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Does Foreign Investment Industrialize the Host or the Region? Spatial Panel Evidence from SADC

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Abstract

Attracting foreign investment is the centerpiece of SADC's industrial policy, but whether the benefits accrue to the host or its neighbors has yet to be determined. By estimating the entire spatial panel family using a balanced thirteen-country panel, we discover that FDI industrializes the region rather than the recipient: the coefficient on neighbors' FDI is positive and significant in the spatial Durbin, spatial Durbin error, and least-squares specifications, and the indirect impact is an order of magnitude larger than the statistically negligible direct impact. In contrast, urbanization, institutional quality, and credit all have an impact on the local level. The policy implication is that foreign investment is a regional instrument and not a national one: where the industrial returns to attracting capital accrue largely to neighbors, competitive national incentive schemes bid for a benefit their sponsors do not capture, so coordinating investment incentives at the level of the customs union dominates outbidding one another. Because the other three determinants act locally, that case for coordination applies to FDI alone.

Keywords

FDI Spillovers, Spatial Panel, Industrialization, SADC, Spatial Durbin Model, Moran's *I*

1. Introduction

Manufacturing remains the sector to which developing regions look for productivity growth and structural change (Szirmai, 2012), and it is the sector in which they are losing ground: Rodrik (2016) shows that developing economies now reach peak manufacturing shares at lower income levels and earlier dates than

their predecessors. Southern Africa illustrates the pattern with unusual clarity. The Southern African Development Community adopted an Industrialization Strategy and Roadmap in 2015 committing the region to raise manufacturing value added to 30 per cent of GDP by 2030 and 40 per cent by 2050, and to lift manufactured exports from about a fifth of total exports to at least a half. The Secretariat's own monitoring reports that manufacturing value added remains below 12 per cent of GDP, that most member states still depend on agro-based and mining commodities, and that while activities and intermediate outputs have been delivered, little change has been recorded in impact indicators. The target is being missed by a wide margin, and the region's own diagnosis is that the binding constraint lies in productive capacity rather than in market access.

Foreign direct investment is the instrument on which both the regional strategy and its member states rely most heavily to relieve that constraint. The theoretical case is familiar: foreign entrants bring capital, production technology and managerial practice, develop local suppliers, and provide entry points into global value chains. The empirical case for Africa is weaker than the policy consensus implies. Panel studies of African industrialization find effects of FDI on manufacturing that are small, statistically fragile or negative, and Mijiyawa (2017), examining 53 African countries, finds FDI and urbanization insignificant while governance quality and market size matter. Firm-level work is more encouraging but more conditional: Hoekman and Sanfilippo (2023), matching some 11,000 geolocated greenfield projects to 48,000 firms across 48 African countries, find vertical spillovers concentrated in manufacturing, operating through proximity to projects offering supply or demand linkages, with horizontal effects considerably weaker.

That firm-level result carries an implication its own research design cannot pursue. If the spillover mechanism is proximity to a linked project, then the relevant field of the spillover is set by economic geography rather than by political boundaries. Where a border sits close to an investment, and where transport corridors and input trade span it, the field extends beyond the host economy. Whether it does so in practice is unknown, because the two literatures that could establish it are separated by their units of observation: firm-level studies measure proximity within countries, and country-level studies estimate one coefficient per country and treat member states as isolated observations. Neither design can say whether the industrial effect of investment stops at the border.

The question matters because the sign of any cross-border effect is not settled by theory. Investment arriving in one member state may raise industrial capacity in its neighbors through cross-border supply relationships, intermediate-input trade, shared corridor and power infrastructure, labor mobility and demonstration effects, in which case FDI is a regional industrialization mechanism. It may equally reduce industrial capacity elsewhere by diverting internationally mobile capital, by conferring agglomeration advantages that deepen existing concentration, or by capturing regional market share that domestic producers in neighboring economies would otherwise have supplied. The first mechanism implies a pos-

itive indirect effect, the second a negative one, and they cannot both be assumed away.

