Regional inequalities in productivity: multiscale evidence on structural trajectories in Mexico

Roberto Yoan Castillo Dieguez[1]
(corresponding author)
Email: roberto.castillo@uaq.mx

Samuel Arturo Mongrut Montalván[1 2]

Ma. Benilde Rincón García[1]

Graciela Lara Gómez[1]

This study analyses the persistence of regional inequalities in productivity in Mexico during the period 2010–2023 through a multiscalar structural approach. By integrating nonlinear functional models, interpretable machine learning, and spatial econometric validation, this study identifies the economic growth trajectories of federal entities and the structural factors underlying them. Using a double-well potential model, states are classified into convergence, stagnation, or divergence regimes, capturing their long-term dynamic behaviour. Subsequently, the CatBoost algorithm with SHapley Additive exPlanations decomposetion is applied to estimate the marginal importance of variables such as digital connectivity, government efficiency, and labour productivity. Finally, a spatial fixed-effects model and territorial cluster analysis reinforce the consistency of the findings, highlighting the institutional and spatial dimensions of inequalities. Results confirm that regional growth in Mexico responds to persistent structural configurations, implying the need to design differentiated and territorially sensitive policies.

Keywords:
regional productivity,
structural inequality,
nonlinear modelling,
SHAP,
spatial econometrics,
Mexico,
multiscalar analysis,
convergence,
territorial development

Online first publication date: 5 May 2026

For affiliation see: [1] Facultad de Contaduría y Administración, Universidad Autónoma de Querétaro (UAQ), México; [2] Departamento de Finanzas, Universidad del Pacífico, Perú.

Introduction

During the recent decades, the persistence of productivity gaps between regions has been one of the main challenges for balanced economic development in emerging economies. Mexico, with a complex federal system and marked structural heterogeneity among its federative entities, represents a paradigmatic case for the study of regional inequalities in terms of productive capacity, economic resilience, and access to opportunities (Aguilar–Hernandez-Lozano 2024, Ayvar-Campos–Giménez García 2024).

Despite the growth observed at the national aggregate level, various studies have documented a profound territorial divergence reflecting differences in capital endowments and infrastructure, unequal historical trajectories, institutional structures, and patterns of public investment (Beramendi–Rogers 2022, Martinelli et al. 2013, Schneider–Cottineau 2019). This configuration raises fundamental questions about the effectiveness of regional development policies implemented in the country, as well as about the underlying factors that perpetuate or amplify such disparities (Davidescu et al. 2024, Uzuner et al. 2025).

Regions with greater integration into global value chains, logistical connectivity, and accumulation of human capital – such as the northern part of the country – have maintained a superior dynamic in terms of labour productivity and Gross Domestic Product (GDP) per capita. By contrast, regions in the south and southeast continue to show persistent lags that reflect long-standing structural limitations. These inequalities are not static; their spatiotemporal evolution evidences processes of asymmetric accumulation, negative feedback effects, and, in many cases, structural entrapment in low-growth trajectories (Capello–Dellisanti 2024, Coveri et al. 2024, Newman–Hoole 2024). Although previous studies have addressed regional disparities, most have done so from linear, sectoral, or descriptive standpoints, without capturing the dynamic, structural, and territorial interactions that this study aims to identify.

This phenomenon has been widely examined in the literature on territorial development, particularly from evolutionary and institutional perspectives. Various researchers have emphasized how factors influencing regional competitiveness operate in a systemic, cumulative, and often nonlinear manner, requiring analytical approaches capable of capturing these complexities (Garcia-Lopez–del Carpio Castro 2025, Nijkamp–Reggiani 1995, Rezaei et al. 2025). In this context, multiscale analysis becomes key to understanding how internal determinants of each region interact with supraregional structures, differentiated public policies, and divergent institutional capacities.

This study analyses the evolution of productivity gaps among Mexican states from 2010 to 2023, with a focus on identifying persistent patterns, structural transitions, and key explanatory factors. Drawing on official data with annual and state-level coverage, the study explores economic growth trajectories through a multiscale quantitative approach. The analysis incorporates variables such as human capital, physical infrastructure, institutional performance, and socioeconomic context – treated as composite constructs operationalized through measurable indicators.

This study assumes that regional productivity inequalities are not merely residual or cyclical but rather stem from relatively stable territorial configurations and structural accumulation processes that condition regional trajectories. Based on this premise, the research question guiding the analysis is as follows: what economic, institutional, and territorial structures explain the persistence or transformation of regional productivity inequalities in Mexico during the period 2010–2023?

This study contributes to the literature by articulating a multiscalar structural approach for the identification of differentiated regional trajectories in Mexico, distinguishing between regimes of convergence, stagnation, and divergence based on nonlinear functional modelling. Unlike previous studies that describe regional disparities from descriptive or parametric approaches, this study integrates potential models, interpretable machine learning techniques (SHapley Additive exPlanations [SHAP]), and spatial econometric validation, offering an integrative and explanatory perspective of persistent territorial inequalities. The void that fills this proposal lies in the scarcity of studies that combine functional models with explanatory methods of high spatial granularity. The implications of the results are relevant for designing territorially differentiated public policies, beyond uniform national strategies, by demonstrating that regional growth patterns are structurally conditioned.

The main contribution of this study lies in its methodological integration, which enables the capture of nonlinear regional growth trajectories through a functional formulation inspired by double-well potential models, interpreted through machine learning, and validated through spatial econometric techniques. Although the topics of inequality and regional productivity have been addressed previously, this multitechnique and structural approach had not been applied until now for the Mexican case. Therefore, the contribution is empirical and methodological, aimed at enriching territorial diagnoses from an integrative perspective and greater explanatory precision. This framework had not yet been applied to Mexico despite its marked territorial inequalities and complex federal dynamics, making the case particularly suitable for methodological innovation.

The study is organized as follows. Initially, a literature review is presented that contextualizes the main debates on regional inequality, productive trajectories, and territorial structures. Subsequently, the methodology employed, focused on multiscale analysis of structural trajectories, is outlined. The empirical results of the study are then detailed, followed by a discussion of their implications for public policy. Finally, general conclusions and projections for future research in this area are presented.

Literature review

The analysis of regional inequalities, particularly differences between subnational areas, has long been a focus of academic attention. While development economics provided early conceptualizations about territorial trajectories (Hirschman 1958, Rostow 1956), contemporary analyses of subnational disparities have been largely shaped by regional economics and economic geography (Dijkstra et al. 2020, Rodríguez-Pose 2013), disciplines that emphasize structural conditions, spatial interaction, and local institutional capacities. Neoclassical growth models initially predicted regional convergence in income and productivity, driven by factor mobility and diminishing returns to capital (Brondino et al. 2025, Martin–Sunley 1998). However, the empirical evidence accumulated over several decades has questioned this hypothesis of automatic convergence, particularly in contexts marked by institutional heterogeneity such as Latin America, where disparities have not only persisted but in many cases have intensified (Gómez–Rodríguez 2024, Navarro-Chávez 2025).

Given the limitations of the neoclassical paradigm, endogenous growth models emerged as an alternative framework in which human capital, innovation, infrastructure, and institutional quality became the primary drivers of regional growth (Acs–Sanders 2021, Cvetanović et al. 2015, Harris 2011). This perspective helped explain why some regions can sustain divergent growth trajectories, even when starting from similar levels of per capita income. Moreover, the perspective contributed to the formalization of the concept of "local increasing returns" as a key mechanism for understanding the persistence of productivity gaps. Nevertheless, such models have been criticized for being overly aggregated and abstract, limiting their capacity to capture the specific territorial dynamics and spatial–temporal interdependencies that shape regional development processes (Camagni 2019, Harris 2011).

Current approaches to regional development have evolved in response to such criticisms, placing central importance on a structural and multiscalar understanding of territory. In this sense, territory is not merely physical space but a distinct configuration shaped by institutional, social, and productive characteristics. Barca (2025), Cordini et al. (2021), and Trejo Nieto (2024) argue that effective development policies must be place-sensitive – i.e., tailored to the unique opportunities and constraints of each region. This territorial turn has contributed to a more sophisticated analysis of regional inequality, incorporating key concepts such as path dependence, structural resilience, and institutional embeddedness.

Empirical evidence consistently shows that territorial productivity gaps persist across developed and developing countries. In the European context, Kouskoura et al. (2024) and Tsiapa et al. (2025) reported that regions with the strongest growth performance tend to exhibit not only higher levels of investment in innovation and human capital formation but also superior institutional quality and more effective governance. In Latin America, various studies (Dilla et al. 2024, Pinilla-Rodríguez–Hernández-Medina 2024) show that uniform national policies can lead to territorially divergent outcomes when local institutional capacities or the structural specificities of individual regions are overlooked.

