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Determinants of Regional Economic Growth and Spatial Spillover Effects in Morocco: Evidence from Spatial Panel Models

Abir ZAITER
Laboratory of Economic Analysis and Modelling, Faculty of Law, Economics and Social Sciences Souissi, Mohammed V University in Rabat, Rabat, Morocco

Fatine FILALI ADIB
Laboratory of Economic Analysis and Modelling, Faculty of Law, Economics and Social Sciences Souissi, Mohammed V University in Rabat, Rabat, Morocco

Abstract. The objective of this paper is to investigate the drivers of regional GDP growth in Morocco while quantifying their spatial spillovers. Previous empirical research on the Moroccan economy has largely focused on regional growth determinants in isolation, without accounting for spatial dependencies. Consequently, how a region's economic features impact the growth trajectory of adjacent regions remains unexplored. Based on a panel dataset covering Morocco's twelve regions over the period 2017–2022, this study evaluates four key drivers of regional growth: the activity rate, higher-education enrollment (serving as a proxy for human capital), local authority expenditure, and population density. Methodologically, global Moran's *I* and local Getis-Ord Gi* statistics are employed to detect spatial patterns, followed by a Spatial Durbin Model with two-way fixed effects (region and time) to isolate the direct and indirect (spillover) effects of each determinant. The exploratory spatial data analysis reveals persistent geographical clustering for higher-education enrollment, territorial expenditure, and population density. Additionally, spatial clustering of GDP growth and activity rates was observed in the southern regions during the 2020 economic shock. The econometric results show that the activity rate raises growth both in the region concerned and in neighboring regions, with a total effect of about two percentage points; this result is confirmed by a restricted specification in which only the activity rate is spatially lagged. Conversely, local public expenditure yields purely local growth benefits, whereas human capital and population density have no statistically significant effect. This study contributes to the literature by offering a spatial decomposition of regional growth determinants for Morocco over a recent period and by identifying labor-force participation as the primary transmission mechanism for interregional spillovers. These results support labor-market and investment policies coordinated among neighboring regions.

Keywords: *Determinants; economic growth; Spatial econometrics; Spatial Durbin Model; Morocco.*

1. Introduction

Morocco's regional economic dynamics display marked spatial heterogeneity. Over 2017–2022, average annual regional GDP growth ranged from 0.9% in Fès-Meknès and Béni Mellal-Khénifra to 7.0% in Laâyoune-Sakia El Hamra, against a cross-regional average of about 3.0% (authors' calculations based on data from the High Commission for Planning, HCP). The gap between the best- and worst-performing regions reached 30.9 percentage points in 2020, when growth ranged from −15.5% in Marrakech-Safi to 15.4% in Laâyoune-Sakia El Hamra. This disparity raises two questions: which factors drive region-specific growth, and whether spatial spillovers connect contiguous regions.

The study of growth determinants can be traced back to the neoclassical exogenous growth models of (Solow, 1956) and (Swan, 1956), later extended by (Mankiw et al., 1992) to incorporate human capital. Endogenous growth theory (Lucas, 1988; Romer, 1986) emphasized increasing returns derived from human capital, innovation, and knowledge

externalities. Both strands of the literature, however, largely neglect the spatial dimension of growth. New Economic Geography (Fujita et al., 1999; Krugman, 1991) addressed this gap by demonstrating that a region's performance depends not only on its own characteristics but also on those of its neighbors, a premise subsequently formalized through the spatial econometrics literature (Anselin, 1988; LeSage & Pace, 2009).

The research problem addressed in this paper is therefore distinct from the general issue of territorial inequality. The question is not only how large regional disparities are, but whether the factors that drive growth in one region also affect growth in its neighbors. Conventional growth regressions cannot fully answer this question. Standard cross-section and panel models treat regions as independent observations, so that the growth of each region depends only on its own characteristics. When spatial dependencies are present, this assumption leads to biased and inconsistent estimates if the dependence manifests through the dependent variable, or to invalid statistical inference if it operates through the error terms (Anselin, 1988; Elhorst, 2014). Beyond these estimation issues, non-spatial models fail to quantify cross-regional impacts. Spatial panel models address both problems: they incorporate the values observed in neighboring regions and allow the total effect of each determinant to be decomposed into a direct effect, within the region, and an indirect effect transmitted to neighboring regions (LeSage & Pace, 2009). This decomposition is the specific contribution of the spatial approach to the research question.

Empirically, (Lesage & Fischer, 2008) demonstrate that accounting for spatial interactions is essential to understanding the determinants of regional growth. Employing a Spatial Durbin Model in combination with Bayesian Model Averaging, they find that long-run equilibrium income is jointly determined by a region's own characteristics, the characteristics of neighboring regions, the underlying spatial connectivity structure, and the intensity of spatial dependence. (Yuliadi, 2020) finds that foreign and domestic investment, regional expenditure, exchange rates, the human development index, and road infrastructure raise regional growth in Indonesia, whereas total population shows no statistically significant effect. (Mose, 2021) identifies public investment, public consumption, electrical infrastructure, and governance quality as the principal long-run determinants of regional growth in Kenya, while human capital and budget execution emerge as the main short-run drivers.

For Morocco, the empirical literature remains comparatively limited and rarely incorporates a spatial dimension. Using panel data over 2014–2020, (Guati. R et al., 2022) report a positive relationship between consumption, investment, population density, and regional growth, and identify the human development index and local capital expenditure as further significant regional determinants, while the employment rate and higher-education attainment prove statistically insignificant. On public investment specifically, two studies reach contrasting conclusions: (Bouamoud & Kassaoui, 2023), applying the quasi-maximum likelihood estimator of (Lee & Yu, 2010) over 2015–2019, find only a marginal role for regional public investment and confirm employment as the principal growth driver, whereas (ELKOHLI Loubna, 2025), covering the period 2015–2022, shows that public investment has contributed to uneven growth across regions—positive in poorer regions, marginal in wealthier ones—reinforcing the case for spatially differentiated investment policy.

Three gaps motivate this study. First, few papers jointly model growth determinants and their spatial spillovers, leaving the extent to which a region's growth depends on the characteristics of its neighbors largely undocumented for Morocco. Second, regarding labor-market dynamics, existing Moroccan studies present mixed findings using different econometric frameworks: (Guati. R et al., 2022) find an insignificant effect for the employment rate in a non-spatial setup, whereas (Bouamoud & Kassaoui, 2023) employ spatial econometric techniques and identify employment as a key regional growth driver. However, previous

spatial literature on Morocco focuses exclusively on employment metrics rather than the activity rate. Unlike the employment rate, which reflects effective labor demand, the activity rate captures the total mobilization of the working-age population (including active job seekers) and thus measures the overall labor supply available to a regional economy. In a context of cross-regional commuting and worker mobility, the activity rate represents a distinct and highly plausible transmission mechanism for spatial spillovers (Moretti, 2011). Third, the 2017–2022 period has not yet been analyzed from a spatial perspective. It covers the consolidation of the Advanced Regionalization reform launched in 2015, which extended the economic competences of the regions, and ends with the first years following the presentation of the New Development Model (NDM) report in 2021. The period therefore largely precedes the implementation of the NDM, whose effects cannot yet be assessed with the available data.