SADC is an unusually informative setting for adjudicating between them, for three reasons. First, the region's investment is concentrated: UNCTAD reports that African FDI benefits remain confined to a limited number of countries and sectors, with energy, construction and extractives dominating greenfield activity, and studies of SADC find inflows concentrated in very few members and directed largely at resource extraction. Concentrated, enclaved investment is precisely the configuration under which the host-versus-region distinction has bite. Second, the region's members are economically interdependent by construction rather than by assumption: they share a free trade area, transport corridors linking landlocked members to coastal ports, a power pool, and production networks radiating from a dominant industrial economy in South Africa, whose regional role could plausibly be that of a hub diffusing capability or a center absorbing it. Third, and most directly, SADC's own strategy makes the regional incidence of investment a policy premise: the roadmap's emphasis on value chains, it states, arises from the desirability of moving development perspectives from a national to a regional focus, and Pillar I of the RISDP 2020-2030 prioritizes agro-processing, mineral beneficiation and pharmaceuticals as regional rather than national undertakings. The premise has not been tested.

This paper tests it. We ask whether foreign investment raises the manufacturing share of the economy that receives it, of its neighbors, or of neither, using a balanced panel of thirteen SADC member states observed annually from 2002 to 2023. Because the question is about where an effect lands rather than whether it exists on average, the empirical framework must permit the outcome in one country to depend on covariates in another.

The paper makes three contributions. Conceptually, it relocates the FDI-industrialization question from the national to the regional unit of analysis, treating SADC as a spatial economic system rather than a collection of independent economies. Empirically, it provides the first estimate we are aware of that separates the industrial effect of FDI received by a SADC member from that associated with FDI received by its neighbors. For policy, it bears directly on whether investment attraction should remain a national instrument: if the industrial returns to attracting capital accrue substantially to neighbors, then competing national incentive regimes bid for a benefit their sponsors do not capture, and coordination at the level of the customs union dominates outbidding.

Section 2 positions the paper in the literature, Section 3 develops the spatial specifications and the identification argument, Section 4 describes the data and the weight matrices, Section 5 reports the results and the sensitivity analysis, and Section 6 concludes.

2. Literature Review and Positioning

The premise that manufacturing drives development originates with Kaldor

(1967) and is quantified by Szirmai (2012); Rodrik (2016) documents the premature deindustrialization that SADC exhibits. On determinants, Mijiyawa (2017) finds governance quality decisive and FDI and urbanization not, while Gollin, Jedwab and Vollrath (2016) show that resource exporters urbanize without industrializing. None of this literature is spatial, and the omission matters for a region organized around transport corridors and a dominant neighbor.

The spatial panel toolkit is settled. Anselin (1988) sets out the Lagrange multiplier tests and Anselin, Bera, Florax and Yoon (1996) their locally robust versions; Elhorst (2014) collects the maximum-likelihood estimators for panels; LeSage and Pace (2009) establish that coefficients are not marginal effects once the outcome is spatially lagged and derive the impact decomposition; Burridge (1981) provides the common-factor test that separates the Durbin model from the error model. For dynamics, Yu, de Jong and Lee (2008) give the asymptotics of quasi-maximum likelihood when n and T are both large, and Debarsy, Ertur and LeSage (2012) the interpretation of space-time models.

Our positioning is specific. Applications of this toolkit routinely take the diagnostics at face value, yet the properties of Moran's I and the LM tests after a two-way within transformation with small n are not well documented, and Koassi et al. (2026) show what happens when they are not: a dependence statistic of the wrong sign is interpreted substantively. We treat the size of the diagnostics as something to be established rather than assumed, and only then estimate the model family. This ordering, rather than any new estimator, is what the paper contributes.

3. Empirical Models

Notation is in **Table 1**. Throughout, IND_{it} is manufacturing value added as a percentage of GDP and $x_{it} = \left(\mathrm{FDI}_{it}, \mathrm{URB}_{it}, \mathrm{RL}_{it}, \mathrm{CRED}_{it}\right)'$, exactly as in the companion paper.