In the case of Mexico, the specialized literature has extensively documented a consistent pattern of divergence between the northern and southern regions of the country. Chiquiar–Hanson (2005) noted that prior to the implementation of the North American Free Trade Agreement, there was a period of regional convergence; however, trade liberalization strengthened the comparative advantages of the industrialized north while exacerbating the structural lag of the agricultural and less integrated south. This theory is supported by more recent studies that highlight the unequal productive trajectories across federal entities due to disparities in public investment, infrastructure quality, and integration into global value chains (Fuentes–Pipkin 2025, Hoyos 2025).

Moreover, Del-Valle-Soto et al. (2024) have demonstrated that relative deficiencies in innovation, digitalization, and institutional capital impede regional convergence in Mexico. Methodologically, recent advances in spatial statistics, multivariate econometrics, and machine learning have opened new avenues for the analysis of regional inequalities. In particular, multiscale approaches have proven effective in examining how structural variables – such as human capital, governance, and connectivity – interact with long-term temporal dynamics (Matos-Vila 2025, Temple 2021). These approaches highlight that economic growth cannot be fully explained by direct linear relationships among observed variables, due to the mediation of complex structures and nonlinear interactions between endogenous factors, whether observable or latent (Durlauf et al. 2005). Consequently, clustering techniques, trajectory analysis, and interpretable machine learning methods – such as SHAP – have been increasingly adopted to identify and characterize patterns of regional divergence and their associated structural configurations.

SHAP decomposes each prediction into the marginal contribution of individual predictors, as determined by a trained model. The value of each variable is estimated as the expected marginal gain when added to all possible subsets of predictors. This allows identifying not only the most influential variables but also how each one affects individual predictions. Unlike coefficients in linear models, SHAP values enable a local and nonparametric interpretation, without assuming linearity or variable independence (Lundberg–Lee 2017).

Furthermore, recent studies have begun to introduce more elaborate theoretical frameworks – drawing on insights from statistical physics and dynamical systems theory – to examine phenomena related to divergence and structural lock-in. For instance, potential-based or multifinality models have been employed to illustrate how regions with similar initial conditions can ultimately follow markedly different development trajectories, particularly when threshold effects, negative feedback loops, or cumulative shocks are considered (Chen et al. 2025, Margarian 2024). Although these analytical approaches remain relatively underutilized in the Latin American context, they offer valuable conceptual tools for understanding long-term regional processes in environments characterized by persistent structural frictions and institutional bottlenecks.

Overall, the specialized literature indicates that regional productivity inequalities cannot be understood as static or merely circumstantial phenomena. On the contrary, these inequalities constitute territorial expressions of complex economic, social, and institutional structures, whose evolution depends on multiple cumulative factors and their interaction with specific contexts. This review highlights the need to apply integrative approaches that combine multiscale structural analysis with robust explanatory techniques capable of capturing the diversity of regional trajectories. In this framework, the methodology proposed in this study articulates a quantitative strategy that allows modelling regional productivity dynamics through functional trajectories, structural analysis of explanatory importance, and comparative validation of space–time patterns.

The gap that this study addresses is the lack of studies that combine nonlinear functional modelling techniques with automated structural interpretation tools for the analysis of territorial inequalities. Although there are spatial analyses and studies on convergence, few studies have estimated dynamic trajectories with potential structures and multitechnical validation. Furthermore, the use of SHAP decomposition in Latin American subnational contexts is practically nonexistent, which makes this proposal a methodological and applied contribution of original character for the study of regional inequalities.

Methodology

The methodological choice reflects the need to capture persistent regional dynamics that conventional linear techniques fail to adequately represent. Functional modelling with double-well potential allows the identification of multiple equilibriums and structural traps characteristic of territories with institutional heterogeneity. The use of the CatBoost algorithm with SHAP decomposition responds to the need for interpretability and robustness in contexts with high collinearity and nonlinear effects. Finally, the incorporation of spatial fixed effects enables control over unobservable heterogeneity and spatial dependence inherent in subnational data. Alternative methods, such as ordinary linear models or simple parametric techniques, would be insufficient to capture the structural complexity detected empirically.

Data and construction of variables

The methodological strategy of the present study is based on a multiscalar structural perspective, which allows capturing the regional productivity trajectories in Mexico throughout the period 2010–2023. To do this, a panel data set was constructed with annual and state coverage, harmonized from public official sources. This configuration enables comparing dynamics between federal entities under the same temporal and spatial frameworks, respecting the structural heterogeneity of each region.

The real GDP per capita at the state level, the main dependent variable of the analysis, was obtained from the Economic Information Bank (BIE) of INEGI and deflated to 2018 constant prices. The structural explanatory variables include average schooling, the share of the population with higher education, per capita public spending, internet access in households, labour informality, and composite indices from IMCO capturing innovation, infrastructure, governmental efficiency, and competitiveness. In addition, GDP growth rate and labour productivity (pesos per hour worked) are incorporated to account for dynamic and functional performance.

To mitigate potential endogeneity issues, the PROD_HOUR indicator was used as an annual average with a one-period lag, ensuring that it does not contemporaneously influence the outcome variable $\phi(t)$. This choice strengthens the model's temporal consistency and reduces simultaneity concerns. The description and sources of all variables are summarized in Table 1.

Table 1

Variables used in the analysis

Variable	Acronyms	Source	Frequency	Type
Real GDP per capita	RGDPpc	INEGI-BIE	annual	continuous
Average education level	EDU_avg	SEP/INEGI	annual	continuous
State per capita public spending	SPCPS	SHCP	annual	continuous
Digital connectivity (households with internet, %)	DIGCONN	ENDUTIH	annual	continuous
Productivity per hour worked (MXN/h)	PROD_HOUR	IMCO/How are we doing?	quarterly/ annual average	continuous
GDP growth rate (%)	GDP_GROWTH	INEGI	annual	continuous
Rate of informality in the labour force	INFORM_RATE	ENOE	annual	continuous
Infrastructure index (ICE)	ICE_INFRA	IMCO	annual	index
Innovation index (ICE)	ICE_INNOV	IMCO	annual	index
Efficient government index (EGI)	EGI	IMCO	annual	index
Competitiveness index	COMP_INDEX	IMCO	annual	index

The data were cleaned, transformed, and normalized when necessary, and a balanced panel structure was used. The data normalization involved minimum–maximum scaling for index-based indicators and z-score standardization for continuous variables. These transformations were necessary to ensure comparability across heterogeneous units and reduce potential scale-driven distortions in the modelling process. All transformations were applied consistently across time and regions and evaluated for stability and distributional integrity.

The final database comprises 32 federal entities observed over 15 years (2010–2023), totaling 480 observations. The model includes 11 explanatory indicators covering human capital, public finance, productive structure, digital access, labour informality, innovation, infrastructure, institutional quality, competitiveness, and dynamic performance.

To ensure the completeness of the panel, missing values corresponding to the years 2012 and 2019 in the digital connectivity indicator (percentage of households with internet access), as well as the year 2023 in the IMCO indices of infrastructure, innovation, efficient government, and competitiveness, were imputed. The imputation was performed using the MissForest algorithm, a nonparametric method based on random forests, which enables preserving complex nonlinear relationships and minimizing bias in multivariate structures (Stekhoven–Bühlmann 2012). In this way, a balanced and coherent panel was maintained for use in multiscale structural analysis.

Due to the absence of a complete and consistent annual time series reporting the number of formal companies per federal entity from 2010 to 2023, the indicator "Formal companies per 10,000 inhabitants" was excluded from the final model. However, structural dimensions related to economic density and dynamism are adequately captured through alternative variables – such as competitiveness, productivity, and innovation indices – thereby preserving the explanatory consistency of the analytical framework.

Functional modelling of productive trajectories

Regional productivity can be represented as a continuous scalar field $\phi_i(t)$, where i represents each federal entity and t the corresponding year. This approach is supported by recent developments in dynamic functional modelling in complex environments, particularly in territorial economics (Baaquie 2007, Martini–Giannini 2020).

The use of potential-based models, such as the double-well potential function, has been theoretically developed within the frameworks of stochastic dynamics and economic field theory (Baaquie 2007, Bouchaud–Potters 2003), enabling the representation of multiple equilibria or metastable regimes. In addition, the notion of multifinality stems from the study of complex systems and developmental pathways, where similar initial conditions may lead to diverging structural outcomes (Cicchetti–Rogosch 1996, Masten–Cicchetti 2010).

The temporal evolution of $\phi(t)$ is described using a Lagrangian-type functional action, defined as follows:

$$S[\phi] = \int_{t_0}^{t_T} \left[\frac{1}{2}\left(\frac{d\phi}{dt}\right)^2 - V(\phi)\right] dt \quad (1)$$

The first term represents the temporal variation in productivity, while the second term corresponds to the associated structural potential. To capture trajectories characterized by multiple equilibria or structural blockages, a double-well potential is employed as follows:

$$V(\phi) = \alpha\phi^2 - \beta\phi^4 \quad (2)$$

This specification allows modelling trajectories that may become trapped in a low productivity equilibrium or transition to a higher state if structural conditions are modified. The parameters α and β are estimated using nonlinear least squares applied to each series $\phi_i(t)$.

