven, chronically under-absorbed, and volatile from year to year in ways that standard fiscal indicators do not fully explain. Static analysis has established that this spending is spatially interdependent, but it leaves the temporal structure of the problem untouched. If capital budgets are sticky, then a disbursement delay or a wage-bill shock in one year will echo into later years, and the full cost of such a shock will be larger than any single-year estimate suggests. If spillovers operate with a lag, then a county's spending decisions are shaped not only by its neighbors' current budgets but by their past ones. And if the equitable-share pass-through builds over time, then the long-run return to a transfer increase differs from its first-year effect, which is the number that matters for medium-term fiscal planning. None of these quantities can be recovered from a static model, and none has been estimated for Kenyan county development expenditure. That is the gap this study fills.

1.3. Objectives of the study

The broad objective is to examine the dynamic and spatial determinants of development expenditure in Kenya's 47 county governments over fiscal years 2014/15 through 2024/25. Specifically, the study seeks to (a) measure the degree of temporal persistence, or budget inertia, in county development spending; (b) distinguish contemporaneous cross-county spillovers from any lagged reaction to neighbors' spending; and (c) decompose the effect of each fiscal driver into short-run and long-run direct and indirect components.

2. Literature review

2.1. Theoretical framework

The study rests on fiscal federalism theory and on the economics of spatial externalities. Oates's (1972) decentralization theorem holds that decentralized provision of public goods is welfare-superior when local preferences differ and spillovers across jurisdictions are either absent or internalized through grants. A recurring empirical wrinkle is the flypaper effect, the finding that intergovernmental grants raise local spending by more than an equivalent rise in local income, as if money sticks where it lands (Hines & Thaler, 1995). In a devolved system where the equitable share is unconditional and makes up most of county revenue, the flypaper effect predicts that transfer increases translate into more than proportionate development spending.

The independence assumption behind the basic theorem breaks down when public goods generate benefits that cross jurisdictional borders, a situation studied under the headings of fiscal competition, yardstick competition, and expenditure spillovers (Besley & Case, 1995; Brueckner, 2003; Tiebout, 1956). When spillovers are positive, local governments underprovide the spillover-generating good because they cannot capture its full return. Spatial econometrics gives these ideas empirical content: Anselin (1988) distinguished a spatial lag process, in which an outcome depends on neighbors' outcomes, from a spatial error process, and Case, Rosen, and Hines (1993) showed that U.S. states' spending moves with that of their neighbors. The impact-matrix framework of LeSage and Pace (2009) separates the total effect of a driver into a direct own-unit component and an indirect spillover component.

What these static tools omit is time. Capital budgets are rarely rebuilt from scratch each year. The incrementalist account of public budgeting, which dates to Davis, Dempster, and Wildavsky (1966), holds that each year's budget is largely last year's budget adjusted at the margin, because administrative routines, multi-year commitments, and bargaining costs all anchor spending to its recent history. Multi-year capital projects and procurement cycles reinforce this persistence in the specific case of development spending. Modeling it calls for a dynamic panel, in which a lagged dependent variable captures the carry-over (Nickell, 1981). Combining the two ideas, a dynamic spatial panel carries a temporal lag, a contemporaneous spatial lag, and potentially a space-time lag of the dependent variable, so that persistence and spillovers are estimated jointly rather than one at the expense of the other.

2.2. Empirical and Methodological Literature

The empirical study of fiscal interaction among neighboring governments begins with Case, Rosen, and Hines (1993), who showed that a U.S. state's spending rises when its neighbors spend more, and argued that such budget spillovers must be modeled explicitly rather than treated as noise. Besley and Case (1995) gave the behavior a political mechanism through yardstick competition, in which voters judge their own incumbent against neighboring jurisdictions, so that tax and spending choices are set with an eye on neighbors. Brueckner (2003) organized the subsequent work into two broad explanations, spillover models and resource-flow models, and noted that both imply a spatially lagged fiscal variable. The European municipal evidence is consistent and substantial: Allers and Elhorst (2005) found robust tax mimicking among Dutch municipalities, Solé-Ollé (2006) documented expenditure interactions among Spanish local governments, and Baicker (2005) estimated that a dollar of one U.S. state's spending induces sizeable spending in its neighbors. Revelli (2005) cautioned, however, that an estimated spatial coefficient can reflect genuine interaction, common unobserved shocks, or spatial sorting, so identification and specification matter as much as the point estimate.