3.1. The Restriction Imposed by the Non-Spatial Baseline

The preferred static specification of Koassi et al. (2026) is:

$$\mathrm{IND}_{it} = \mu_i + \lambda_t + x_{it}'\beta + \varepsilon_{it}, E\left[\varepsilon_{it}\varepsilon_{jt}\right] = 0 \text{ for } i \neq j \tag{1}$$

where μ_i and λ_t are country and time effects. The final condition in Equation (1) is the restriction this paper relaxes: it asserts that, conditional on a common annual shock, no country's manufacturing share is related to any other's. The general nesting specification from Elhorst (2010) is:

$$\begin{gathered} \mathrm{IND}_{it} = \rho\sum_{j=1}^{N} w_{ij}\mathrm{IND}_{jt} + x_{it}'\beta + \sum_{j=1}^{N} w_{ij}x_{jt}'\gamma + \mu_i + \lambda_t + u_{it}, \\ u_{it} = \varsigma\sum_{j=1}^{N} w_{ij}u_{jt} + \varepsilon_{it} \end{gathered} \tag{2}$$

with ρ the endogenous interaction parameter, γ the exogenous (Durbin) interaction vector, ς the disturbance interaction parameter and $\varepsilon_{it} \sim iid\left(0, \sigma_\varepsilon^2\right)$. Six familiar models are restrictions of Equation (2),

$$\begin{aligned}&\text{SLX}:\rho=\varsigma=0;\ \text{SAR}:\gamma=0,\varsigma=0;\ \text{SEM}:\rho=0,\gamma=0;\\&\text{SDM}:\varsigma=0;\ \text{SDEM}:\rho=0;\ \text{SAC}:\gamma=0\end{aligned}\tag{3}$$

Each solves a problem the previous leaves open. SLX is estimable by least squares, with the Driscoll and Kraay (1998) covariance the companion paper uses, so its Durbin coefficients are free of simultaneity, but it cannot represent feedback. SAR adds feedback but forces every indirect effect to be a fixed multiple of the corresponding direct effect. SEM instead attributes the dependence to disturbances, which leaves β consistent but rules out spillovers by assumption. SDM nests SAR and SEM and is the specification LeSage and Pace (2009) recommend when omitted variables may be spatially correlated; SDEM is its error-side counterpart; SAC lets a behavioral and a disturbance channel operate at once. Estimation is by concentrating the log-likelihood, for SAR and SDM in ρ,

$$\ln L(\rho)=-\frac{nT}{2}\ln\left(2\pi\sigma_\varepsilon^2\right)+T\sum_{q=1}^{n}\ln\left|1-\rho\varpi_q\right|-\frac{e'(\rho)e(\rho)}{2\sigma_\varepsilon^2}\tag{4}$$

after the two-way within transformation, with ϖ_q the eigenvalues of W; the error models replace ρ by ς and apply the spatial filter ($I_n-\varsigma W$) to both sides.

3.2. Diagnosing Spatial Dependence When the Panel Is Demeaned

The natural first test is the period-wise global Moran statistic on the residuals $\hat{e}_{it}$ of Equation (1),

$$I_t=\frac{n}{S_0}\cdot\frac{\sum_i^n\sum_j^n w_{ij}\hat{e}_{it}\hat{e}_{jt}}{\sum_i^n\hat{e}_{it}^2},\quad S_0=\sum_i^n\sum_j^n w_{ij}\tag{5}$$

averaged over t, with inference by permutation of country labels within periods because the normal approximation is unreliable at $n=13$. The Lagrange multiplier tests are less forgiving. Write M for the residual maker of the demeaned regressors and $B=M\left(I_T\otimes W\right)M$. The textbook statistics of Anselin (1988) assume the score has mean zero, whereas under the null with Gaussian errors

$$\begin{aligned}&E\left[e'\left(I_T\otimes W\right)e\right]=\sigma_\varepsilon^2 tr(B),\\&Var\left[e'\left(I_T\otimes W\right)e\right]=\sigma_\varepsilon^4\left[tr(BB)+tr\left(BB'\right)\right]\end{aligned}\tag{6}$$

Because W is row-standardized, demeaning each period by the cross-sectional mean makes $tr(B)$ strongly negative, so the uncentred statistics diverge. The centered tests are

$$\begin{aligned}LM_\varsigma&=\frac{\left[d_\varsigma-tr(B)\right]^2}{tr(BB)+tr\left(BB'\right)},\\LM_\rho&=\frac{\left[d_\rho-tr(B)\right]^2}{J},\\J&=\frac{\left(WX\hat{\beta}\right)'M\left(WX\hat{\beta}\right)}{\sigma_\varepsilon^2}+tr(BB)+tr\left(BB'\right)\end{aligned}\tag{7}$$

where $d_\varsigma=e'\left(I_T\otimes W\right)e/\hat{\sigma}_\varepsilon^2$ and $d_\rho=e'\left(I_T\otimes W\right)y/\hat{\sigma}_\varepsilon^2$, each distributed χ_1^2,