The estimated parameters α and β have a structural interpretation. α reflects the degree of rigidity or inertia of the productive trajectory, indicating the depth of the local minimum in the functional potential. β represents the transition capacity toward a higher productivity state, capturing the curvature of the double well. High values of α and low values of β indicate structural trapping, whereas low α and high β suggest potential regime shifts.

Structural learning and explanatory interpretation

In the second phase of the analysis, the CatBoost algorithm (Dorogush et al. 2018) is used, a gradient boosting method specialized in the efficient treatment of categorical and highly correlated variables. This model predicts ϕ(t) as a function of the structural variables of the economic and social environment.

To interpret the results, SHAP decomposition (Lundberg–Lee 2017) is employed. This method provides a game-theoretic metric for evaluating the marginal contribution of each predictor to the prediction of individual observations.

$$\phi_j = \sum_{S \subseteq F \setminus \{j\}} \frac{|S|! \times (|F| - |S| - 1)}{|F|!} \times \left[F_{S \cup \{j\}}(x) - f_s(x)\right] \quad (3)$$

where F denotes the full set of predictors and $f_s(x)$ represents the prediction generated by the model trained solely on the subset S. This technique enables the construction of explanatory maps by state and year, illustrating the specific contribution of each variable to regional productivity.

SHAP values do not imply causal relationships but rather explanatory relevance within the predictive model. The utility of these values lies in identifying which variables have the most weight in each specific observation, considering all possible input combinations. Thus, SHAP values allow for the construction of interpretive maps without assuming direct causal directionality.

Econometric validation and spatial analysis

To validate the detected structural patterns, a spatial fixed-effects model (Elhorst 2014) is estimated, which controls for unobservable heterogeneity between regions and spatial dependence. The general specification is calculated as follows:

$$y_{it} = \alpha_i + \delta_t + X_{it}\beta + u_{it} \tag{4}$$

where α_i represents regional fixed effects, δ_t indicates common year-specific effects, and X_{it} denotes the vector of structural covariates. Spatial structure is evaluated using the Moran (1950) statistic applied to the residuals u_{it}.

In addition, a k-medoids clustering analysis is performed on the estimated parameters of the trajectories $\phi(t)$ to classify federal entities according to patterns of convergence, stagnation, or structural divergence. This procedure allows the generation of structural productivity maps that reflect the territorial segmentation implicit in the data. The cluster analysis does not aim to identify causal relationships but to detect functional groupings in the estimated trajectories. This classification enables the visualization of structural segmentation across regions in terms of their long-term dynamics. The regression tree is not intended as a causal model but as an interpretive tool to explore nonlinear rules in variable segmentation. The tree illustrates how different combinations of conditions – such as low productivity and high informality – coincide with distinct structural regimes.

Classification was based on empirical quartiles of the estimated α and β parameters. Regions with high α and low β were labeled as "stagnant", those with high β and mid-to-low α as "convergent", and those with extreme or unstable values of both as "divergent". Cluster validity was confirmed using silhouette analysis and visual inspection.

Finally, to empirically validate the average directionality of the structural effects under strict control assumptions, a fixed-effects econometric model was estimated. This strategy does not aim to replace functional structural modelling or the interpretive approach with SHAP but to complement them as a robustness check in the context of balanced panels with unobservable regional heterogeneity.

The recent literature has pointed out that fixed-effects models can act as methodological aids in schemes with nonlinear relationships and complex structures, provided their purpose and limitations are explicitly stated (Acemoglu et al. 2005, Athey–Imbens 2019, Charbonneau 2012, Greene 2001, 2002, Honoré–Kesina 2017, Kim–Sun 2016, Rodríguez-Pose–Ketterer 2020, Sun 2016). In this case, the incorporation of the linear model allows for contrasting the functional results and validating their consistency within a classical econometric framework, thereby reinforcing the empirical credibility of the findings.

Results

According to the established methodological strategy, a sequential and integrative analysis was conducted to examine regional growth trajectories in Mexico between 2010 and 2023. Initially, nonlinear functional paths were inferred using a double-well potential dynamic model, which enabled the classification of states according to their structural growth regimes. Subsequently, the CatBoost algorithm was combined with SHAP decomposition to identify the key structural factors driving regional productivity dynamics. Finally, an econometric validation was conducted using spatial fixed-effects models, along with a territorial clustering analysis based on k-medoids, which reinforced the robustness and multiscale interpretation of the results.

Results of functional modelling of productive trajectories

Starting from the proposed nonlinear functional approach, structural growth trajectories were estimated for the 32 federal entities of Mexico by formulating a double-well potential adapted to the standardized series of real GDP per capita (RGDPpc). The dynamic variable $\phi(t)$, obtained by z-standardized transformation, enabled inferring the energetic behaviour of regional systems, classified based on the parameters α and β of the potential model. This classification distinguishes between convergent regimes (stable trajectories toward average levels), divergent regimes (unstable trajectories or with a tendency to structurally decline), and stagnant regimes (trajectories trapped in relative minima or without observable dynamics).

The results of the nonlinear fit show a remarkably high statistical performance. In most entities, the nonlinear determination coefficient R^2_{nl} exceeds 0.90, confirming the suitability of the model to capture the structural dynamics of regional growth. In addition, complementary indicators – such as mean squared error (MSE), mean absolute error (MAE), and tests for residual normality and autocorrelation – were evaluated, with results systematically presented by federal entity.

Table 2 presents the estimated values of the parameters α and β, along with fitting metrics and statistical tests applied to validate the functional specification in each entity.

The Ljung–Box *p*-value is included as a diagnostic to assess the presence of autocorrelation in model residuals. A low *p*-value indicates that the residuals are not white noise and thus may contain structure not captured by the model.

Table 2

Estimated parameters of the functional model and statistical diagnostics by entity (2010–2023)

Entity	Alpha	Beta	R2_nl	R2_lin
Aguascalientes	1.0499	0.0444	0.9484	0.8029
Baja California	0.6360	−0.0060	0.9415	0.8848
Baja California Sur	0.2208	−0.0198	0.9265	0.7813
Campeche	0.8833	0.0040	0.9070	0.8801
Coahuila de Zaragoza	0.5055	−0.0102	0.9465	0.9090
Colima	0.0439	−0.0420	0.9347	0.8123
Chiapas	−0.0110	−0.0437	0.9429	0.6801
Chihuahua	0.0296	−0.0483	0.9285	0.9307
Ciudad de México	−0.1945	−0.2164	0.4559	0.0713
Durango	−0.0150	−0.5111	0.8837	0.5251
Guanajuato	0.1251	−0.2649	0.9420	0.6706
Guerrero	0.1182	−0.1894	0.9421	0.7389
Hidalgo	0.3210	1.2241	−0.4945	0.2147
Jalisco	0.1710	−0.0388	0.9302	0.8445
México	0.0330	0.0335	−0.2224	0.5562
Michoacán de Ocampo	0.1053	0.2716	−0.3971	0.0017
Morelos	0.0947	0.2808	−0.3867	0.1732
Nayarit	0.1336	0.1480	−0.0796	0.0039
Nuevo León	2.2986	0.0371	0.9530	0.8847
Oaxaca	0.0507	−1.4137	0.9847	0.2645
Puebla	0.2464	1.5248	0.0550	0.0450
Querétaro	1.0239	0.0273	0.9286	0.7966
Quintana Roo	−0.0346	−0.0607	0.8699	0.4097
San Luis Potosí	0.0029	−0.1270	0.9302	0.8404
Sinaloa	0.0118	−0.7238	0.9334	0.5423
Sonora	3.0908	0.13405	0.9348	0.9270
Tabasco	0.0759	−0.0265	0.9526	0.8821
Tamaulipas	0.1026	−0.1634	0.9433	0.8721
Tlaxcala	−0.0547	−0.1595	0.5412	0.2140
Veracruz de Ignacio de la Llave	0.0515	0.0811	−0.3463	0.3600
Yucatán	0.0178	−0.2479	0.7129	0.4194
Zacatecas	0.2849	0.8775	−0.2543	0.0023

(Table continues on the next page.)