A parallel literature explains why public spending is sticky over time. The incrementalist theory of budgeting of Davis, Dempster, and Wildavsky (1966) treats each year's appropriation as a modest adjustment of the previous year's, a regularity they documented across U.S. federal agencies and attributed to administrative routine and the cost of annual bargaining. In a panel setting this persistence is captured by a lagged dependent variable, but Nickell (1981) showed that doing so under fixed effects induces a bias of order 1/T that is severe when the time dimension is short. The dynamic panel-data literature responded with instrumental-variables and generalized-method-of-moments estimators that remain consistent at fixed T: the Anderson and Hsiao (1981) instrumental-variables estimator, the Arellano and Bond (1991) difference estimator, and the Blundell and Bond (1998) system estimator, the last of which is more efficient

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when the series are persistent and the first-difference instruments are weak. These estimators provide a non-spatial benchmark against which a spatial model's persistence parameter can be judged.

Bringing space and time together, the econometrics of dynamic spatial panels is by now well developed. Yu, de Jong, and Lee (2008) derived the quasi-maximum-likelihood estimator for spatial dynamic panel data with fixed effects and established its asymptotic properties, and Lee and Yu (2010) set out the bias correction needed when the time dimension is short relative to the cross-section. Elhorst (2012) organized the resulting family of models, distinguishing the temporal lag, the contemporaneous spatial lag, and the space-time lag, and laid out how each is estimated and tested. Debarsy, Ertur, and LeSage (2012) showed how to interpret such models by decomposing their effects into short-run and long-run, direct and indirect components, which is the interpretive apparatus this paper adopts.

Evidence for sub-Saharan Africa, and for Kenya in particular, has concentrated on the institutions of devolution rather than on spatial or temporal dynamics. Studies document thin own-source revenue, weak expenditure management, and the political economy of intergovernmental transfers (Barasa et al., 2021; Cheeseman et al., 2016; Mbate, 2021; Smoke, 2015). Most recently, a static spatial analysis of these same 47 counties established that development spending is spatially interdependent and that national transfers dominate its determinants (Benedict et al., 2026). None of these works, however, models the temporal persistence of county spending or separates contemporaneous from lagged spatial interaction.

2.3. Research Gap

Three gaps follow. First, although the spatial dependence of Kenyan county development spending is now established, its temporal persistence has not been measured, so budget inertia remains an open quantity. Second, no study separates the contemporaneous spatial spillover from a lagged one, leaving the timing of cross-county interaction unresolved. Third, the short-run and long-run decomposition that a dynamic spatial model makes possible has not been applied to this spending, so the medium-term return to a transfer increase, and the accumulating cost of a wage-bill or pending-bills shock, are unknown. This study addresses all three within a single dynamic spatial panel.

3. Data and Methodology

3.1. Data and Deflation

The study uses a balanced panel of Kenya's 47 county governments over 11 fiscal years, 2014/15 through 2024/25, for 517 county-year observations; a fiscal year is labeled by the calendar year in which it ends, so 2014/15 is written as 2015. Financial data come from the annual County Governments Budget Implementation Review Reports of the Controller of Budget and the audited statements of the Auditor-General, and county boundaries come from the official Independent Electoral and Boundaries Commission shapefile. Because nominal spending growth would otherwise contaminate every coefficient, each monetary variable is converted to constant 2014/15 shillings using a Kenya consumer price index deflator, with each fiscal year's index taken as the average of the two calendar years it spans and rebased so that the first fiscal year equals 100. The resulting deflator rises to 180.4 by 2025, implying cumulative price growth of about 80% over the panel.