This study addresses these gaps on three fronts. Methodologically, we combine global Moran's I, local Getis-Ord Gi* statistics, and three spatial panel specifications (SDM, SLM, SEM) to both identify spatial growth clusters and decompose total effects into direct impacts and indirect spillovers on neighboring regions. Thematically, we introduce the activity rate as a spatial determinant of regional growth and show, using both the full Spatial Durbin Model and a restricted specification in which only the activity rate is spatially lagged, that it generates measurable positive externalities for surrounding regions. Temporally, focusing on 2017–2022 provides a recent assessment of regional growth determinants under the Advanced Regionalization framework, over a period that also includes the 2020 pandemic shock and the first years following the NDM report. The paper pursues two objectives: to test empirically for the existence and intensity of spatial spillovers among Moroccan regions, and to identify which determinants carry the greatest explanatory weight for regional growth once spatial dependence is taken into account.

The remainder of the paper proceeds as follows. Section 2 presents the methodological framework. Section 3 defines the variables, describes the data sources and reports descriptive statistics. Section 4 discusses the empirical results. Section 5 concludes.

2. Methodology

2.1. Study scope

Morocco, with an estimated population of 36.83 million in 2024, is divided into twelve regions under the 2015 Advanced Regionalization reform: Tangier-Tétouan-Al Hoceïma, Oriental, Fès-Meknès, Rabat-Salé-Kénitra, Béni Mellal-Khénifra, Casablanca-Settat, Marrakech-Safi, Drâa-Tafilalet, Souss-Massa, Guelmim-Oued Noun, Laâyoune-Sakia El Hamra, and Dakhla-Oued Ed-Dahab. Population is highly concentrated in the northern and central regions: Casablanca-Settat (7.65 million), Rabat-Salé-Kénitra (5.08 million), Marrakech-Safi (4.86 million) and Fès-Meknès (4.43 million) alone account for roughly 60% of the national population, a share that rises to nearly 79% once Tangier-Tétouan-Al Hoceïma and Souss-Massa are included (Figure 1).

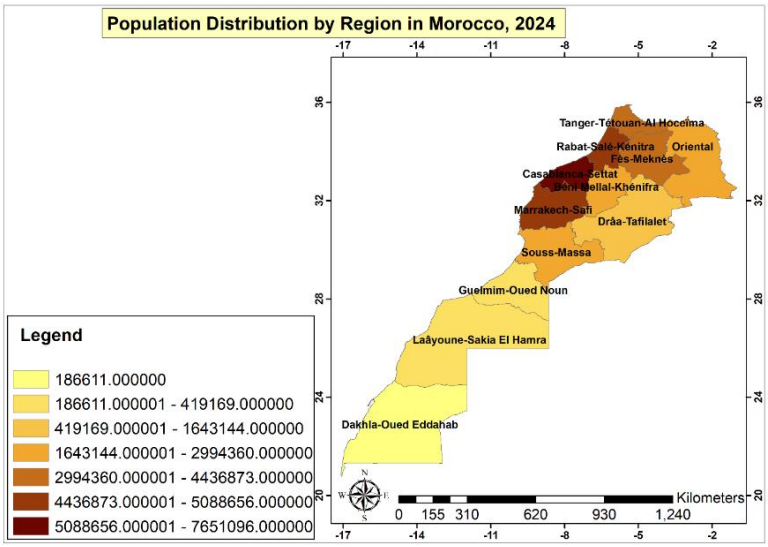


Figure 1: Population distribution by region in Morocco, 2024

Note: population is expressed in millions of inhabitants, classified into seven interval categories from light (low) to dark (high). Source: authors' elaboration under ArcGIS 10.7 based on HCP data.

2.2. Spatial autocorrelation: Moran's *I* and Getis-Ord Gi*

Following Tobler's First Law of Geography (Tobler, 1970), "everything is related to everything else, but near things are more related than distant things", spatial econometrics distinguishes between two forms of spatial effects: spatial dependence, whereby values observed at location i systematically influence values at neighboring locations j, and spatial heterogeneity, whereby the relationship between variables varies across geographic space. This section examines spatial dependence through global Moran's I and local Getis-Ord Gi* statistics, prior to the estimation of three spatial panel models.

Global Moran's I measures the overall degree of spatial clustering across all observational units:

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j\neq i} w_{ij}} \cdot \frac{\sum_{i=1}^{n}\sum_{j\neq i} w_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2} \qquad (1)$$

where x_i and x_j denote the observed values at locations i and j, $\bar{x}$ is the overall mean, and w_{ij} is a queen-contiguity spatial weight ($w_{ij} = 1$ if regions i and j share a common boundary, 0 otherwise). Under a row-standardized weight matrix, I ranges approximately from -1 to 1: $I > 0$ indicates positive spatial autocorrelation, reflecting the clustering of similar values; $I < 0$ indicates dissimilarity between neighboring units; and $I \approx 0$ corresponds to spatial randomness. The null hypothesis of no spatial autocorrelation is tested against the alternative of significant positive or negative autocorrelation.

Local Getis-Ord Gi* (Getis & Ord, 1992) identifies local concentrations of high or low values (hot spots and cold spots) that global indices may not fully capture:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{ij}\, x_j - \bar{X}\sum_{j=1}^{n} w_{ij}}{S\sqrt{\frac{n\sum_{j=1}^{n} w_{ij}^2 - \left(\sum_{j=1}^{n} w_{ij}\right)^2}{n-1}}}, \qquad S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \bar{X}^2} \qquad (2)$$

Gi^* is a z-score; statistically significant positive values indicate hot spots (clustering of high values) and significant negative values indicate cold spots (clustering of low values).

2.3. Spatial panel model specifications

Spatial econometrics generally distinguishes three forms of spatial interaction: endogenous interaction effects, arising from spillovers in the dependent variable; exogenous interaction effects, arising from spatial dependence in the regressors; and interaction effects among the error terms (Elhorst, 2014; Wang et al., 2019). The Spatial Lag Model (SLM), also referred to as the Spatial Autoregressive (SAR) model, captures the first:

$$y_{it} = \delta \sum_{j=1}^{N} w_{ij}\, y_{jt} + x_{it}\beta + \mu_i + \xi_t + \varepsilon_{it} \qquad (3)$$

where $\sum_{j=1}^{N} w_{ij}\, y_{jt}$ denotes the spatial lag of the dependent variable, δ the spatial autoregressive parameter, x_{it} a vector of regressors with coefficients β, μ_i region and ξ_t time fixed effects, and ε_{it} the idiosyncratic error term. The Spatial Error Model (SEM), by contrast, locates spatial dependence within the disturbance term rather than the dependent variable itself:

$$y_{it} = x_{it}\beta + \mu_i + \xi_t + u_{it}, \qquad u_{it} = \lambda \sum_{j=1}^{N} w_{ij}\, u_{jt} + \varepsilon_{it} \qquad (4)$$

where λ denotes the spatial autoregressive parameter of the error term. The Spatial Durbin Model (SDM) generalizes both specifications by additionally incorporating spatially lagged regressors, and is thus particularly well suited to capturing spatial spillover effects:

$$y_{it} = \delta \sum_{j=1}^{N} w_{ij}\, y_{jt} + x_{it}\beta + \sum_{j=1}^{N} w_{ij}\, x_{jt}\theta + \mu_i + \xi_t + \varepsilon_{it} \qquad (5)$$

As illustrated in Table 1, the SDM reduces to the SLM when $\theta = 0$ and to the SEM when $\theta = -\delta\beta$, which justifies its use as the general specification from which the SLM and SEM can be derived as special cases (Elhorst, 2014).