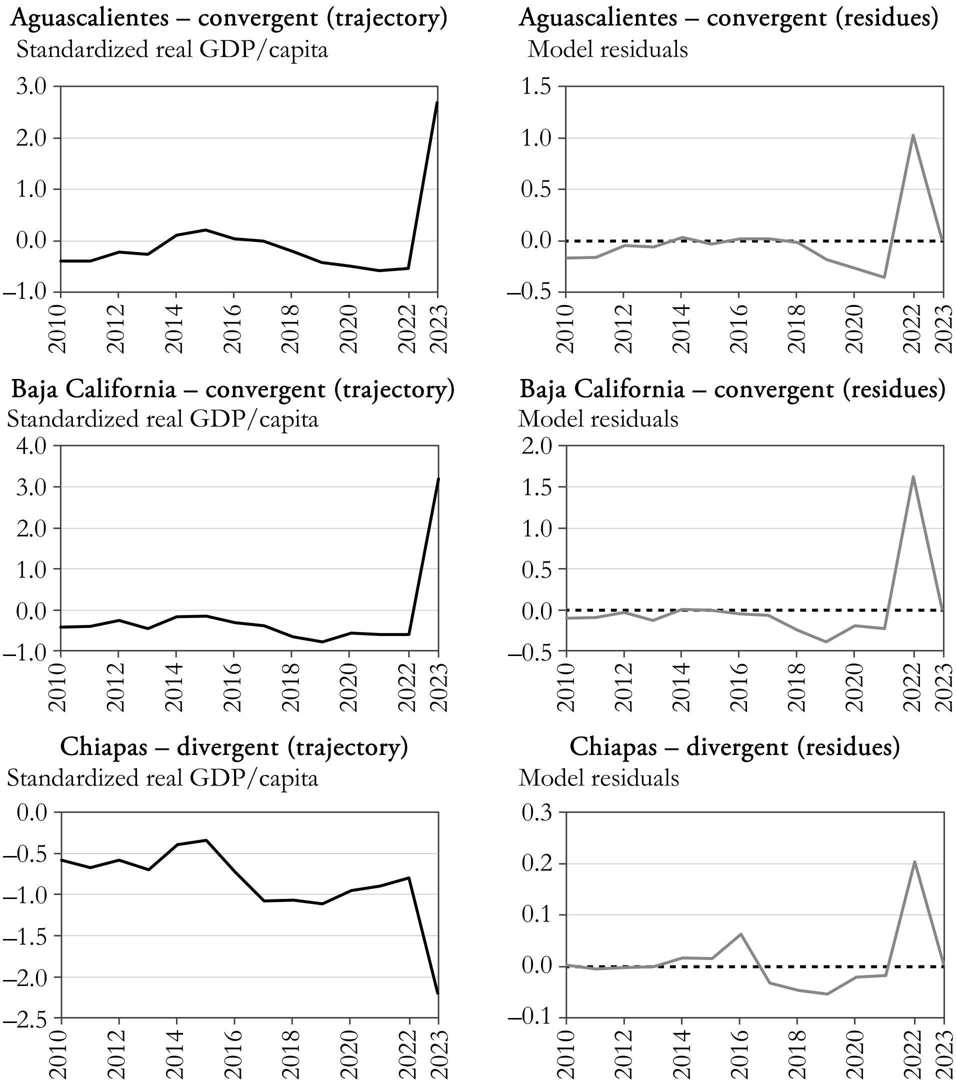
(Continued.)

Entity	MSE	MAE	Durbin–Watson	Ljung–Box (*p*-value)	Regimen
Aguascalientes	0.0959	0.1741	2.2246	0.5921	convergent
Baja California	0.2103	0.2268	2.0712	0.8758	convergent
Baja California Sur	0.0403	0.0954	2.1012	0.6244	convergent
Campeche	14.6701	1.8276	1.7915	0.6940	convergent
Coahuila de Zaragoza	1.4350	0.7037	2.0199	0.9267	convergent
Colima	0.0119	0.0457	2.0217	0.9093	convergent
Chiapas	0.0037	0.0343	1.9255	0.9555	divergent
Chihuahua	0.2529	0.1569	1.9890	0.8148	convergent
Ciudad de México	0.0107	0.0723	0.7055	0.0371	divergent
Durango	0.0029	0.0264	1.9653	0.4683	divergent
Guanajuato	0.0092	0.0434	1.9579	0.8106	convergent
Guerrero	0.0076	0.0332	2.0152	0.5958	convergent
Hidalgo	0.0004	0.0156	1.5557	0.7167	stagnant
Jalisco	0.0285	0.0581	1.9932	0.8269	convergent
México	0.0001	0.0075	0.8968	0.4616	stagnant
Michoacán de Ocampo	0.0002	0.0098	1.6756	0.8874	stagnant
Morelos	0.0001	0.0069	1.3601	0.6739	stagnant
Nayarit	0.0004	0.0119	2.0427	0.7400	stagnant
Nuevo León	2.6713	0.9185	2.1310	0.7433	convergent
Oaxaca	0.0008	0.0226	1.1469	0.0970	convergent
Puebla	0.000067	0.0066	1.4633	0.4256	stagnant
Querétaro	0.4220	0.2674	2.1697	0.6767	convergent
Quintana Roo	0.0570	0.1073	1.8037	0.9074	divergent
San Luis Potosí	0.0374	0.0698	1.9829	0.7250	convergent
Sinaloa	0.0022	0.0287	2.2703	0.1459	convergent
Sonora	0.3179	0.2920	1.8475	0.7632	convergent
Tabasco	0.2856	0.1701	1.9995	0.6817	convergent
Tamaulipas	0.0579	0.1102	1.9703	0.9652	convergent
Tlaxcala	0.0005	0.0170	1.3015	0.3360	divergent
Veracruz de Ignacio de la Llave	0.0002	0.0095	0.7513	0.3875	stagnant
Yucatán	0.0001	0.0077	1.5335	0.4660	convergent
Zacatecas	0.0002	0.0114	2.1448	0.4673	stagnant

After parameter estimation, representative trajectory examples were selected according to structural regime type. These are presented in a 4 × 4 panel, with eight entities: two for each structural category. The trajectories show the temporal behaviour of $\phi(t)$, while the residuals of the nonlinear fit allow visualizing the degree of systematic error in the energy representation. The choice of these cases aims to reflect robust convergence (e.g., Nuevo León), stagnation (e.g., Zacatecas), and divergence (e.g., Mexico City).

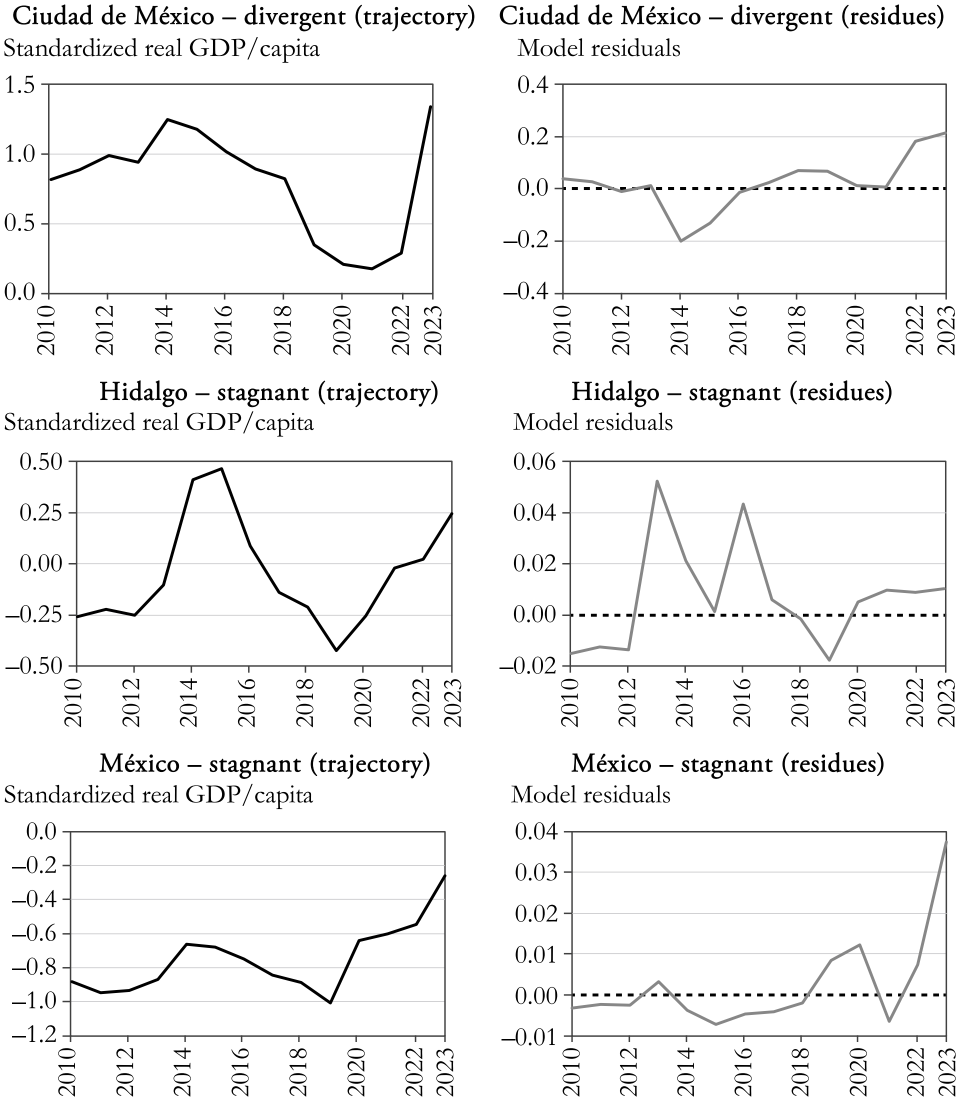
Figure 1

Selected growth trajectories and residuals by regime type



(Figures continue on the next page.)