The dependent variable is county development expenditure (DE), actual capital spending. The fiscal regressors are the wage bill (WB), own-source revenue (OSR), national government fiscal transfers or equitable share (NGF), development partner funds (DPF), and pending bills (PB), all in constant prices. Two binary indicators capture the political and electoral environment: a political coalition indicator (PC), equal to one when a county's governor is aligned with the national ruling coalition, and an election-year indicator (EL), equal to one for the fiscal years tied to the 2017 and 2022 general elections. A fiscal-year inflation rate (INFL) and a linear time trend (TREND) are included as common-time controls. Each constant-price monetary variable is transformed using the natural logarithm of one plus the value, as in Equation (1), with pending bills Winsorized at its 99th percentile before transformation to limit the influence of a single extreme observation. Because any such cutoff is to a degree arbitrary, the pending-bills elasticity is re-estimated at the 95th and 98th percentiles and under a raw logarithmic transformation; as Section 4.6 shows, the coefficient stays negative and strongly significant throughout.

$$y_{it} = \ln\left(1 + \mathrm{DE}_{it}^{r}\right) \tag{1}$$

3.2. Model Specification

The point of departure is the static spatial autoregressive model with county fixed effects used in earlier work on these counties (Benedict et al., 2026), shown in Equation (2), where the subscript i indexes counties and t indexes fiscal years:

$$y_{it} = \rho \sum_{j=1}^{N} w_{ij} y_{jt} + x_{it}'\beta + \mu_i + \varepsilon_{it} \tag{2}$$

Here the dependent variable is log constant-price development expenditure, the term in w_ij is the row-standardized spatial weight linking counties i and j, ρ is the spatial autoregressive parameter, μ_i is a county fixed effect, and the regressor vector collects the five log fiscal variables together with PC, EL, INFL, and TREND. This specification captures same-year co-movement but imposes no temporal structure. The extension adds a one-year lag of development spending, giving the dynamic spatial autoregressive model in Equation (3):

$$y_{it} = \tau y_{i,t-1} + \rho \sum_{j=1}^{N} w_{ij} y_{jt} + x_{it}'\beta + \mu_i + \varepsilon_{it} \tag{3}$$

The new parameter τ measures temporal persistence, or budget inertia: the fraction of this year's development spending carried over from last year. A more general dynamic spatial Durbin form, used here to test whether anything is lost by the simpler model, also includes a space-time lag of the dependent variable and spatial lags of the regressors, as in Equation (4):

$$\begin{aligned} y_{it} = \tau y_{i,t-1} + \rho \sum_{j=1}^{N} w_{ij} y_{jt} + \eta \sum_{j=1}^{N} w_{ij} y_{j,t-1} \\ + x_{it}'\beta + \sum_{j=1}^{N} w_{ij} x_{jt}'\theta + \mu_i + \varepsilon_{it} \end{aligned} \tag{4}$$

In Equation (4), η captures a county's reaction to its neighbors' spending in the previous year, and θ collects the spillovers of neighbors' characteristics. Year-constant regressors (EL, INFL, TREND) are excluded from the spatial-lag terms because a row-standardized weighting of a variable that is identical across counties within a year reproduces that variable exactly, making the spatial lag collinear with the level. County fixed effects, rather than two-way effects, are retained so that the year-to-year national variation that identifies EL, INFL, and TREND is preserved.

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Spatial relationships are encoded through a Queen contiguity matrix, in which two counties are neighbors when they share a border or a boundary point. The matrix is row-standardized as in Equation (5), so that the spatial lag reads as a weighted average of neighboring counties' values; under this scheme the 47 counties have 5.19 neighbors on average. Since the choice of neighborhood is itself a modeling decision, the model is also estimated with k-nearest-neighbor and inverse-distance weight matrices; the spatial autoregressive parameter keeps its sign and significance across all of them, as reported in Section 4.6.

$$w_{ij}^{*} = \frac{w_{ij}}{\sum_{j=1}^{N} w_{ij}} \tag{5}$$

3.3. Estimation, Diagnostics, and effects

The dynamic spatial models are estimated by quasi-maximum likelihood (Lee & Yu, 2010; Yu et al., 2008). Because the time dimension is short, the quasi-maximum-likelihood estimate of τ is biased downward by the familiar fixed-effects mechanism (Nickell, 1981) and is cross-checked against the Anderson and Hsiao (1981) instrumental-variables estimator and the Arellano and Bond (1991) difference generalized-method-of-moments estimator, both consistent at fixed T; these cross-checks are reported in Table 4. The final model is screened against a full battery of residual diagnostics, covering normality, homoskedasticity, residual spatial autocorrelation, serial correlation, cross-sectional dependence, dynamic stability, and multicollinearity. Because serial correlation and cross-sectional dependence can persist even in a well-specified spatial panel, inference rests on cluster-robust standard errors (Arellano, 1987), and Driscoll and Kraay (1998) standard errors, which are robust to cross-sectional dependence as well, are reported as a further check.