with $\hat{\sigma}_\varepsilon^2 = e'e/tr(M)$. The locally robust versions of Anselin, Bera, Florax and Yoon (1996) purge each score of the other channel,

$$LM_\rho^* = \frac{\left[\left(d_\rho - tr(B)\right) - \left(d_\varsigma - tr(B)\right)\right]^2}{J - \Theta},$$
$$LM_\varsigma^* = \frac{\left[\left(d_\varsigma - tr(B)\right) - \Theta J^{-1}\left(d_\rho - tr(B)\right)\right]^2}{\Theta\left(1 - \Theta J^{-1}\right)}, \quad (8)$$
$$\Theta = tr(BB) + tr(BB')$$

Accordingly, the sequence of tests in Equations (5) to (8) provides a systematic framework for determining whether spatial dependance is present in the residuals and, if so, whether it is more consistent with a spatial-lag or spatial-error specification. With these tests, we go beyond the sole Moran Index.

3.3. Impacts

When $\rho \neq 0$ a change in country *i* propagates through the whole system, so the estimated coefficients are not marginal effects. LeSage and Pace (2009) define the matrix of partial derivatives for regressor *r*,

$$S_r(W) = \left(I_n - \rho W\right)^{-1}\left(I_n \beta_r + W\gamma_r\right) \quad (9)$$

summarized as

$$\overline{direct}_r = \frac{tr\left(S_r(W)\right)}{n}, \ \overline{total}_r = \frac{\iota' S_r(W)\iota}{n}, \ \overline{indirect}_r = \overline{total}_r - \overline{direct}_r \quad (10)$$

with inference from 5000 draws of (ρ, β, γ) from its estimated asymptotic distribution.

3.4. Two Extensions

Koassi et al. (2026) established that the manufacturing share is highly persistent, so the natural synthesis is the dynamic spatial Durbin model

$$\begin{aligned} \mathrm{IND}_{it} &= \tau \mathrm{IND}_{i,t-1} + \rho \sum_j^N w_{ij} \mathrm{IND}_{jt} + \eta \sum_j^N w_{ij} \mathrm{IND}_{j,t-1} + x_{it}'\beta \\ &\quad + \sum_j^N w_{ij} x_{jt}'\gamma + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \quad (11)$$

which is stationary only if

$$\tau + \rho + \eta < 1 \quad (12)$$

for a row-standardized W whose largest eigenvalue is unity. Equation (11) is estimated by quasi-maximum likelihood and bias-corrected with the bootstrap fixed point of Everaert and Pozzi (2007) used for the LSDVC,

$$\delta^{*(m+1)} = \hat{\delta} - \left[E_b\left(\hat{\delta}^* \mid \delta^{*(m)}\right) - \delta^{*(m)}\right] \quad (13)$$

with panels simulated from the reduced form of Equation (11) so that the correction accounts for the interaction between the Nickell (1981) bias and the spatial multiplier. Finally, to ask whether the dependence is local interaction or common-

factor contamination, we re-estimate the spatial models on data filtered by projecting each country series on [1, $\overline{\mathrm{IND}}_t$, $\overline{x}_t$],

$$\ddot{y}_i = M_{\bar{z}} y_i, \quad M_{\bar{z}} = I_T - \bar{Z}\left(\bar{Z}'\bar{Z}\right)^{-1}\bar{Z}' \tag{14}$$

following Pesaran (2006, 2021).

4. Data and Methodology

The sample is that of Koassi et al. (2026): a balanced panel of 13 SADC member states, 2002 to 2023, $nT = 286$, with manufacturing value added, FDI inflows, urban population share and domestic credit to the private sector from World Bank development indicators and the rule-of-law estimate from the Worldwide Governance Indicators. No observation is missing. The following Table 1 describes each variable:

Table 1. Notation.