Table 1: Nesting relationships among the SDM, SLM, and SEM specifications

Spatial Durbin Model (SDM)	$\theta = 0$ **→ SLM**	$\theta = -\delta\beta$ **→ SEM**

Spatial Durbin Model (SDM)	$\theta = 0$ → **SLM**	$\theta = -\delta\beta$ → **SEM**
$y_{it} = \delta \sum_j w_{ij} y_{jt} + x_{it}\beta + \sum_j w_{ij} x_{jt}\theta + \mu_i + \xi_t +$	$y_{it} = \delta \sum_j w_{ij} y_{jt} + x_{it}\beta + \mu_i + \xi_t + \varepsilon_{it}$	$y_{it} = x_{it}\beta + \mu_i + \xi_t + u_i$ $u_{it} = \lambda \sum_j w_{ij} u_{jt} + \varepsilon_{it}$

Source: adapted from (Elhorst, 2014).

2.4. Estimation and model selection procedure

Since OLS estimates are biased and inconsistent under spatial autocorrelation, all models are estimated by Maximum Likelihood (Elhorst, 2014), with the SDM log-likelihood:

$$\ell(\beta, \theta, \delta, \sigma^2) = -\frac{NT}{2}\ln(2\pi) + T\ln|I - \delta W| - \frac{NT}{2}\ln(\sigma^2) - \frac{1}{2\sigma^2}\varepsilon'\varepsilon \qquad (6)$$

where $\varepsilon = (I - \delta W)Y - X\beta - WX\theta - \mu - \xi$, and the maximum likelihood estimator is obtained by maximizing this function with respect to $(\beta, \theta, \delta, \sigma^2)$.

Model selection follows the hybrid testing strategy proposed by (Elhorst, 2014), which combines the specific-to-general and general-to-specific approaches (Florax et al., 2003; Le Gallo, 2002; Mur & Angulo, 2009). A non-spatial panel model is first estimated, and Lagrange Multiplier (LM) tests are used to detect the presence of spatial lag or spatial error dependence. Where spatial dependence is detected, the SDM is estimated, after which Wald and Likelihood Ratio (LR) tests of $H_0: \theta = 0$ and $H_0: \theta + \delta\beta = 0$ assess whether the model can be simplified to the SLM or the SEM. If both restrictions are rejected, the SDM is retained as the preferred specification (Elhorst, 2014).

3. Variables and Data

Access to regional-level statistical data in Morocco remains constrained, as certain information is either unavailable or incomplete, a limitation that shaped the selection of variables retained for this study. Table 2 presents the definitions of the five variables used in the analysis: regional GDP growth, the dependent variable, together with four explanatory variables: the activity rate, higher-education enrollment (used as a proxy for human capital), territorial community expenditure, and population density.

Table 2: Variable definitions

Type	Name	Symbol	Definition
Dependent	Regional GDP growth (%)	*GDP*	Annual percentage change in regional GDP at constant prices
Independent	Activity rate (%)	*AR*	Share of population aged ≥ 15 employed or actively seeking employment
	New higher-education enrollment share (%)	*SH_ENR*	Regional share of new enrollments in open- and regulated-access higher-education institutions; proxy for human capital
	Territorial community expenditure share (%)	*TETC*	Regional share of mandatory territorial-community expenditures (staff salaries, debt interest, investment)
	Population density	*DENS*	Number of inhabitants per km ^{2}; proxy for

Type	Name	Symbol	Definition
	(inhabitants/km ^{2})		agglomeration economies

Source: HCP Regional Statistical Yearbook; Ministry of Economy and Finance; Ministry of the Interior (DGCL); Ministry of Higher Education (Morocco).

The choice of variables rests on growth theory as well as on data availability. First, the activity rate (TX_ACT) captures labor-market participation and serves as a proxy for the mobilization of regional labor resources. In the neoclassical growth framework, output depends on factor accumulation and technological progress (Solow, 1956), while endogenous growth theories emphasize the role of human capital and knowledge accumulation (Lucas, 1988; Romer, 1986). Although the activity rate does not directly measure employment or labor productivity, it provides an indicator of the potential labor supply available to regional economies. Second, higher-education enrolment (LOG_EDU) is included as a proxy for human-capital formation, consistent with the augmented Solow model of (Mankiw et al., 1992) and the endogenous growth literature, which highlights the contribution of skills and knowledge to productivity. Third, territorial community expenditure (DEP_TER) captures the potential contribution of subnational public spending to regional economic performance. This choice is consistent with (Barro, 1990), who shows that productive public services can contribute to growth by entering the production function. However, the expected effect depends on the composition, efficiency, and productive orientation of expenditure. Finally, population density (densite_1) proxies for the spatial concentration of population and economic activity. As stressed by New Economic Geography frameworks, agglomeration can boost productivity through market access, scale economies, labor pooling, and knowledge spillovers, though these advantages may be offset by congestion and factor price pressures (Fujita et al., 1999; Krugman, 1991).

Several theoretically relevant determinants, like private investment, infrastructure endowment and quality, productive structure, regional exports, and climatic conditions, could not be incorporated due to the lack of consistent regional data over the 2017–2022 panel. Their explicit discussion is nonetheless essential. Private investment drives capital accumulation, and its exclusion may confound the coefficient of territorial spending if public and private capital are correlated. Infrastructure lowers transport and trade costs, so omitting it may leave part of public spending effects unaccounted for. Productive structure dictates regional vulnerability to sectoral shocks, while regional exports drive growth through external demand and scale economies. Finally, Climatic conditions, particularly droughts and rainfall variability, may affect agricultural output and regional demand, generating heterogeneous growth shocks across Moroccan regions.

The empirical strategy addresses these limitations in three ways, yet specific econometric limitations remain. Region fixed effects absorb time-invariant unobservables, such as baseline infrastructure stocks, geographic features, and long-standing structural characteristics. Year fixed effects absorb macro-shocks common to all regions. Furthermore, the Spatial Durbin Model (SDM) accommodates spatial dependencies in both the dependent variable and the regressors, capturing cross-regional spillover dynamics (LeSage & Pace, 2009). However, spatially lagged variables do not fully eliminate omitted variable bias when unobserved factors vary simultaneously across time and space. Consequently, the estimated parameters are best interpreted as conditional spatial associations rather than strictly causal effects. This qualification is particularly relevant for territorial community expenditure, whose coefficient may absorb correlated, unobserved movements in private investment, infrastructure rollouts, or localized climate shocks.

The analysis relies on a balanced panel covering Morocco's twelve regions over the period 2017–2022, yielding 72 region-year observations. The data are drawn primarily from the Regional Statistical Yearbook published by the High Commission for Planning (HCP), and supplemented by information from the Ministry of Economy and Finance, the Ministry of the Interior (General Directorate of Local Authorities), and the Ministry of Higher Education. Regional-level statistics in Morocco remain incomplete for several potentially relevant determinants, notably private investment and infrastructure quality, which constrained the set of variables retained for this study to those offering consistent regional coverage over the full period.