In a spatial model the coefficients are not the full marginal effects, because a change in one county feeds back through the spatial multiplier to every other county, and in a dynamic model it also propagates forward through time. Following Debarsy et al. (2012) and LeSage and Pace (2009), the short-run (impact) effect of a change in regressor k is given by the impact matrix in Equation (6), and the long-run effect, once the system has fully adjusted, by Equation (7):

$$S_k^{SR} = (I_N - \rho W)^{-1} \beta_k \tag{6}$$

$$S_k^{LR} = ((1-\tau) I_N - \rho W)^{-1} \beta_k \tag{7}$$

For each matrix, the average of the diagonal elements is the direct effect, the average of the off-diagonal row sums is the indirect (spillover) effect, and their sum is the total effect. Standard errors and 95% confidence intervals for these quantities are obtained from 2,000 Monte Carlo draws of the parameter vector. Cross-sectional dependence is tested with the Pesaran CD statistic in Equation (8):

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \right) \tag{8}$$

4. Results and discussion

4.1. Descriptive Statistics

Table 1 defines the variables and Table 2 reports descriptive statistics for the constant-price series. In real terms, development expenditure averaged KES 1.63 billion per county-year, with wide dispersion between the largest and smallest counties. Pending bills is the most skewed series, which the logarithmic transformation and Winsorization bring under control. Election-year fiscal years account for 188 of the 517 observations, and the fiscal-year inflation rate averaged 6.14% over the panel.

Table 1. Variable definitions and sources.

Variable	Definition	Source
DE	Development (capital) expenditure	COB
WB	Wage bill (employee compensation)	COB
OSR	Own-source revenue	COB
NGF	Equitable-share transfer	COB
DPF	Development partner funds	COB
PB	Pending bills at year-end	COB
PC	Political coalition (0/1)	IEBC
EL	Election year (0/1)	IEBC
INFL	Fiscal-year inflation rate (%)	KNBS
TREND	Linear time index (1–11)	Constructed

Table 2. Descriptive statistics for constant-price variables.

Variable	M	SD	Min	Max
DEr (KES bn)	1.628	1.000	0.083	11.910
WBr	2.556	1.501	0.631	13.920
OSRr	0.633	1.304	0.024	11.500
NGFr	4.901	1.834	1.722	13.698
DPFr	0.390	0.335	0.000	2.761
PBr	1.525	6.654	0.000	68.387
lDE	0.912	0.316	0.079	2.558
lNGF	1.732	0.289	1.002	2.688
INFL	6.141	0.960	4.275	7.667

4.2. From the Static Baseline to the Dynamic model

Estimated on the same constant-price data, the static spatial autoregressive model of Equation (2) returns a spatial parameter of 0.270, close to the value reported for these counties in earlier work and confirming same-year co-movement in development spending. The question is whether that static picture is complete. A likelihood-ratio test decisively rejects the static restriction in favor of the dynamic model of Equation (3): the test statistic is 28.5 on 8 degrees of freedom ($p < .001$), so temporal structure genuinely belongs in the specification. Within the richer dynamic spatial Durbin form of Equation (4), the space-time lag η is small and far from significant ($p = .54$), which says that counties move with their neighbors in the same year rather than reacting to what those neighbors spent a year earlier. The parsimonious dynamic spatial autoregressive model of Equation (3) is therefore retained as the final specification.