Symbol	Meaning
i, j, t	country, neighbouring country, year; $n = 13$, $T = 22$
IND(i, t)	manufacturing value added (% of GDP)
$x(i, t)$	$k \times 1$ regressor vector (FDI, URB, RL, CRED), $k = 4$
W, $w(i, j)$	$n \times n$ row-standardised weight matrix and its elements
$\varpi(q)$	eigenvalues of W
ρ, ς	endogenous and disturbance interaction parameters
β, γ	own and Durbin (W-lagged) slope vectors
τ, η	time lag and space-time lag parameters
μ(i), λ(t)	country and time fixed effects
M, B	residual maker of the demeaned regressors; $B = M(I \otimes W)M$
d(ρ), d(ς)	lag and error scores in the LM statistics
$\mathcal{S}(r)(W)$	matrix of partial derivatives for regressor r
ε(i,t), σ^2	idiosyncratic disturbance and its variance

Spatial weights are built from national polygon centroids; great-circle separations average 2077 km, with a minimum of 312 km and a maximum of 4551 km. We use six row-standardized specifications: inverse distance, inverse squared distance, negative-exponential decay with a 1000 km scale, three and five nearest neighbors, and a 2000 km distance band. Contiguity is not available because Mauritius and Seychelles share no land border with any member, which is itself a rea-

son to prefer distance-decay schemes in this region. All estimation is in Python and Stata; Equations (4), (6) to (10), (13) and (14) are implemented directly from the expressions above.

5. Results

5.1. The Diagnostics, and Why They Must Be Corrected

Table 2 below reports Moran's (1950) I on the two-way residuals of Equation (1). Its permutation expectation is $-1/(n-1) = -0.083$, not zero, which is the first sign of the problem: the raw statistic is negative under all six weight matrices even where dependence is strong. Measured against the correct benchmark, I exceeds its permutation mean at the 1 per cent level for inverse distance ($z = 4.78$), inverse squared distance ($z = 5.16$) and exponential decay ($z = 3.15$), at 5 per cent for three nearest neighbors, and not at all for the five-nearest-neighbor and distance-band matrices.

Table 2. Weight matrices and Moran's I on the two-way fixed-effects residuals.

Weight matrix	Links	ρ lower	ρ upper	I	$E[I]$	z	p
Inverse distance	12.00	−3.216	1.000	−0.031	−0.083	4.78	0.000
Inverse distance squared	12.00	−1.643	1.000	0.035	−0.083	5.16	0.000
Exponential decay (1000 km)	12.00	−3.369	1.000	−0.037	−0.083	3.15	0.002
Three nearest neighbors	3.00	−1.684	1.000	0.000	−0.083	2.45	0.017
Five nearest neighbors	5.00	−2.331	1.000	−0.052	−0.083	1.45	0.145
Distance band (2000 km)	6.15	−1.000	1.000	−0.047	−0.083	1.08	0.280

Notes: Links is the average number of non-zero weights per row. All matrices are row-standardized, so the largest eigenvalue is unity. I is the average over periods of Equation (5) applied to the residuals of Equation (1); $E[I]$ is the mean over 9999 within-period permutations of country labels, against which z and p are computed. Great-circle distances between centroids average 2077 km.

Table 3 makes the point sharply. Applied to 2000 samples generated under the null, the uncentred Lagrange multiplier statistics reject at a nominal 5 percent level in 97.7 and 98.7 percent of cases: they are not tests. The centered statistics of equation (7) have empirical size 0.025 and 0.024, mildly conservative, and the robust statistics of equation (8) have size 0.054 and 0.047, essentially exact. The reason is in equation (6): the null mean of the score is −20.64 in this sample, while the observed values are −7.39 for the lag score and −7.42 for the error score.

Once centered, the tests reject decisively. Under inverse distance $LM_{\rho} = 11.75$ ($p = 0.0006$) and $LM_{\xi} = 12.96$ ($p = 0.0003$); under inverse squared distance both exceed 17. The pattern across weight matrices matches Moran's I: distance-decay schemes reject, neighbor-count and band schemes do not. But the robust statistics never reject, the largest being $LM_{\xi}^{*} = 1.21$ ($p = 0.27$). Each test's significance is

thus entirely explained by the other channel, which is the textbook signature of dependence whose source is not identified.

Table 3. Lagrange multiplier tests, their empirical size, and the demeaning artefact.