The selection of the 2017–2022 period is primarily driven by data availability; it is the period for which all variables are available on a consistent basis for the twelve regions. The period includes the 2020 pandemic recession, during which regional GDP fell in nine of the twelve regions. This exceptional shock is accounted for in three ways in the empirical strategy. First, all models include time fixed effects, which absorb the component of the shock common to all regions; Likelihood Ratio tests confirm that these effects are strongly significant (Section 4.3). Second, the year-by-year spatial analysis (Sections 4.1 and 4.2) documents explicitly how the shock modified the spatial distribution of growth. Third, region-specific responses to the shock, which are not absorbed by the time effects, remain part of the variation used for estimation; the estimated relationships should therefore be read as average effects over a period that includes an exceptional year.

Table 3 reports descriptive statistics for the study variables. Regional GDP growth exhibits considerable volatility (mean $= 2.956\%$; S.D. $= 5.907$ percentage points; range: -15.5% to 15.4%). This variability is predominantly temporal rather than cross-regional: the within-region standard deviation (5.66 percentage points) is more than three times the between-region standard deviation (1.75), reflecting the dominant role of common annual shocks, above all the 2020 pandemic recession, relative to persistent differences in regional growth rates. The activity rate displays moderate cross-regional dispersion (mean $= 45.797\%$; S.D. $= 6.080$ percentage points), while SH_ENR and TETC show comparatively wide dispersion relative to their means (S.D./mean ratios of 0.79 and 0.58, respectively), consistent with unequal distributions of educational and fiscal resources across regions. Population density is the most dispersed variable, with a standard deviation (118.363 inhabitants/km ^{2}) exceeding its mean (106.941 inhabitants/km ^{2}), reflecting the marked contrast between the densely populated northern regions and the sparsely populated southern regions.

Table 3: Descriptive statistics

	GDP	AR	SH_ENR	TETC	DENS
Mean	2.956	45.797	8.333	8.329	106.941
Maximum	15.4	71.9	21.35	21.7	391.35
Minimum	−15.5	38.3	0.05	1.7	1.22
Std. deviation	5.907	6.080	6.592	4.836	118.363
Observations	72	72	72	72	72

Source: authors' own work.

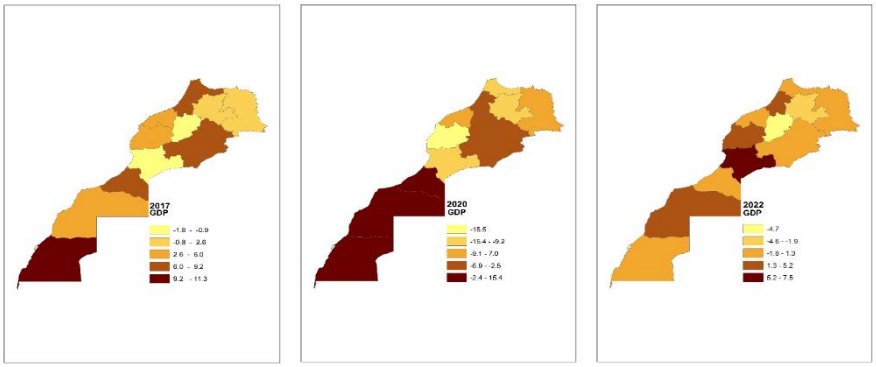
4. Results and Discussion

4.1. Spatio-temporal patterns

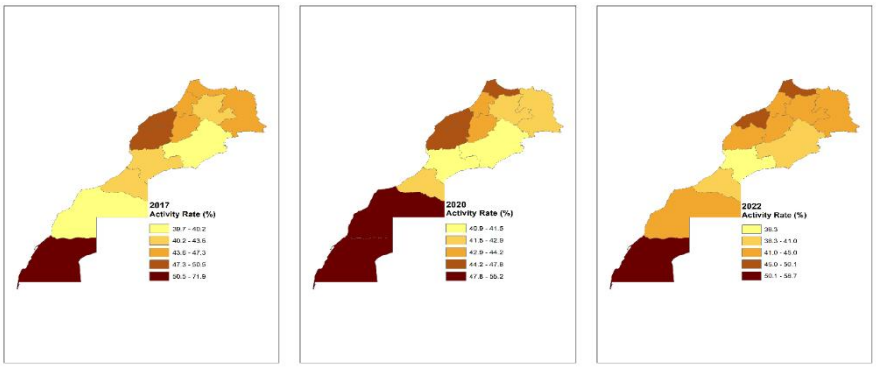
Figure 2 maps the spatial distribution of GDP growth, the activity rate, higher-education enrollment, and territorial expenditure for 2017, 2020, and 2022. GDP growth shows marked spatial heterogeneity, whose configuration changes considerably from one year to the next. In

2017, the highest growth rate is recorded in Dakhla-Oued Ed-Dahab (11.3%), followed by Guelmim-Oued Noun, Tangier-Tétouan-Al Hoceïma, Rabat-Salé-Kénitra, and Drâa-Tafilalet, while Béni Mellal-Khénifra and Souss-Massa record negative growth. In 2020, the year of the pandemic shock, the southern regions, Guelmim-Oued Noun, Laâyoune-Sakia El Hamra, and Dakhla-Oued Ed-Dahab, form a contiguous cluster of relative resilience, while most other regions record sharply negative growth. In 2022, the highest growth rate shifts to Souss-Massa (7.5%), followed by Rabat-Salé-Kénitra and Marrakech-Safi, whereas Béni Mellal-Khénifra again ranks lowest (−4.7%). Although the southern regions record the highest average growth over the period as a whole (Laâyoune-Sakia El Hamra, Guelmim-Oued Noun, and Dakhla-Oued Ed-Dahab), the identity of the leading regions changes from one year to the next, consistent with the absence of significant global spatial autocorrelation in GDP growth outside 2020 (Table 4).

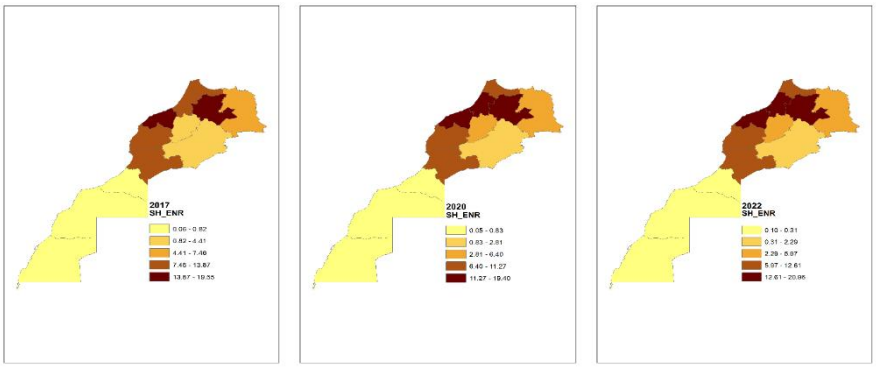
The activity rate is spatially stable: Tangier-Tétouan-Al Hoceïma, Rabat-Salé-Kénitra, Casablanca-Settat, Marrakech-Safi, and Dakhla-Oued Ed-Dahab consistently remain in the highest classes, reflecting favorable demographic structures and the concentration of economic activity (Ibourk & Ghazi, 2024), while Drâa-Tafilalet, Souss-Massa, Guelmim-Oued Noun, and Fès-Meknès remain in the lowest classes. Higher-education enrollment likewise concentrates in Fès-Meknès, Rabat-Salé-Kénitra, Casablanca-Settat, Marrakech-Safi, and Tangier-Tétouan-Al Hoceïma, consistent with the location of universities and higher population density, while the southern regions record persistently low enrollment, reflecting limited local supply and student mobility toward the other regions. Territorial expenditure follows a similarly polarized pattern, concentrated in Tangier-Tétouan-Al Hoceïma, Rabat-Salé-Kénitra, Casablanca-Settat, and Marrakech-Safi, while Drâa-Tafilalet and Souss-Massa remain in the lowest categories, a distribution consistent with agglomeration effects and a possible cumulative growth process in already-developed regions (Ouhakki et al., 2022; Wahyudi, 2020).