4.3. The Final Dynamic model

Table 3 reports the final dynamic spatial autoregressive model with both maximum-likelihood and cluster-robust standard errors. Two structural parameters stand out. Temporal persistence is positive and significant, with $\tau = 0.152$ under robust inference ($p = .015$): about fifteen percent of a county's development spending carries over from the previous year, the signature of incremental budgeting and multi-year projects. Contemporaneous spatial dependence remains, with $\rho = 0.237$ ($p < .001$), so a county's capital spending still moves with its neighbors' within the year, even after persistence is accounted for. Among the fiscal drivers, the equitable share is dominant and positive (0.755, $p < .001$), the wage bill is negative (−0.333, $p < .001$), pending bills are negative (−0.096, $p < .001$), development partner funds are positive (0.140, $p = .035$), and the election-year indicator

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is negative and strongly significant (−0.148, p < .001). Own-source revenue and political coalition are not significant.

Table 3. Final dynamic spatial autoregressive model (county fixed effects).

Parameter	Estimate	ML SE	Robust SE	p (robust)
ρ (spatial lag)	0.237	0.058	—	< .001
τ (temporal lag)	0.152	0.038	0.063	.015
lWB	−0.333	0.101	0.085	< .001
lOSR	0.096	0.070	0.153	.532
lNGF	0.755	0.130	0.192	< .001
lDPF	0.140	0.052	0.066	.035
lPB	−0.096	0.021	0.022	< .001
PC	0.041	0.032	0.026	.114
EL	−0.148	0.026	0.027	< .001
lNFL	0.036	0.012	0.011	.001
TREND	0.003	0.004	0.004	.516

The persistence estimate deserves a word on its reliability. With only eleven years, the within-county and quasi-maximum-likelihood estimates of τ are biased toward zero by the fixed-effects mechanism, so two estimators that stay consistent when the time dimension is fixed were run as cross-checks. Table 4 collects them. The non-spatial within-county estimator puts τ at 0.129, the spatial quasi-maximum-likelihood model at 0.152, and the two fixed-T estimators higher still: the Anderson–Hsiao instrumental-variables estimator at 0.230 ($p = .045$) and the Arellano–Bond difference GMM estimator at 0.201 ($p = .050$). The point estimates rise as the downward bias is removed, exactly as theory predicts, and all four agree that inertia is positive and moderate. The Arellano–Bond specification passes its specification tests: the test for second-order serial correlation in the differenced residuals does not reject ($p = .06$), and the Sargan test does not reject the overidentifying restrictions ($p = 1.00$ on 24 degrees of freedom, with the instrument set held to lags two through four to keep it from proliferating). Budget inertia is therefore a real feature of county spending, if a moderate one.

Table 4. Temporal persistence across estimators.

Estimator	τ	SE	p
Within-county FE (non-spatial)	0.129	0.040	.001
Spatial QML (final dynamic SAR-FE)	0.152	0.063	.015
Arellano–Bond difference GMM	0.201	0.102	.050
Anderson–Hsiao IV	0.230	0.115	.045

4.4. Model Assumptions

Table 5 reports the assumption battery for the final model. The central spatial assumption is satisfied: Moran's I on the residuals is insignificant in every one of the ten estimation years, so the spatial lag has absorbed the dependence present in the raw data. The homoskedasticity check is also passed (Breusch–Pagan p = .117), which is notable because the static models of earlier work could not clear it. The lagged dependent variable does most of its job on serial correlation: the strong positive serial correlation of the static specification is removed, leaving only a mild negative residual autocorrelation that, while small, is still statistically distinguishable from zero. Dynamic stability holds comfortably, since $\tau + \rho = 0.39$ is well below one, and multicollinearity is not a concern, with a maximum variance inflation factor of 5.40.

Two conditions are not met on a panel of this size. Residuals depart from exact normality, though with 470 observations the central limit theorem keeps the estimators approximately normal, so inference is protected without any correction. More consequentially, cross-sectional dependence remains strong (Pesaran CD = 7.06, p < .001): county residuals are correlated across counties within a fiscal year, as shared national shocks would imply. The source of this dependence is not hard to name. County budgets respond to forces that reach the whole country at once rather than spreading from one neighbor to the next: the national macroeconomic cycle, nationwide changes in fiscal policy and the timing of transfers, and climatic shocks such as the recurring droughts that strain many county budgets in the same year. A single contemporaneous spatial lag and the common-time controls absorb part of this, but not all of it, so some correlation survives in the residuals. It is precisely this cross-sectional dependence, together with the mild residual serial correlation, that calls for robust standard errors, and the reported significance levels in Table 3 rest on cluster-robust errors for that reason. The robust errors are not a response to heteroskedasticity, which the model satisfies; they are needed because classical maximum-likelihood errors assume disturbances that are independent across both counties and years, an assumption these two residual features violate.