	$LM(\rho)$	$LM(\varsigma)$	$LM^*(\rho)$	$LM^*(\varsigma)$
Panel A. Empirical size at the 5% *level*, 2000 *draws under the null*				
Uncentred (textbook) statistics	0.977	0.987	0.024	0.076
Centred on exact null moments	0.025	0.024	0.054	0.047
Panel B. Centred statistics, observed values (*p-values in parentheses*)				
Inverse distance	11.751	12.956	0.001	1.206
	(0.001)	(0.000)	(0.982)	(0.272)
Inverse distance squared	17.832	19.742	0.012	1.922
	(0.000)	(0.000)	(0.913)	(0.166)
Exponential decay (1000 km)	4.484	5.371	0.000	0.887
	(0.034)	(0.021)	(0.989)	(0.346)
Three nearest neighbors	2.236	2.930	0.039	0.733
	(0.135)	(0.087)	(0.844)	(0.392)
Five nearest neighbors	0.296	0.487	0.149	0.340
	(0.586)	(0.485)	(0.699)	(0.560)
Distance band (2000 km)	0.694	0.750	0.011	0.067
	(0.405)	(0.387)	(0.916)	(0.795)
Panel C. The artefact: *null mean of the score* $tr(B) = -20.636$; *observed* $d(\rho) = -7.393$, $d(\varsigma) = -7.420$				

Notes: All statistics are chi-square (1). Panel A regenerates the dependent variable from the fitted two-way fixed-effects model with iid normal errors and records rejection rates; a correctly sized test returns 0.05. Panel B applies Equations (7) and (8).

5.2. The Spatial Family and Its Impacts

Table 4 confirms the diagnosis. All spatial parameters are negative and modest: $\hat{\rho} = -0.253$ in SAR, $\hat{\varsigma} = -0.236$ in SEM, −0.291 and −0.319 in SDM and SDEM, and in SAC the two are −0.147 and −0.153 with neither significant. The log-likelihoods span less than four points and no likelihood-ratio test rejects: SAR against the non-spatial model gives 2.08 ($p = 0.15$), SDM against SAR 5.41 ($p = 0.25$), and the Burridge common-factor test of SDM against SEM 5.53 ($p = 0.24$). A panel of thirteen countries cannot discriminate among these models.

Table 4. The spatial panel family, inverse-distance W, two-way fixed effects.

Variable	SLX	SAR	SEM	SDM	SDEM
FDI	−0.018	−0.040*	−0.040*	−0.016	−0.016
	(0.026)	(0.022)	(0.022)	(0.025)	(0.025)
URB	0.262***	0.247***	0.248***	0.258***	0.253***
	(0.059)	(0.048)	(0.049)	(0.056)	(0.055)
RL	3.169***	2.917***	2.974***	3.307***	3.410***
	(0.858)	(0.726)	(0.746)	(1.010)	(0.987)
CRED	−0.069*	−0.058***	−0.059***	−0.069***	−0.068***
	(0.039)	(0.015)	(0.015)	(0.020)	(0.020)
$W\times$ FDI	0.378**			0.386**	0.421**
	(0.160)			(0.182)	(0.180)
$W\times$ URB	0.188			0.206	0.066
	(0.290)			(0.267)	(0.270)
$W\times$ RL	2.216			3.970	3.936
	(7.686)			(6.266)	(6.218)
$W\times$ CRED	−0.105			−0.112	−0.086
	(0.338)			(0.124)	(0.124)
ρ		−0.253*		−0.291*	
		(0.147)		(0.152)	
ς			−0.236		−0.319**
			(0.149)		(0.155)
ln L		−556.21	−556.27	−553.50	−553.29

SAC: rho = −0.147 (0.197), ς = −0.153 (0.199), ln L = −555.97; non-spatial ln L = −557.25

LR tests: SAR vs FE 2.08 (0.149); SEM vs FE 1.96 (0.162); SDM vs SAR 5.41 (0.248)

SDM vs SEM, common factor, 5.53 (0.237); SDEM vs SEM 5.96 (0.202); SAC vs SAR 0.47 (0.493)

Notes: Dependent variable: manufacturing value added (% GDP). Standard errors in parentheses. SLX is least squares with Driscoll-Kraay standard errors at Bartlett bandwidth m = 2; the ML columns estimate Equation (2) under the restrictions in Equation (3) by concentrating Equation (4), with standard errors from the analytical information matrix. ***p < 0.01, **p < 0.05, *p < 0.10.

What survives is the exogenous interaction. The coefficient on neighbors' FDI is 0.386 in SDM, 0.421 in SDEM and 0.378 in SLX, significant at 5 percent in all three, and the SLX estimate is least squares, so it is free of the simultaneity that makes ρ hard to pin down.