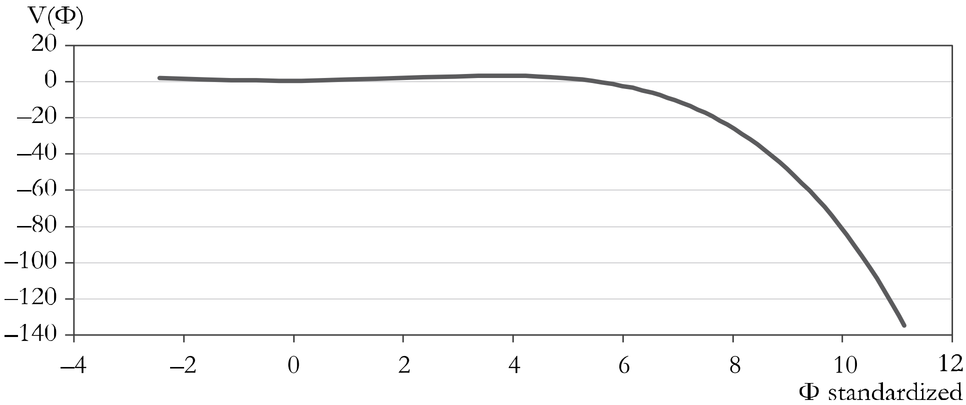
(Continued.)



In aggregate, the average potential was constructed using the mean values of α and β estimated in all entities. This double-well potential has two local minima, indicating the existence of multiple possible equilibria: a low one associated with trapped trajectories and a high one linked to sustained growth trajectories. This energy representation allows interpreting the territorial system as a dynamic field where structural transitions are not gradual but require overcoming potential barriers.

Figure 2

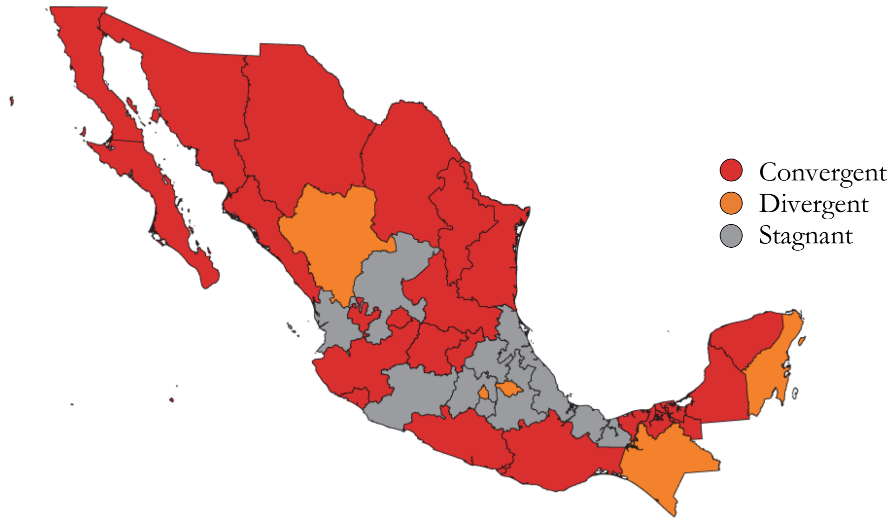
Estimated average double-well potential function



Spatially, a choropleth map was generated to visualize the territorial distribution of growth regimes. The resulting classification indicates that convergent states are primarily clustered in the north and center of the country, while divergent and stagnant states are predominantly located in the south and some saturated urban areas. This structural geography reflects well-documented patterns of regional inequality in Mexico.

Figure 3

Regional classification of structural growth regime

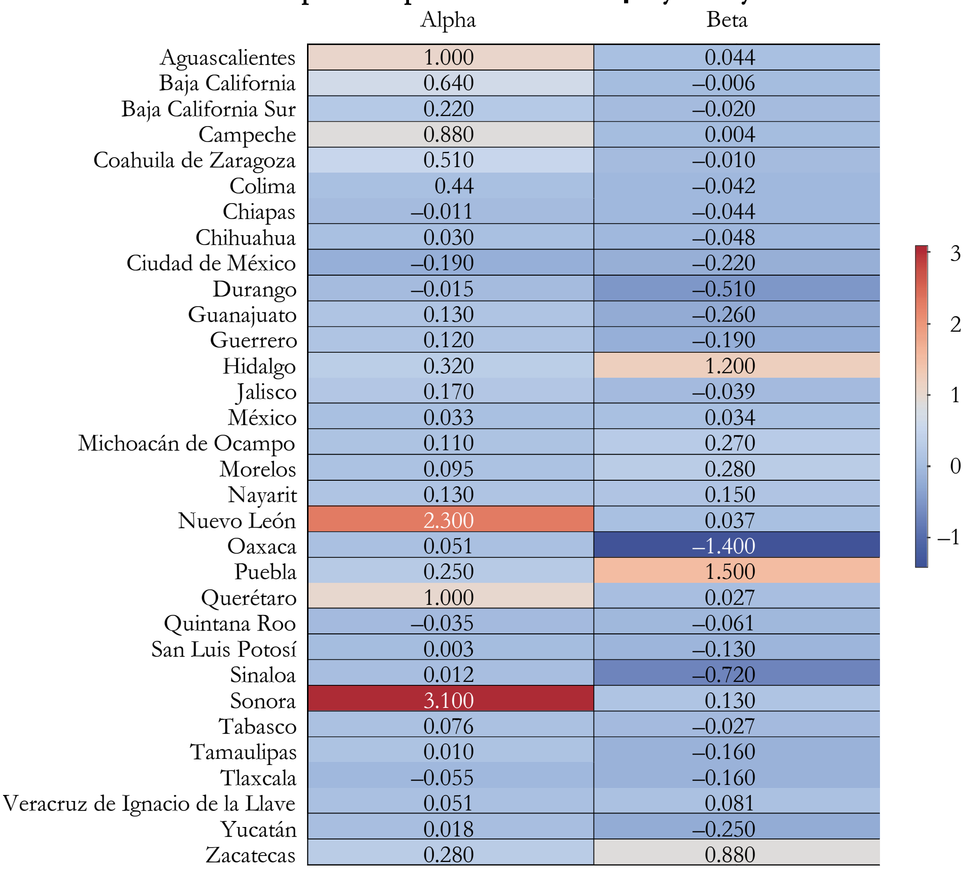


In addition, a heat map of the parameters α and β was constructed to visually represent their relative dispersion among entities. This exercise allows identifying outliers, such as Sonora, whose α magnitude indicates intense acceleration in structural trajectories, or entities with β close to zero, such as Mexico City, where the potential shape tends to collapse.

A temporal sensitivity analysis was performed using 5-year moving windows (2010–2019) to assess the stability of α and β. For each entity, the largest absolute change between windows was computed, flagging values above the 90th percentile nationally. The most pronounced shifts occurred in Sonora (α and β), Campeche and Jalisco (α), and Zacatecas and Puebla (β). Meanwhile, Guanajuato, Guerrero, Tabasco, and Michoacán showed sustained instability. In Appendix Table A1 and Figure A1 visualizes these dynamics through heatmaps, outlier annotations, and ranked bar plots.

Figure 4

Heat map of the parameters α and β by entity*



* Ordered alphabetically.

This temporal behaviour reinforces the structural interpretation of α and β. In Sonora, a sharp increase in β was observed in 2016 (from moderate to over 130), indicating a potential acceleration in its ability to transition toward higher productivity states. Concurrently, Sonora's α parameter increased considerably in 2019, indicating rising inertia or structural resistance. This juxtaposition reflects a conflicting trajectory: while opportunities for transition emerged, institutional frictions may have simultaneously deepened. Conversely, Campeche exhibited a large change in α in 2019 without a corresponding shift in β, pointing to increasing rigidity without enhanced transition capacity. These patterns illustrate that divergent dynamics can stem not only from low growth but also from asymmetric evolutions in structural parameters. Such divergences are particularly relevant for policy, as they highlight territories where volatility in institutional conditions undermines long-term productivity improvements.

These empirical results are consistent with recent studies such as those by Aroca–Atienza (2016), Rey–Casimiro Vieyra (2023) and Jiménez-Bandala (2018), who identify growth traps in the southern region of the country, and Castellanos-Sosa (2020), who documents persistent productivity gaps despite convergence policies. In addition, Mendoza-González et al. (2024), Ramirez-Urquidy et al. (2024), and Villegas Mateos–Amorós (2019) argued that institutional weakness and low connectivity account for a significant share of the stagnant trajectories observed in entities across Mexico's central-southern region. The coherence between the results obtained in this study and the existing literature suggests that the proposed functional approach aligns with previous empirical observations and enables a more nuanced representation of territorial dynamics.

In conclusion, this study develops a method to distinguish among different structural growth regimes, not only in terms of intensity but also in nature and stability – an aspect that is fundamental for designing differentiated policies. However, this model does not directly account for the explanatory drivers behind these trends. Therefore, the next section introduces a structural learning approach using CatBoost and SHAP decomposition, which enables the measurement of the influence of institutional, educational, and technological dimensions on the generation of $\phi(t)$ for a given entity and year.