To confirm that the remaining dependence does not distort inference, the model was re-estimated with Driscoll–Kraay standard errors, which are robust to cross-sectional dependence in addition to heteroskedasticity and serial correlation. Every substantive coefficient keeps its sign and significance: temporal persistence, the equitable share, the wage bill, pending bills, development partner funds, and the election indicator all remain significant at conventional levels. These errors call for some caution, since their large-sample justification rests on a long time dimension and this panel has only eleven years, but they move in step with the cluster-robust errors and so reinforce the main conclusions rather than unsettle them. The main results are likewise unchanged under two-way clustering. On balance, the dynamic model satisfies more of the standard assumptions than the static model it extends, and handles the remainder through valid inference.

Table 5. Residual diagnostics for the final dynamic model.

Assumption	Test	Statistic	p	Status
Spatial autocorrelation	Moran's I (10 yrs)	0/10 significant	> .05	Satisfied
Homoskedasticity	Breusch–Pagan	LM = 2.45	.117	Satisfied
Serial correlation	Residual AR(1)	−0.126	.009	Robust SE
Cross-sectional dep.	Pesaran CD	7.06	< .001	Robust SE
Normality	Shapiro–Wilk	$W = 0.978$	< .001	CLT; $n = 470$
Dynamic stability	$\tau + \rho$	0.389	—	Satisfied
Multicollinearity	Max VIF	5.40	—	Satisfied

4.5. Short-Run and Long-Run effects

Because a change now echoes forward through persistence and outward through the spatial multiplier, the dynamic model yields two horizons for every driver. Table 6 reports the total effects on impact and in the long run, with the equitable share and the election indicator shown in full direct–indirect detail. The equitable share tells the clearest story: its pass-through into development spending is 0.99 on impact and builds to 1.24 in the long run, with the long-run interval lying above one, so a sustained rise in the equitable share eventually raises aggregate development spending slightly more than one-for-one once spillovers and persistence have worked through. The wage-bill crowd-out deepens from −0.44 to −0.54, the pending-bills drag from −0.13 to −0.16, and the election-year slowdown from −0.19 to −0.24; development partner funds add a positive 0.18 on impact, rising to 0.23. Own-source revenue and political coalition are insignificant at both horizons. In every case the long-run effect exceeds the short-run, which is the dynamic

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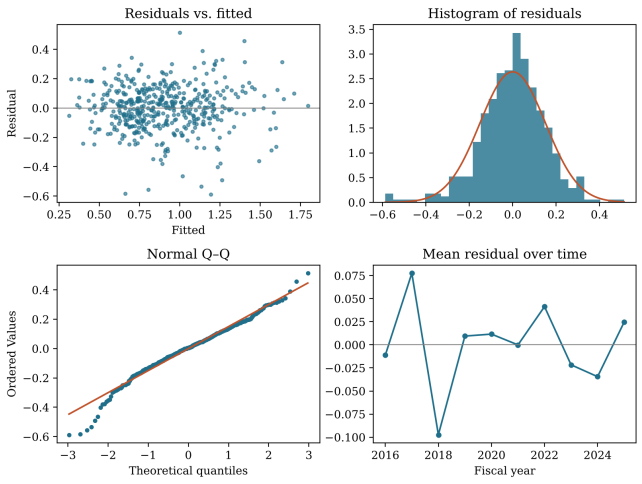


Figure 1. Residual diagnostic plots for the final dynamic model.