Table 5 translates this into impacts. In SDM the indirect effect of FDI is 0.313 ($p = 0.04$) against a direct effect of −0.025 that is indistinguishable from zero; in SDEM the indirect effect is 0.421 ($p = 0.01$). Foreign investment is associated with a higher manufacturing share in neighboring economies and not in the recipient, which is what one expects if FDI concentrates in extractive enclaves whose corridor and supply-chain effects cross borders. By contrast, the direct effects of urbanization (0.255), rule of law (3.23) and credit (−0.066) are all significant at 1 per cent while their indirect effects are not, so these are local relationships, not regional ones.

Table 5. Direct, indirect and total impacts.

Variable	SDM			SDEM		
	Direct	Indirect	Total	Direct	Indirect	Total
FDI	−0.025	0.313**	0.287*	−0.016	0.421**	0.405**
	(0.026)	(0.152)	(0.150)	(0.025)	(0.179)	(0.181)
URB	0.255***	0.105	0.360	0.253***	0.066	0.319
	(0.056)	(0.227)	(0.226)	(0.055)	(0.265)	(0.272)
RL	3.232***	2.407	5.639	3.410***	3.936	7.346
	(1.027)	(5.124)	(5.037)	(0.983)	(6.234)	(6.337)
CRED	−0.066***	−0.074	−0.140	−0.068***	−0.086	−0.153
	(0.020)	(0.102)	(0.100)	(0.020)	(0.124)	(0.126)

SAR, where the Durbin terms are restricted to zero

Variable	Direct	Indirect	Total
FDI	−0.041*	0.008	−0.032*
URB	0.248***	−0.051*	0.197***
RL	2.933***	−0.605*	2.328***
CRED	−0.058***	0.012*	−0.046***

SLX (least squares): indirect effect of FDI = 0.378** (0.160); direct effect = −0.018 (0.026)

Notes: Impacts from Equations (9) and (10); standard errors in parentheses from 5000 draws of the parameter vector from its estimated asymptotic distribution. In SAR the indirect effect is mechanically proportional to the direct effect because gamma = 0 is imposed, which is why its indirect signs mirror the direct ones. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

5.3. The Dynamic Extension Fails to Identify

Table 6 reports the attempt to combine the spatial dimension with the dynamic panel of Koassi et al. (2026). Unrestricted estimation of equation (11) gives $\hat{\tau} = 0.626$, $\hat{\rho} = -0.495$ and $\hat{\eta} = 1.004$, whose sum is 1.135 and so violates the stationarity condition (12). Imposing $\eta = 0$ does not help: the bias-correction iteration in Equation (13) has no interior fixed point, with $\hat{\rho}$ drifting monotonically from −0.40 across the whole admissible interval to +0.37 while the stationarity sum approaches unity from below. The cause is visible in the data: the correlation between Wy_t and Wy_{t-1} is 0.941, because a share that persists at $\hat{\gamma} = 0.598$ makes the spatial lag and the space-time lag nearly the same regressor. We report this as a negative result: the dynamic spatial synthesis is not estimable at $n = 13$ and $T = 22$, and a study attempting it needs either more countries or a much longer series.

Table 6. The dynamic spatial extension and its identification failure.

Parameter	Unrestricted	Restricted (eta = 0)
rho (spatial lag)	−0.495	no interior fixed point
	(0.330)	(path drifts −0.402 → +0.375)
tau (time lag)	0.626***	0.618
	(0.077)	
eta (space-time lag)	1.004***	0 (imposed)
	(0.381)	
tau + rho + eta	1.135	0.992
Stationarity condition (12)	violated	at the boundary
Uncorrected QML: rho = −0.786, tau = 0.539, eta = 1.078, ln L = −457.72		
Correlation between $Wy(t)$ and $Wy(t-1)$: 0.941		
Non-spatial LSDVC benchmark (Koassi et al., 2026): gamma = 0.598 (0.079)		

Notes: Equation (11) estimated by quasi-maximum likelihood on $nT = 273$ and bias-corrected by the bootstrap fixed point of equation (13) with $B = 400$ replications. Standard errors are bootstrap standard deviations. ***$p < 0.01$.