The parameter α reflects the structural rigidity of the system, i.e., the depth of the local minimum in which a productive trajectory can become trapped. By contrast, the parameter β captures the possibility of escape or bifurcation toward a new structural equilibrium and is associated with the curvature of the estimated potential. High values of α indicate regions with high institutional or economic inertia, while high values of β suggest more dynamic structures with the possibility of functional transition.

Structural determinants of regional growth: an interpretable machine learning approach

Based on the functional trajectories obtained in the previous section, which enabled the classification of entities into convergence, stagnation, or divergence regimes, the structural factors underlying these dynamics were identified. To achieve this, a supervised model using the CatBoost algorithm was employed, complemented by SHAP decomposition to evaluate the marginal impact of each variable on the prediction of $\phi(t)$.

The model achieved robust predictive performance in the training sample (RMSE = 0.15, MAE = 0.12, R^2 = 0.98) and acceptable generalizable capacity in the test sample (RMSE = 0.47, MAE = 0.32, R^2 = 0.55). Threefold cross-validation reinforces these results, with an average RMSE of 0.73 and an average R^2 of 0.44. These indicators indicate that the model successfully captures complex patterns in the evolution of regional productivity, empirically supporting the findings of the functional model (Table 3).

Table 3

Performance metrics of the CatBoost model

Set	RMSE	MAE	R^2
Training	0.153516	0.118753	0.978833
Experiment	0.474618	0.315371	0.554685
Cross-validation (mean)	0.7353	0.368976	0.437955

Figure 5 shows the mean absolute SHAP values for each variable. The most influential variables in explaining growth are digital connectivity (DIGCONN), the government efficiency index (EGI), and labour productivity per hour (PROD_HOUR). These variables concentrate the highest explanatory weight, indicating that technological, institutional, and human capital capabilities are key determinants in the functional evolution of $\phi(t)$.

Figure 5

Mean absolute importance of variables according to SHAP values

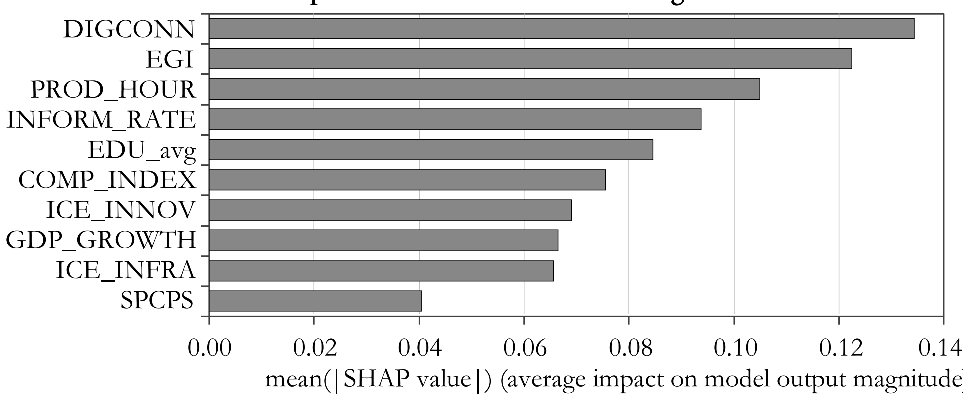


Figure 6

Summary SHAP graph of marginal impact per variable

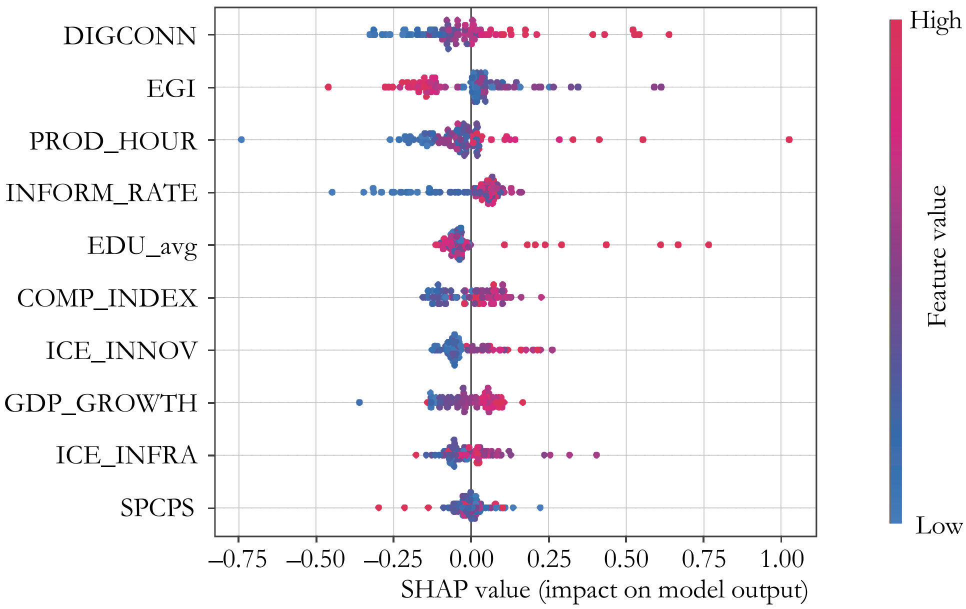


Figure 7

Impact of digital connectivity conditioned by governmental efficiency

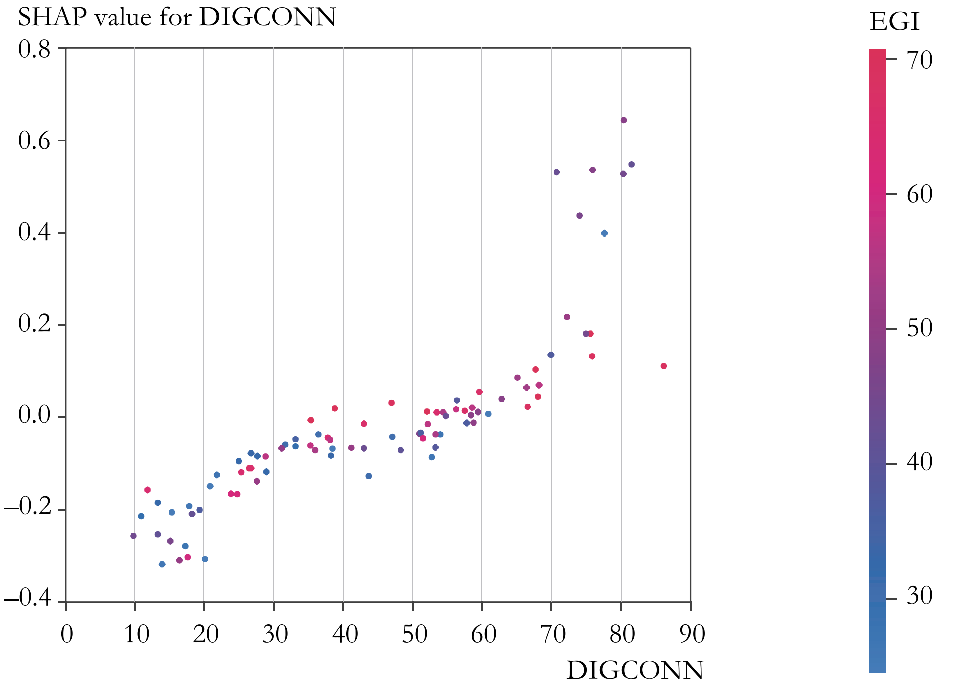


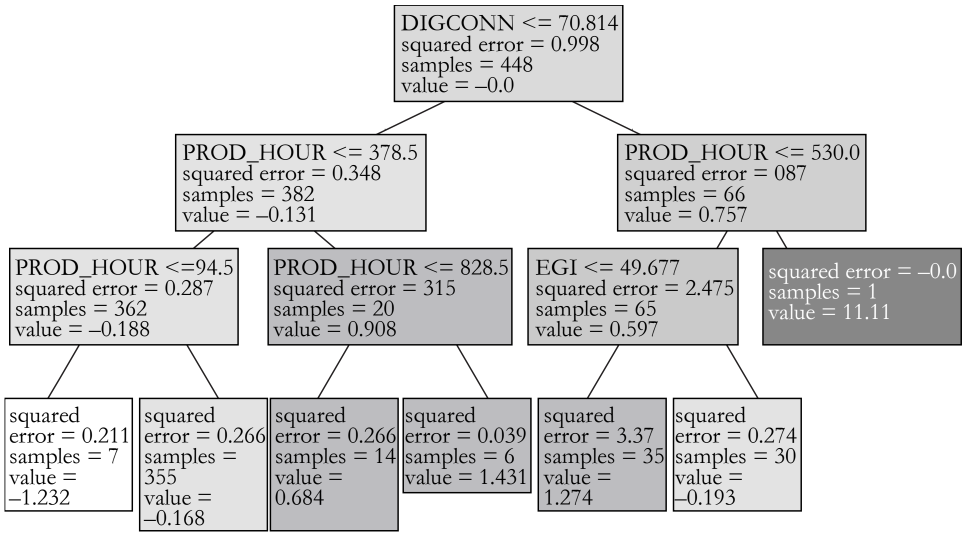
Figure 6 shows the summary SHAP graph, which allows interpreting how different levels of each variable influence growth. In general, high values of DIGCONN, EGI, and average schooling exert positive effects, whereas elevated informality rates and low productivity levels tend to negatively influence the trajectory.