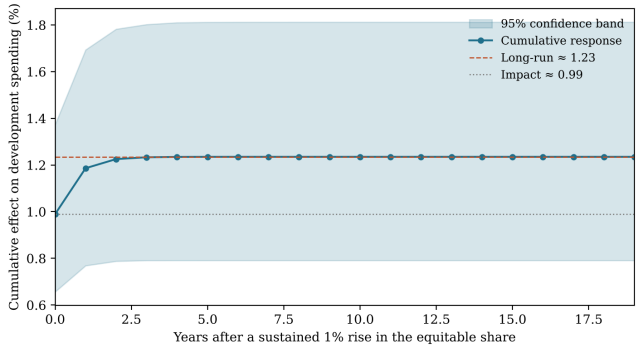


Figure 2. Adjustment path of development spending to a sustained 1% rise in the equitable share, with 95% confidence band.

multiplier at work: because spending is sticky, a shock keeps acting in later years, so its cumulative effect is larger than its first-year impact.

Table 6. Short-run and long-run effects.

Driver	Horizon	Direct	Indirect	Total	95% CI
Equitable share	Short-run	0.790	0.199	0.989	[0.652, 1.366]
Equitable share	Long-run	0.964	0.271	1.235	[0.793, 1.803]
Wage bill	Short-run	—	—	−0.436	[−0.713, −0.176]
Wage bill	Long-run	—	—	−0.544	[−0.907, −0.219]
Pending bills	Short-run	—	—	−0.126	[−0.182, −0.071]
Pending bills	Long-run	—	—	−0.158	[−0.233, −0.087]
Donor funds	Short-run	—	—	0.183	[0.056, 0.318]
Donor funds	Long-run	—	—	0.229	[0.069, 0.409]
Election year	Short-run	−0.155	−0.039	−0.194	[−0.260, −0.133]
Election year	Long-run	−0.193	−0.049	−0.242	[−0.340, −0.161]

Figure 2 traces this adjustment for the equitable share. A sustained one-percent increase raises development spending by about 0.99% on impact, and the effect climbs to its long-run level of roughly 1.24% within a few fiscal years, with about half of the remaining adjustment completed in the first year after impact. The shaded band in Figure 2 is the 95% confidence region around this path, built from the same 2,000 Monte Carlo draws of the parameter vector used for the effect estimates. The band is wide enough that the individual year-to-year steps along the trajectory are not precisely pinned down, but it lies above zero at every horizon and brackets a long-run response close to one, so the cumulative return is estimated with enough precision to carry the policy reading. The practical message is that the full return to a transfer increase is not visible in the year it is granted; it accumulates, which is precisely why the timing and predictability of disbursement matter as much as the amount.

4.6. Robustness Checks

Two modeling choices invite scrutiny: the Winsorization of pending bills and the definition of the spatial weight matrix. Neither drives the results. Table 7 re-estimates the model with pending bills Winsorized at the 95th and 98th percentiles, and under a raw logarithmic transformation with no Winsorization at all. The pending-bills elasticity stays negative and significant at the 0.1% level in every case, between −0.10 and −0.13, and temporal persistence and spatial dependence hardly move, so the negative coefficient is a property of the data and not an artifact of the chosen cutoff. Table 8 then replaces the Queen contiguity matrix with k-nearest-neighbor matrices for k of four, six, and eight, and with an inverse-distance matrix. The spatial autoregressive parameter is positive and significant under every definition. Its magnitude grows as the neighbor set widens, from 0.24 under Queen contiguity to 0.57 under inverse distance, which is what one expects when a denser matrix spreads each county's influence over more partners; what matters for the argument is that the sign, the significance, and the coefficients on the equitable share and pending bills are stable across all of them.

Table 7. Sensitivity of the pending-bills elasticity to the Winsorization cutoff.

Pending-bills treatment	τ	ρ	lPB	p(lPB)
Raw log (no Winsorization)	0.153	0.236	−0.096	< .001
95th percentile	0.147	0.240	−0.129	< .001
98th percentile	0.148	0.241	−0.112	< .001
99th percentile (reported)	0.152	0.237	−0.096	< .001

Table 8. Sensitivity of the spatial parameter to the weight matrix.