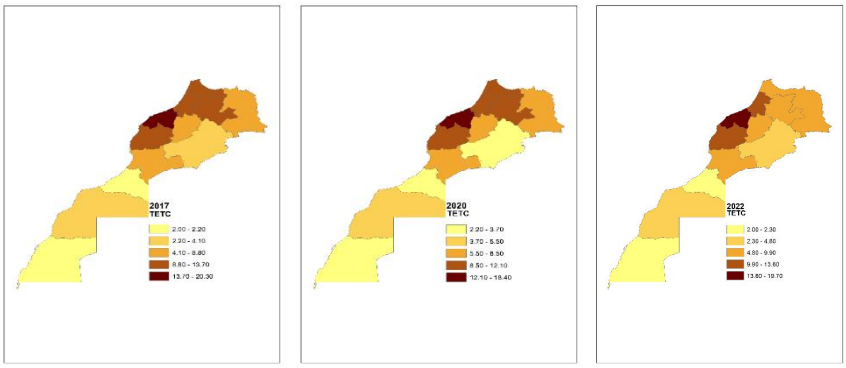
(a) GDP growth



(b) Activity rate (AR)



(c) New higher-education enrollments (SH_ENR)



(d) Territorial community expenditures (TETC)

Figure 2: Spatio-temporal distribution of GDP growth, activity rate (AR), higher-education enrollment (SH_ENR), and territorial expenditure (TETC) across Moroccan regions, 2017 (left), 2020 (center) and 2022 (right)

Source: authors' elaboration under ArcGIS 10.7.

4.2. Spatial autocorrelation

Table 4 reports annual global Moran's I statistics. SH_ENR, TETC, and DENS show positive, statistically significant spatial autocorrelation throughout 2017–2022 (at the 10% level only for SH_ENR in 2017–2019), indicating persistent geographic clustering. GDP growth and the activity rate show no significant global autocorrelation in most years, the exception being 2020 ($I = 0.552$, $p = 0.001$ for GDP; $I = 0.497$, $p = 0.003$ for AR), consistent with the uneven regional impact of the pandemic shock visible in Figure 2. The absence of a stable global pattern for these two variables motivates the local Getis-Ord Gi* analysis.

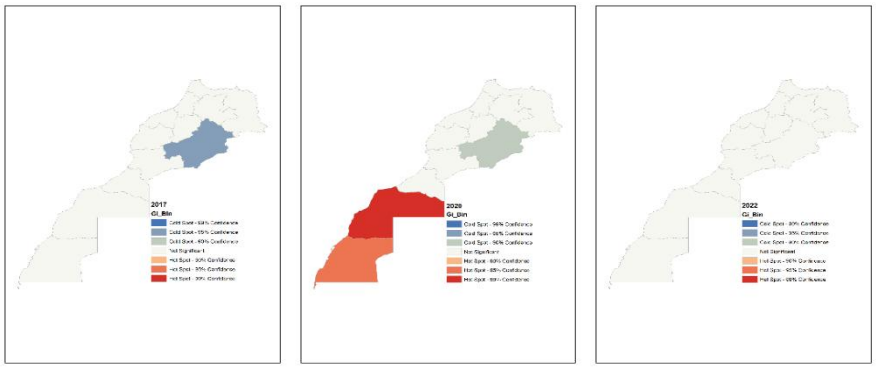
Table 4: Annual global Moran's I statistics for regional GDP growth and its determinants

	GDP		AR		SH_ENR		TETC		DENS	
Year	I	p	I	p	I	p	I	p	I	p
2017	−0.301	0.328	−0.249	0.198	0.331*	0.054	0.419**	0.011	0.376**	0.020
2018	−0.237	0.423	−0.164	0.533	0.319*	0.061	0.375**	0.018	0.374**	0.021
2019	−0.074	0.919	−0.309	0.108	0.324*	0.053	0.260*	0.085	0.373**	0.021
2020	0.552***	0.001	0.497***	0.003	0.363**	0.038	0.322**	0.039	0.371**	0.022
2021	0.175	0.207	−0.231	0.458	0.337**	0.048	0.272**	0.048	0.370**	0.022
2022	−0.060	0.878	0.007	0.565	0.355**	0.040	0.381**	0.017	0.369**	0.022

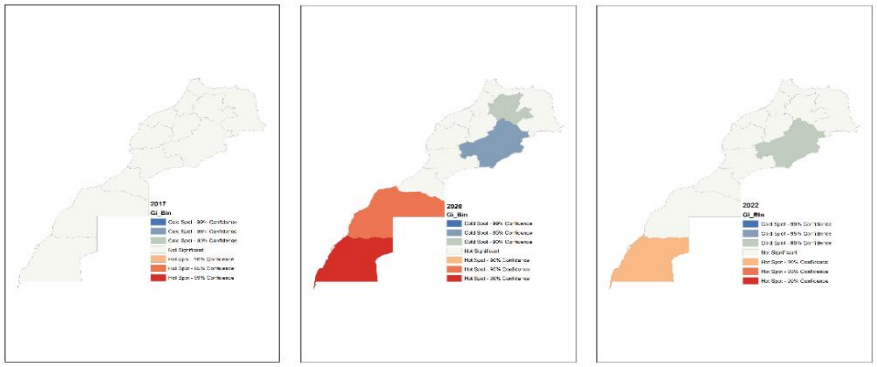
Notes: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. *Inference by random permutation (999 iterations). Row-standardized queen contiguity matrix. Source: authors' own work.*