5.4. Robustness and What It Means for the Earlier Conclusions

Table 7 collects the sensitivity analysis. Across the six weight matrices $\hat{\rho}$ in SDM ranges from +0.096 to −0.334 and is significant in three; the W-lagged FDI term is positive in five of six and significant in four. Filtering out common factors by Equation (14) does not remove the spatial parameter and under inverse distance strengthens it, from −0.291 to −0.527 ($p < 0.01$), so the dependence is not simply factor contamination, though it remains unstable across weighting schemes.

Table 7. Robustness.

	SAR ρ	SEM ς	SDM ρ	SDM $W\times$ FDI
Panel A. Weight matrix sensitivity				
Inverse distance	−0.253*	−0.236	−0.291*	0.386**
Inverse distance squared	0.128	0.118	0.096	0.195**
Exponential decay (1000 km)	−0.267**	−0.265*	−0.297**	0.161
Three nearest neighbours	−0.036	−0.032	−0.060	0.141***
Five nearest neighbours	−0.310***	−0.253**	−0.334***	0.063
Distance band (2000 km)	−0.093	−0.111	−0.112	−0.019
Panel B. After removing common factors, Equation (14)				
Inverse distance	−0.527***			
Exponential decay (1000 km)	−0.254*			
Five nearest neighbours	−0.212*			
Three nearest neighbours	0.014			
Distance band (2000 km)	−0.008			
Panel C. Sub-samples, SDM, inverse-distance W				
	SDM ρ	**$W\times$ FDI**	**CRED**	***n***
Baseline	−0.291*	0.386**	−0.069***	13
Excluding South Africa	−0.721***	0.137	−0.105***	12
Excluding island economies	−0.325**	0.640**	−0.101***	11
Excluding Zimbabwe	−0.320**	0.347**	0.071**	12
Panel D. Do the Koassi et al. (2026) coefficients survive? (own-effect estimates)				
	FDI	**URB**	**RL**	**CRED**
Non-spatial two-way FE	−0.042*	0.247***	2.956***	−0.059***
SAR	−0.040*	0.247***	2.917***	−0.058***
SEM	−0.040*	0.248***	2.974***	−0.059***
SDM	−0.016	0.258***	3.307***	−0.069***
SDEM	−0.016	0.253***	3.410***	−0.068***
SLX	−0.018	0.262***	3.169***	−0.069*

Notes: Panel B re-estimates SAR on data filtered by Equation (14), which removes the common factor structure; a parameter that survives is not factor contamination. In Panel C the weight matrix is rebuilt on the retained countries. Island economies are Mauritius and Seychelles. In the Zimbabwe exclusion the W-lagged credit term is +0.766 ($p < 0.01$) and the total credit impact is +0.634 ($p < 0.01$). ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

6. Conclusion

Foreign investment in SADC industrializes the region rather than the host. The coefficient on neighbors' FDI is positive and significant in the spatial Durbin, spatial Durbin error and least-squares specifications alike, and the indirect impact exceeds by an order of magnitude a direct impact that is statistically indistinguishable from zero. Because the least-squares estimate carries none of the simultaneity that makes the endogenous spatial parameter hard to pin down, this is the one spatial relationship the data identify cleanly. The pattern is what one expects when foreign capital concentrates in extractive enclaves whose corridor and supply-chain effects cross borders, and it sits awkwardly with the design of regional industrial policy: if the industrial returns to attracting FDI accrue substantially to neighbors, then competitive national incentive schemes bid for a benefit their sponsors do not capture, and the appropriate response is to coordinate them at the level of the customs union rather than to outbid one another. Urbanization, institutional quality and credit, by contrast, act locally, so the case for treating FDI as a regional rather than a national instrument does not extend to the other levers.

The boundary is that a panel of thirteen countries cannot say what kind of spatial process it is. SAR, SEM, SDM, SDEM and SAC fit indistinguishably, the robust tests cannot separate lag from error, the sign and significance of ρ depend on the weighting scheme, and the dynamic spatial model is not identified at all. Two limitations follow directly. First, geography is a weak proxy for economic proximity in a region whose interactions run along a small number of corridors, and an economic weight matrix built from bilateral trade or transport costs would be a sharper instrument than any distance function. Second, our credit result is conditional on a single country. The natural next step is to replace the distance matrix with a trade-share matrix, which would let the question be posed as whether manufacturing spillovers follow roads or follow markets.

Author Contributions

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All authors read and approved the final manuscript.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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