Weight matrix	Avg. N	ρ	$p(\rho)$	τ	lNGF
Queen contiguity (reported)	5.19	0.237	< .001	0.152	0.755
k-nearest neighbors ($k = 4$)	4.00	0.250	< .001	0.160	0.761
k-nearest neighbors ($k = 6$)	6.00	0.314	< .001	0.161	0.772
k-nearest neighbors ($k = 8$)	8.00	0.350	< .001	0.158	0.772
Inverse distance	46.00	0.567	< .001	0.155	0.739

4.7. Discussion

Three findings carry the paper. First, county development spending is persistent: a shock to this year's budget is partly carried into next year's, so the costs of disbursement delays, wage-bill growth, and pending bills accumulate rather than resolving within the year. Second, the spatial interaction between counties is contemporaneous rather than lagged, which points to shared shocks and same-year strategic behavior rather than slow imitation of neighbors' past budgets. Third, the equitable-share pass-through builds over time to a long-run elasticity above one, the clearest possible expression of the flypaper effect (Hines & Thaler, 1995) in a devolved setting, and consistent with the dominant role of national transfers found in the static analysis of these counties (Benedict et al., 2026). The election-year slowdown, which a static constant-price model finds fragile, returns to significance once persistence is modeled and deepens over the long run, suggesting that the disruption to procurement and project execution around general elections is not confined to the election year itself but spills into adjacent budgets.

The wage-bill result has the sharpest policy edge. Payroll growth crowds out development spending on impact and more so in the

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long run, and because the effect propagates across county borders, one county's payroll pressure becomes a regional drag rather than a purely local one. Own-source revenue and political coalition remain insignificant, as they were in the static analysis, which suggests that neither local revenue effort nor alignment with the national ruling coalition independently moves development spending once the equitable share, the wage bill, and the dynamics are accounted for.

The own-source revenue result is worth dwelling on, because raising local revenue is one of the central promises of devolution, and a null relationship with capital spending is a finding in its own right. The explanation is more structural than statistical. Own-source revenue is small in these counties, averaging well under a fifth of the equitable share in constant terms, and most of what counties collect is committed to recurrent obligations, payroll, operations, and the running of the county executive and assembly, before any of it can reach capital projects. Collections are also volatile from one year to the next, which makes them a weak foundation for the multi-year commitments that development spending requires; a county facing uncertain local receipts will sensibly anchor its capital plans to the predictable equitable share rather than to revenue it may or may not raise. Read this way, the result does not say that local revenue is unimportant. It says that expanding own-source revenue will do little for development spending on its own, unless it is paired with expenditure controls that keep the extra revenue from being absorbed into the recurrent budget.

5. Conclusion and Policy Recommendations

This study extended the spatial analysis of Kenyan county development expenditure from a static to a dynamic setting, estimating a dynamic spatial autoregressive model with county fixed effects on constant-price data for all 47 counties over financial year 2014/15 to 2024/25. The dynamic structure earns its place: the static restriction is rejected, budget inertia is positive and significant, and adding the temporal lag clears the serial correlation and heteroskedasticity that static models could not. Development spending co-moves with neighbors within the year but shows little delayed reaction to their past budgets, and every fiscal driver's effect is larger in the long run than on impact. National transfers remain the dominant driver, with a long-run pass-through above one; the wage bill and pending bills drag development spending down, and the drag deepens over time; and the election-year slowdown, fragile in a static model, is firm and persistent in the dynamic one.

Four recommendations follow. Because the equitable-share pass-through accumulates over several years, the National Treasury should move to a statutory, predictable disbursement calendar, so that counties can plan multi-year capital projects against reliable cash flows rather than deferring them. Because wage-bill growth crowds out development spending with effects that persist and spill across borders, a binding ceiling on payroll as a share of county revenue, enforced nationally, is warranted. The counties must also restrict themselves to the human resource they need and not the labour-force politicians want. Because pending bills exert a persistent drag, a structured settlement framework with independent verification and phased clearance is needed. And because development spending slows around elections and the slowdown lingers, procurement and disbursement planning should build in the electoral calendar, front-loading multi-year projects into non-election years. Future work could disaggregate spending by sector and apply the bias-corrected dynamic spatial estimator as the panel lengthens, which would sharpen the long-run magnitudes reported here.

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