The local Getis-Ord Gi* analysis (Figure 3) reveals contrasting spatial dynamics across the four variables. For GDP growth, significant clusters are episodic rather than persistent: Drâa-Tafilalet forms a cold spot in 2017 (95% confidence) and again, more weakly, in 2020 (90%), while Laâyoune-Sakia El Hamra (99%) and Dakhla-Oued Ed-Dahab (95%) emerge as hot spots only in 2020; no significant cluster is detected in 2022. The southern hot spot is therefore tied to the 2020 shock, during which the southern regions proved more resilient than the rest of the country, rather than to a durable growth advantage. The activity rate displays a similar pattern: no cluster in 2017, hot spots in Dakhla-Oued Ed-Dahab (99%) and Laâyoune-Sakia El Hamra (95%) in 2020, with Drâa-Tafilalet and Fès-Meknès as cold spots, and a weaker configuration in 2022, limited to a hot spot in Dakhla-Oued Ed-Dahab and a cold spot in Drâa-Tafilalet (both at 90%). Higher-education enrollment shows the reverse geography: Rabat-Salé-Kénitra forms a hot spot throughout the period, joined by Béni Mellal-Khénifra from 2020 and by Casablanca-Settat in 2022, reflecting the concentration of university infrastructure and stronger educational attractiveness, while Laâyoune-Sakia El Hamra (95%) and Dakhla-Oued Ed-Dahab (90%) remain cold spots in every year, consistent with more limited local higher-education provision. Territorial expenditure follows a comparable pattern in 2017 and 2022, with hot spots in Rabat-Salé-Kénitra and Casablanca-Settat, joined by Béni Mellal-Khénifra, and a cold spot in Laâyoune-Sakia El Hamra. The year 2020 is the exception: the northern hot spots disappear, Laâyoune-Sakia El Hamra (99%) and Dakhla-Oued Ed-Dahab (95%) become hot spots, and Drâa-Tafilalet appears as a cold spot.

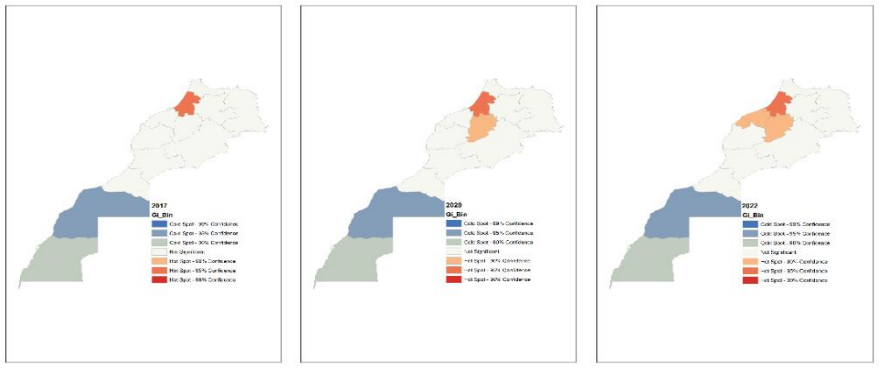
Taken together, these local patterns reinforce the global Moran's I results: SH_ENR exhibits a durable spatial structure, and TETC a largely stable one interrupted in 2020, whereas significant clusters of GDP growth and of the activity rate appear mainly in the south during the crisis year of 2020, when the shock appears to have been transmitted unevenly across contiguous regions.



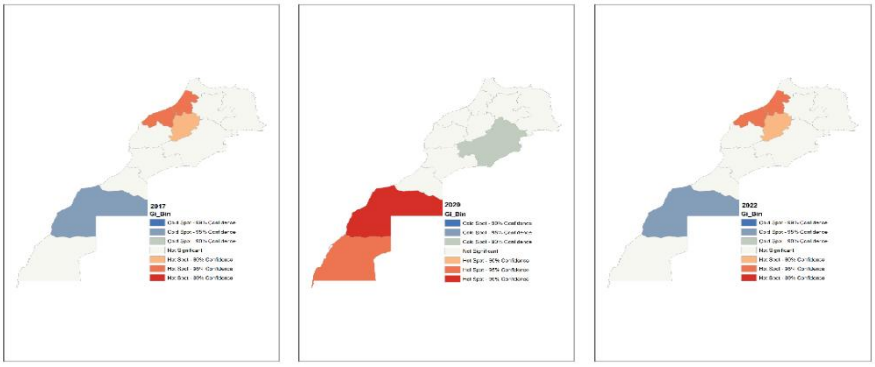
(a) GDP growth



(b) Activity rate (AR)



(c) New higher-education enrollments (SH_ENR)



(d) Territorial community expenditures (TETC)

Figure 3: Local Getis-Ord Gi* clusters for regional GDP growth, activity rate, higher-education enrollment, and territorial expenditure, 2017 (left), 2020 (center) and 2022 (right)

Source: authors' elaboration under ArcGIS 10.7.

4.3. Model selection

Building on the evidence of spatial autocorrelation presented above, the empirical model applied to the Moroccan regional panel takes the following form:

$$GDP_{it} = \delta \sum_{j=1}^{N} w_{ij}\, GDP_{jt} + \sum_{k=1}^{4} \beta_k X_{k,it} + \sum_{k=1}^{4} \theta_k \sum_{j=1}^{N} w_{ij}\, X_{k,jt} + \mu_i + \xi_t + \varepsilon_{it} \qquad (7)$$

where $X_k \in \{AR,\ SH_ENR,\ TETC,\ DENS\}$, with $i, j = 1,2,\ldots,12$ regions and $t = 1,2,\ldots,6$ years. The spatial lag of GDP, $\sum_{j=1}^{N} w_{ij}\, GDP_{jt}$, captures the influence of neighboring regions' growth on region i, while $\sum_{j=1}^{N} w_{ij}\, X_{k,jt}$ captures the corresponding spatial lag of each explanatory variable. μ_i and ξ_t denote region- and time-fixed effects, respectively, and δ, β_k, and θ_k are the parameters to be estimated.

Lagrange Multiplier (LM) tests on the non-spatial panel model (Table 5) reject the null of no spatial dependence for both the lag and error forms (LM lag $= 23.572$, $p < 0.001$; LM error $= 22.589$, $p < 0.001$), and the Moran's I test on the residuals confirms significant spatial autocorrelation ($z = 4.952$, $p < 0.001$). The robust LM tests, however, fail to discriminate between the SLM and SEM (robust LM lag $= 1.140$, $p = 0.286$; robust LM error $= 0.157$, $p = 0.692$). Given this ambiguity, the Spatial Durbin Model, which nests both spatial-lag and spatial-error components, offers the more appropriate specification.

Table 5: Spatial dependence diagnostic tests

Test	Statistic	df	p-value
Spatial error			
Moran's I test on residuals (z)	4.952	1	0.000
Lagrange Multiplier	22.589	1	0.000

Test	Statistic	df	p-value
Robust Lagrange Multiplier	0.157	1	0.692
Spatial lag			
Lagrange Multiplier	23.572	1	0.000
Robust Lagrange Multiplier	1.140	1	0.286

Source: authors' own work.

Wald and Likelihood Ratio (LR) tests of whether the SDM can be simplified (Table 7) reject reduction to the SEM at the 10% level (Wald $= 9.240$, $p = 0.055$; LR $= 7.819$, $p = 0.098$), while reduction to the SLM cannot be rejected at conventional levels (Wald $= 6.671$, $p = 0.154$; LR $= 6.550$, $p = 0.161$). Simplification to the SLM would nonetheless discard the spatial lag of the activity rate, which is individually significant ($W \times$AR $= 1.008$, $p = 0.014$; Table 10), and expose the remaining estimates to omitted-variable bias. The SDM is therefore retained as the preferred specification, as it captures spatial spillovers in both the dependent variable and the explanatory variables (Elhorst, 2014; LeSage & Pace, 2009).