To illustrate the contribution of each variable in a specific entity, Figure 7 shows a SHAP force plot. This visualization demonstrates how certain variables push the prediction toward high or low values of expected growth, enabling the interpretation of individual cases based on their structural configuration.

In addition, a regression tree based on the most relevant SHAP variables was generated (Figure 8). This tree enables the identification of critical combinations of structural factors. For example, entities with low productivity (PROD_HOUR < 94.5) and high informality tend to record negative values of $\phi(t)$, while those with strong digital connectivity and institutional efficiency exhibit more robust growth patterns.

Figure 8

Regression tree constructed with the most essential SHAP variables



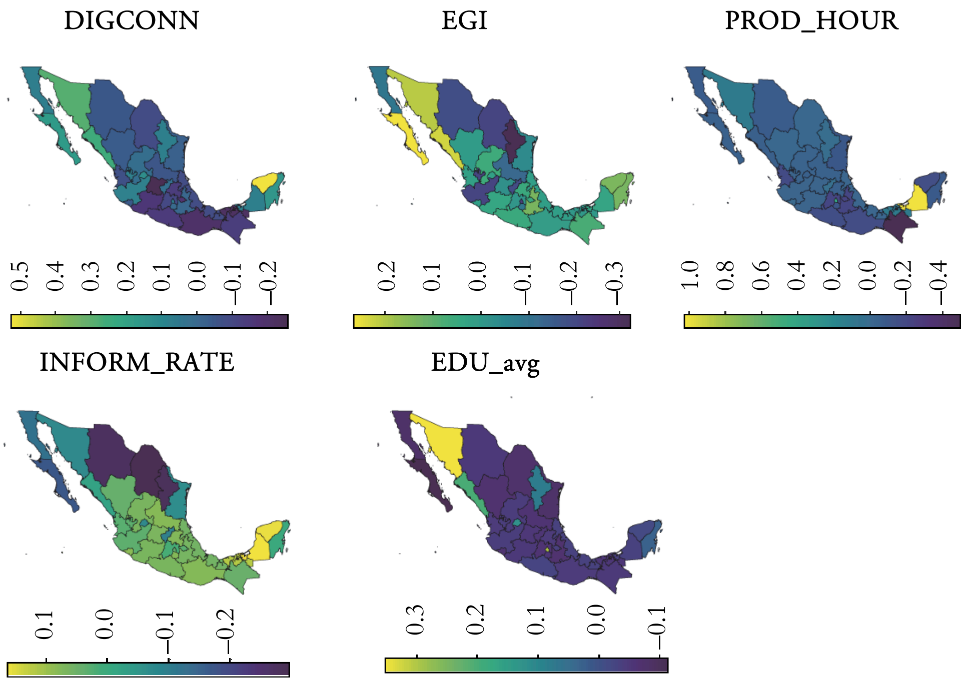
The repeated appearance of PROD_HOUR at different splits reflects its nonlinear and context-dependent influence. Regression trees are capable of modelling such patterns by reusing variables at multiple decision levels, allowing the segmentation of the sample into more refined structural profiles.

While SHAP values offer a granular and individualized decomposition of feature importance, the regression tree provides a complementary interpretative layer by structuring the most relevant variables into a hierarchy of decision rules. This approach reveals threshold effects and interactions that are not immediately evident in the additive SHAP decomposition. For instance, the tree structure identifies digital connectivity (DIGCONN) as the first split variable, underscoring its foundational role in shaping productivity trajectories. Subsequent splits reveal critical productivity thresholds and the moderating effect of government efficiency. This layered representation facilitates policy-relevant insights by outlining distinct combinations of structural conditions that correspond to divergent growth regimes, offering a more intuitive guide for territorial diagnostics and targeted interventions.

To spatially represent the structural effects, choropleth maps of SHAP intensity for the five most influential variables were created (Figure 9). Marked regional contrasts are observed: northern and central states stand out for their positive impact associated with digital connectivity and productivity, whereas the south and some lagging urban areas present consistent negative values indicative of stagnant or divergent trajectories.

Figure 9

Choropleth maps by mean SHAP intensity of the main structural variables



Overall, these results not only strengthen the previously obtained functional classification but also provide empirical evidence on the factors that structurally condition regional growth. The use of an interpretable model enables moving from diagnosis to prescription, identifying priority areas for intervention in connectivity, institutional quality, and labour productivity. This integrated approach offers a more solid foundation for the design of differentiated and sustainable policies.

In this context, and to empirically validate the detected relationships, a panel data model with spatial fixed effects was implemented, which enables controlling unobserved heterogeneity between entities and evaluating the territorial persistence of structural factors in the evolution of $\phi(t)$.

Spatial econometric validation of the structural determinants of regional growth

To validate the robustness of the structural growth patterns identified through functional trajectories and explanatory learning, a spatial fixed-effects model was estimated to account for unobservable heterogeneity across federal entities and spatial dependence in the residuals. This econometric approach, complemented by cluster analysis and territorial mapping, provides additional evidence supporting the strength of the dynamics revealed by the preceding techniques.

The PanelOLS fixed-effects model (entity and time) shows an acceptable goodness of fit (R^2 = 0.10) and a significant overall F-test (p < 0.001), despite the limitations derived from high regional structural heterogeneity. The validity of this specification is confirmed through the Hausman test, along with the Lagrange multiplier and the poolability tests, whose metrics support the use of fixed effects over random effects (Table 4).

Table 4

Estimation results of the fixed-effects model (PanelOLS)

Dependent variable	RGDPpc_std		Effects included		Entity and year	
	parameter	standard error	T-stat	*p*-value	lower CI	upper CI
Const	6.2686	3.9774	1.5761	0.1158	−1.5511	14.088
EDU_avg	−0.3394	0.3729	−0.91	0.3633	−1.0725	0.3937
SPCPS	−1.28E−09	4.05E−09	−0.315	0.7532	−9.25E−09	6.70E−09
DIGCONN	−0.0083	0.0068	−1.219	0.2237	−0.0217	0.0051
PROD_HOUR	−0.003	0.0008	−3.807	0.0002	−0.0045	−0.0015
GDP_GROWTH	0.0316	0.0181	1.7427	0.0822	−0.004	0.0672
INFORM_RATE	−0.0167	0.0225	−0.745	0.4569	−0.0609	0.0274
ICE_INFRA	−0.0147	0.005	−2.973	0.0031	−0.0245	−0.005
ICE_INNOV	0.0311	0.0176	1.7714	0.0773	−0.0034	0.0656
EGI	−0.017	0.0124	−1.367	0.1723	−0.0415	0.0074
COMP_INDEX	−0.0167	0.0341	−0.489	0.6252	−0.0836	0.0503

R^2 adjusted: 0.1028.
F-statistic (robust): 5.627, p = 0.0.
Number of observations: 448.
Poolability test: F(44, 393) = 7.3866, p = 0.000.

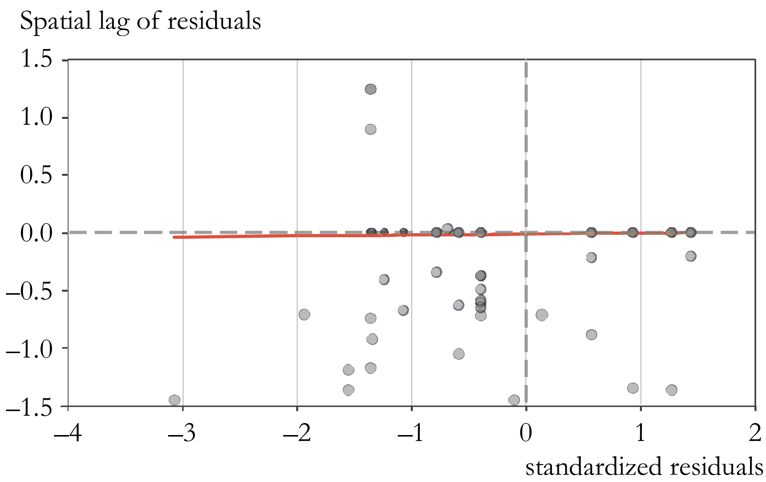
Given the limited number of time periods available (T = 15), the application of unit root tests or cointegration was not considered a priority. Instead, a structural approach with fixed effects and functional validation was chosen, considering that the dependent variable represents an estimated trajectory (ϕ(t)) derived from a potential model and not a raw time series. However, complementary ADF unit root tests (not reported in this document) indicate that most of the variables are stationary at levels with a significance level of 5%.