A restricted SDM in which only the activity rate is spatially lagged confirms this choice (Table 6). This parsimonious specification achieves the lowest AIC (411.12) and BIC (427.05) of all spatial models, below those of the SLM (414.75 and 428.41). A Likelihood Ratio test rejects its reduction to the SLM ($\chi^2(1) = 5.63$, $p = 0.018$), whereas the three additional spatial lags of the full SDM add no explanatory power ($\chi^2(3) = 0.92$, $p = 0.821$). These results indicate that the spillover effect of the activity rate is robust to the choice of spatial specification. Its effects are also very close to those of the full SDM: a direct effect of 0.908, an indirect effect of 1.032, and a total effect of 1.941 (all significant at the 1% level).

Table 6: Robustness check: SLM, restricted SDM, and full SDM (two-way fixed effects)

	SLM	SDM ($W \times$AR only)	Full SDM
Activity rate (AR)	0.500**	0.886***	0.933***
	(0.201)	(0.253)	(0.262)
Human capital (SH_ENR)	1.086	1.252	1.275
	(0.819)	(0.797)	(0.823)
Public expenditure (TETC)	1.239*	1.423**	1.385**
	(0.679)	(0.663)	(0.681)
Population density (DENS)	−0.149	−0.132	−0.041
	(0.199)	(0.193)	(0.242)
$W \times$AR	–	0.943**	1.008**
		(0.395)	(0.410)
$W \times$SH_ENR, $W \times$TETC, $W \times$DENS	–	–	Yes
Spatial autoregressive parameter (δ)	0.216*	0.044	0.019
	(0.122)	(0.144)	(0.147)
Log-likelihood	−201.375	−198.557	−198.099
AIC	414.749	**411.115**	416.198
BIC	428.409	**427.051**	438.965

Notes: LR test, restricted SDM vs SLM: $\chi^2(1) = 5.63$, $p = 0.018$. *LR test, full SDM vs restricted SDM:* $\chi^2(3) = 0.92$, $p = 0.821$. *Effects of the activity rate (restricted SDM): Direct: 0.908*** *(0.255); Indirect:*

*1.032*** (0.381); Total: 1.941*** (0.585). Standard errors in parentheses.* * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. *All models include region and time fixed effects and use the row-standardized queen contiguity matrix. Effects computed by Monte Carlo simulation (1,000 draws). Source: authors' own work.*

The Hausman test (Table 8), which compares fixed- and random-effects SDMs with region-specific effects, yields $\chi^2(4) = 8.09$ ($p = 0.088$): the null hypothesis of no systematic difference between fixed- and random-effects estimators cannot be rejected at the 5% level, though it is rejected at 10%, pointing to non-negligible differences between the two estimators. Given this borderline result, and following standard practice in regional economic analysis, where fixed effects absorb time-invariant regional heterogeneity that would otherwise contaminate the coefficients of interest, the fixed-effects specification is adopted throughout.

Among fixed-effects SDM variants (Table 9), the two-way specification (combining region and time-period effects) achieves the highest log-likelihood and the lowest AIC/BIC. Likelihood Ratio tests strongly reject the joint insignificance of the time-period effects ($\chi^2(6) = 25.44$, $p < 0.001$), which capture common national shocks such as the 2020 pandemic recession. The joint significance of the region effects is not confirmed by the LR test ($\chi^2(12) = 15.21$, $p = 0.230$); they are nonetheless retained, in line with the Hausman test and with standard practice, to control for time-invariant regional heterogeneity that could otherwise bias the coefficients of interest. The detailed estimation results for this two-way specification are discussed in the following section.

Table 7: SDM model-specification tests (Wald and Likelihood Ratio)

Test	Statistic	p-value
Wald test spatial lag ($\theta = 0$)	6.671	0.154
LR test spatial lag ($\theta = 0$)	6.550	0.161
Wald test spatial error ($\theta + \delta\beta = 0$)	9.240	0.055
LR test spatial error ($\theta + \delta\beta = 0$)	7.819	0.098

Source: authors' own work.

Table 8: Hausman test: fixed effects versus random effects (SDM with region effects)

Variable	FE (b)	RE (B)	Difference ($b - B$)	Std. error
Activity rate (AR)	0.539	0.126	0.413	0.192
Human capital (SH_ENR)	1.086	−0.159	1.245	0.839
Public expenditure (TETC)	1.316	0.265	1.051	0.627
Population density (DENS)	−0.033	0.001	−0.034	0.271

Notes: $\chi^2(4) = 8.09$, $p = 0.088$. H_0 *rejected at the 10% level; fixed-effects specification is preferred. Both estimators are SDMs with region-specific effects only, since the random-effects SDM does not accommodate time effects; the coefficients therefore differ from the two-way fixed-effects SDM reported in Table 10. FE = fixed effects; RE = random effects. Source: authors' own work.*

Table 9: Comparison of fixed-effects SDM specifications

Specification	Log-likelihood	AIC	BIC

Specification	Log-likelihood	AIC	BIC
SDM: two-way FE (individual + time)	−198.099	**416.20**	**438.96**
SDM: time FE only	−205.705	431.41	454.18
SDM: individual FE only	−210.821	441.64	464.41

Note: LR tests of joint significance of the fixed effects: Time effects (two-way vs individual FE): $\chi^2(6) = 25.44$, $p = 0.000$*; Region effects (two-way vs time FE):* $\chi^2(12) = 15.21$, $p = 0.230$. *Source: authors' own work.*

4.4. SDM estimation results and spatial spillover effects

Table 10 compares OLS, SLM, SEM, and SDM estimates, all obtained by Maximum Likelihood under two-way fixed effects. Coefficient signs remain consistent across specifications, indicating that model choice does not drive the direction of the results; the SDM attains the highest log-likelihood and is therefore used for the effects decomposition reported in Table 11.

Table 10: Spatial panel model estimation results

	OLS FE (1)	SDM (2)	SLM (3)	SEM (4)
Explanatory variables (X)				
Activity rate (AR)	0.489*	0.933***	0.500**	0.414**
	(0.245)	(0.262)	(0.201)	(0.192)
Human capital (SH_ENR)	1.041	1.275	1.086	1.077
	(1.000)	(0.823)	(0.819)	(0.820)
Public expenditure (TETC)	1.310	1.385**	1.239*	1.179*
	(0.828)	(0.681)	(0.679)	(0.685)
Population density (DENS)	−0.152	−0.041	−0.149	−0.153
	(0.243)	(0.242)	(0.199)	(0.206)
Spatial lags ($W \times X$)				
$W \times$AR	–	1.008**	–	–
		(0.410)		
$W \times$SH_ENR	–	−0.121	–	–
		(1.986)		
$W \times$TETC	–	0.825	–	–
		(1.059)		
$W \times$DENS	–	−0.250	–	–
		(0.497)		
Spatial parameters				
Spatial autoregressive parameter (δ)	–	0.019	0.216*	–
		(0.147)	(0.122)	
Spatial error parameter (λ)	–	–	–	0.182
				(0.136)
Error variance (σ_ε^2)	–	14.365***	15.483***	15.831***
		(2.394)	(2.598)	(2.653)
Log-likelihood	−202.847	−198.099	−201.375	−202.009
AIC	415.694	416.198	414.749	416.018
BIC	427.077	438.965	428.409	429.678
Observations	72	72	72	72

Notes: Standard errors in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. W *= row-standardized queen contiguity matrix. Source: authors' own work.*

Table 11: Direct, indirect, and total effects from the two-way fixed-effects SDM

Variable	Direct effect	Indirect effect (spillover)	Total effect
Activity rate (AR)	0.948***	1.060***	2.008***
	(0.000)	(0.006)	(0.001)
Human capital (SH_ENR)	1.251	−0.020	1.231
	(0.119)	(0.992)	(0.593)
Public expenditure (TETC)	1.468**	0.898	2.366*
	(0.025)	(0.424)	(0.084)
Population density (DENS)	−0.041	−0.263	−0.304
	(0.863)	(0.610)	(0.517)

Notes: p*-values in parentheses.* * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. *Effects estimated via Monte Carlo simulation (1,000 draws) under the SDM with two-way fixed effects and the row-standardized queen contiguity matrix. Source: authors' own work.*

Activity rate (AR). The coefficient on AR is positive and significant across all specifications, ranging from 0.414 under the SEM to 0.933 under the SDM. Decomposing this effect (Table 11), a one-percentage-point rise in the activity rate is associated with a direct gain of 0.948 percentage points in regional GDP growth ($p < 0.001$), alongside an indirect, or spillover, effect of 1.060 ($p = 0.006$), together yielding a total effect of 2.008 ($p < 0.001$). The significant spatial lag ($W \times \text{AR} = 1.008$, $p < 0.05$) points to genuine cross-regional contagion in labor-market participation, a result that fits both endogenous growth theory's emphasis on labor mobilization as a driver of regional performance (Romer, 1986) and the New Economic Geography account of factor mobility and agglomeration (Krugman, 1991; Moretti, 2011). Notably, the spillover effect is even larger than the direct effect: a rise in labor-force participation in one region also raises growth in neighboring regions, likely through commuting, labor mobility, and demand linkages. Labor-market policies targeting a single region may therefore underestimate their true regional impact, since much of the benefit accrues to neighboring areas rather than the targeted region itself.

Public expenditure (TETC). Territorial community expenditure has a positive and significant direct effect on growth in the SDM (coefficient 1.385; direct effect 1.468, $p < 0.05$); the coefficient is also positive, but significant only at the 10% level, in the SLM and SEM. This result is consistent with the endogenous growth literature, in which productive public expenditure contributes to long-run growth (Barro, 1990; Barro & Sala-I-Martin, 1997), and with cross-country evidence on the determinants of growth (Barro, 1996). Beyond the region's own borders, however, the picture changes: the indirect effect is small and statistically insignificant (0.898, $p = 0.424$), the total effect only marginally significant (2.366, $p = 0.084$), and the spatial lag term offers no supporting evidence ($W \times \text{TETC} = 0.825$, $p > 0.10$). Public spending in Morocco thus appears to raise growth mainly within the region where it occurs, with little sign that it benefits neighboring areas. This is consistent with how regional public investment tends to work in practice: infrastructure and service spending are generally absorbed within a region's own administrative boundaries, rather than reaching beyond them.

Human capital (SH_ENR). The coefficient on higher-education enrollment is positive throughout, ranging from 1.041 to 1.275, yet it fails to reach conventional significance in any specification. Table 11 confirms this pattern for the decomposed effects—direct (1.251, $p =$

0.119), indirect (−0.020, $p = 0.992$), and total (1.231, $p = 0.593$)—and the spatial lag term likewise shows no trace of interregional knowledge spillovers ($W \times$SH_ENR $= -0.121$, $p > 0.10$). A first explanation is statistical. SH_ENR varies mainly across regions and very little over time (between-region standard deviation of 6.81 against a within-region standard deviation of 0.60), so that its effect is largely absorbed by the region fixed effects. The variable is also strongly correlated with territorial expenditure ($r = 0.91$) and population density ($r = 0.85$), which reduces the precision of the estimates. The result may also be explained by the panel's short time span: returns to human capital investment typically materialize over a longer horizon than the six years (2017–2022) covered here.

Population density (DENS). The coefficient on population density is negative but statistically insignificant across every specification. Under the preferred SDM, none of the decomposed effects reach conventional significance—direct (−0.041, $p = 0.863$), indirect (−0.263, $p = 0.610$), or total (−0.304, $p = 0.517$)—leaving no measurable evidence of an agglomeration effect on regional growth over the period. As with human capital, this result partly reflects the very limited variation of population density over time (within-region standard deviation of 3.16 inhabitants/km ^{2}, against 122.72 between regions), which makes its effect difficult to distinguish from the region fixed effects. It is also consistent with the descriptive evidence: Figures 1 and 2 show considerable variation in population distribution, economic structures, and agglomeration dynamics across Moroccan regions, and population concentration alone does not appear to translate uniformly into growth. Unlike in many advanced economies, urban density does not emerge here as a decisive growth driver, which points to labor-market participation and public investment as the more consequential determinants over 2017–2022.

5. Conclusion

The determinants of regional economic growth, and the extent to which their effects extend beyond administrative boundaries, remain debated in both the theoretical and the empirical literature. This study examined the determinants of regional GDP growth in Morocco over 2017–2022, a period corresponding to the consolidation of the Advanced Regionalization reform and including the first years following the presentation of the New Development Model report in 2021. The analysis combined global Moran's I and local Getis-Ord Gi* statistics with a Spatial Durbin Model estimated with region and time fixed effects.

The results indicate that spatial interactions affect regional growth in Morocco through a specific channel. The spatial autoregressive parameter is not statistically significant, which suggests that growth rates are not transmitted directly from one region to its neighbors. Spillovers operate instead through labor-market participation: an increase in the activity rate raises growth in the region concerned and in contiguous regions, with a total effect of about two percentage points per percentage-point increase. This result is confirmed by a restricted specification in which only the activity rate is spatially lagged, which is preferred to the Spatial Lag Model on the basis of both information criteria and a Likelihood Ratio test. Territorial community expenditure has a significant positive effect on growth within the region where it occurs, but no significant effect on neighboring regions. Neither human capital nor population density has a significant direct or indirect effect over the period, a result that may partly reflect the limited variation of these variables over time.

These findings have two implications for regional policy. First, since the benefits of higher labor-market participation extend beyond the region in which it occurs, activation policies coordinated among neighboring regions are likely to be more effective than measures confined to a single administrative unit. Second, since the effects of public expenditure remain essentially local, reducing disparities between lagging and leading regions may require

investment planning at an inter-regional scale, for instance through joint infrastructure or transport projects covering contiguous territories, rather than reliance on spillovers from wealthier regions.

These results should be interpreted in light of several limitations. The panel is short and includes the exceptional year 2020, whose region-specific effects are not fully absorbed by the time fixed effects. Several determinants, such as private investment, infrastructure, the sectoral structure of production, exports and climatic conditions, could not be included for lack of consistent regional data. Extending the period as new regional data become available, and incorporating these variables, would make it possible to test the robustness of the spillover effects identified here and to assess the regional impact of the New Development Model.

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