Among the variables with statistical significance, productivity per hour worked (PROD_HOUR, $p < 0.001$), infrastructure index (ICE_INFRA, $p < 0.01$), and, to a lesser extent, economic growth (GDP_GROWTH) and innovation (ICE_INNOV) stand out. These findings reinforce the results obtained through SHAP, where these variables showed a high marginal impact on the trajectories ϕ(t). Conversely, some key variables such as EGI and DIGCONN lose significance, which may be attributed to partial multicollinearity or their mediating role rather than direct.

To evaluate the model's validity, residuals were analysed using autocorrelation tests (Durbin–Watson), normality (Shapiro–Wilk), and heteroscedasticity (Ljung–Box). The metrics are presented below.

Figure 10

Scatter plot of residuals and Moran's I statistics



The Moran's I statistic value (0.3157; $p = 0.029$) indicates significant spatial autocorrelation, validating the inclusion of territorial structure in the analysis. This result, in line with the functional representation and SHAP maps, confirms that the regional productivity pattern is not random or purely temporal but structurally and spatially correlated (Pénzes 2020, Shimamoto 2019).

To avoid biases due to multicollinearity, the variance inflation factor (VIF) was calculated for all covariates. Although most are at acceptable levels, a high VIF was identified in COMP_INDEX, indicating caution in its interpretation or consideration in alternative robustness models (Table 5).

Table 5

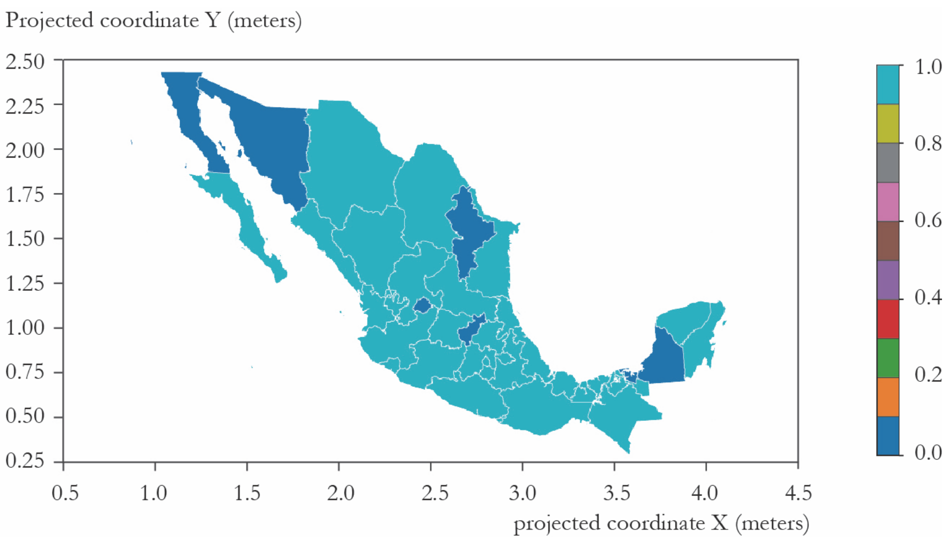
Multicollinearity diagnosis using VIF

Var	VIF	Var	VIF
Const	557.4163	INFORM_RATE	3.780244
EDU_avg	3.353188	ICE_INFRA	3.026557
SPCPS	1.376830	ICE_INNOV	3.417808
DIGCONN	2.703167	EGI	3.859844
PROD_HOUR	1.394422	COMP_INDEX	12.56223
GDP_GROWTH	1.509999		

In addition, entities were classified into structural clusters using an unsupervised k-medoids analysis applied to the α and β parameters of the functional model. Results indicate two main groups: one comprised entities with converging trajectories (cluster 0) and the other with stagnant or diverging trajectories (cluster 1). This segmentation aligns 100% with the original functional classification, reinforcing its empirical validity. No region in the sample presented a divergent regime in the positive sense (i.e., sustained above-average growth). The most dynamic trajectories correspond to stable paths near the upper well boundary, with no robust evidence of structural bifurcation toward a superior regime. This absence is relevant in itself, highlighting the limited nature of sustained structural growth in the country.

Figure 11

Map of Mexico with structural segmentation by k-medoids clusters



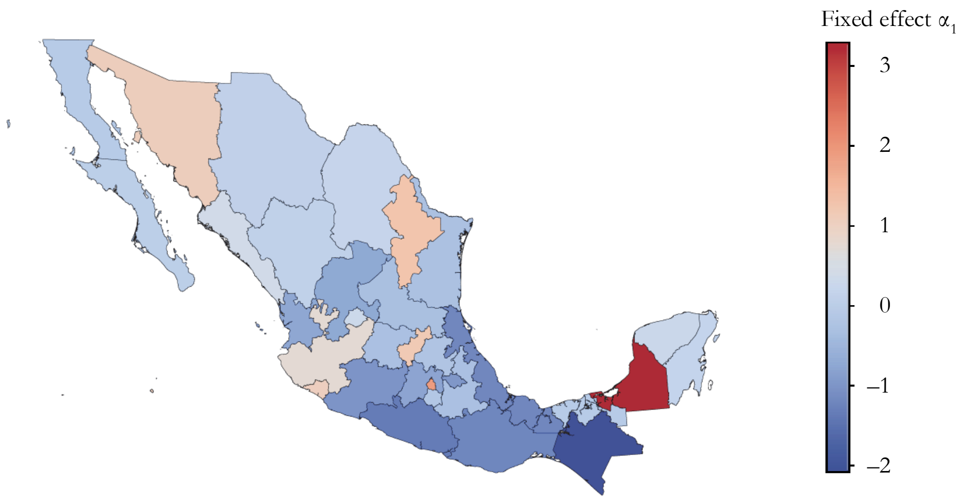
Furthermore, the fixed effects α_i were estimated for each entity and spatially represented. The resulting map shows a clear territorial gradient: entities in the north and center exhibit positive fixed effects, whereas states in the south and southeast show negative values, reflecting persistent structural disadvantage conditions.

These results are consistent with recent studies. For instance, Jiménez-Bandala (2018) and Loría (2020) identified structural trap trajectories in southern Mexico. By contrast, Ramirez-Urquidy et al. (2024) emphasized the role of institutions and infrastructure in explaining territorial segmentation. Furthermore, the negative effects of informality and low productivity are consistent with the evidence from Villegas Mateos–Amorós (2019), who warn about the limitations of convergence policies without accompanying structural improvements.

Overall, this third technique consolidates and empirically validates previous findings: regional growth trajectories are conditioned by persistent economic and institutional structures, manifested in nonlinear functional patterns and explanatory structural determinants. This methodological integration strengthens the diagnostic robustness and paves the way for the proposal of differentiated public policy strategies, a topic further developed in the following conclusions section.

Figure 12

Map of fixed effects α_i by federative entity



Conclusions

This study provides robust empirical evidence on the structural and territorial dynamics of regional productivity in Mexico between 2010 and 2023. Using an integrative methodological approach that combines nonlinear functional modelling, interpretable machine learning, and spatial econometric validation, the existence of persistent growth regimes is demonstrated, characterized by differentiated patterns of convergence, stagnation, and divergence.

The functional approach, based on a double-well potential, enables capturing complex trajectories and classifying entities according to their structural behaviour. This representation is complemented by the use of the CatBoost algorithm and SHAP decomposition, which identify the most influential determinants in the evolution of $\phi(t)$, highlighting variables such as digital connectivity, institutional efficiency, and productivity per hour worked. The econometric validation confirms that these factors have significant and persistent spatial effects, reinforcing the evidence that regional inequalities result from stable structural configurations rather than transient fluctuations.

The findings indicate that homogeneous national strategies are insufficient in the face of territorial disparities. Instead, differentiated public policies are required, with an emphasis on improving local institutional capacities, digital infrastructure, and human capital. The identification of structural clusters and the estimation of spatial fixed effects allow for a more precise focus of these policies.

Finally, the applied multiscale approach demonstrates the potential of articulating structural modelling techniques with advanced explanatory methods for territorial analysis. Future research could enrich this framework by incorporating variables at the meso- or microeconomic level, along with mobility networks or infrastructure, to deepen the understanding of the processes that perpetuate or transform regional inequalities in emerging contexts.

Among the main limitations of the study is the temporal restriction of the database, which ends in 2023. The incorporation of recent structural events or post-pandemic effects could alter the estimated dynamics of some entities. Additionally, while a robust imputation algorithm was used to complete missing values, there are inherent risks to the indirect estimation of indicators such as digital connectivity.

Based on the findings, it is recommended to design public policies differentiated by structural regime. For example, entities classified as convergent can benefit from strategies aimed at strengthening innovation and digital infrastructure. By contrast, states in stagnation or divergence require deeper interventions that address institutional deficiencies, educational lag, and persistent labour informality. The territorial allocation of resources should consider these structural trajectories to prevent the reproduction of inequalities and promote sustainable convergence processes.

Appendix

Table A1

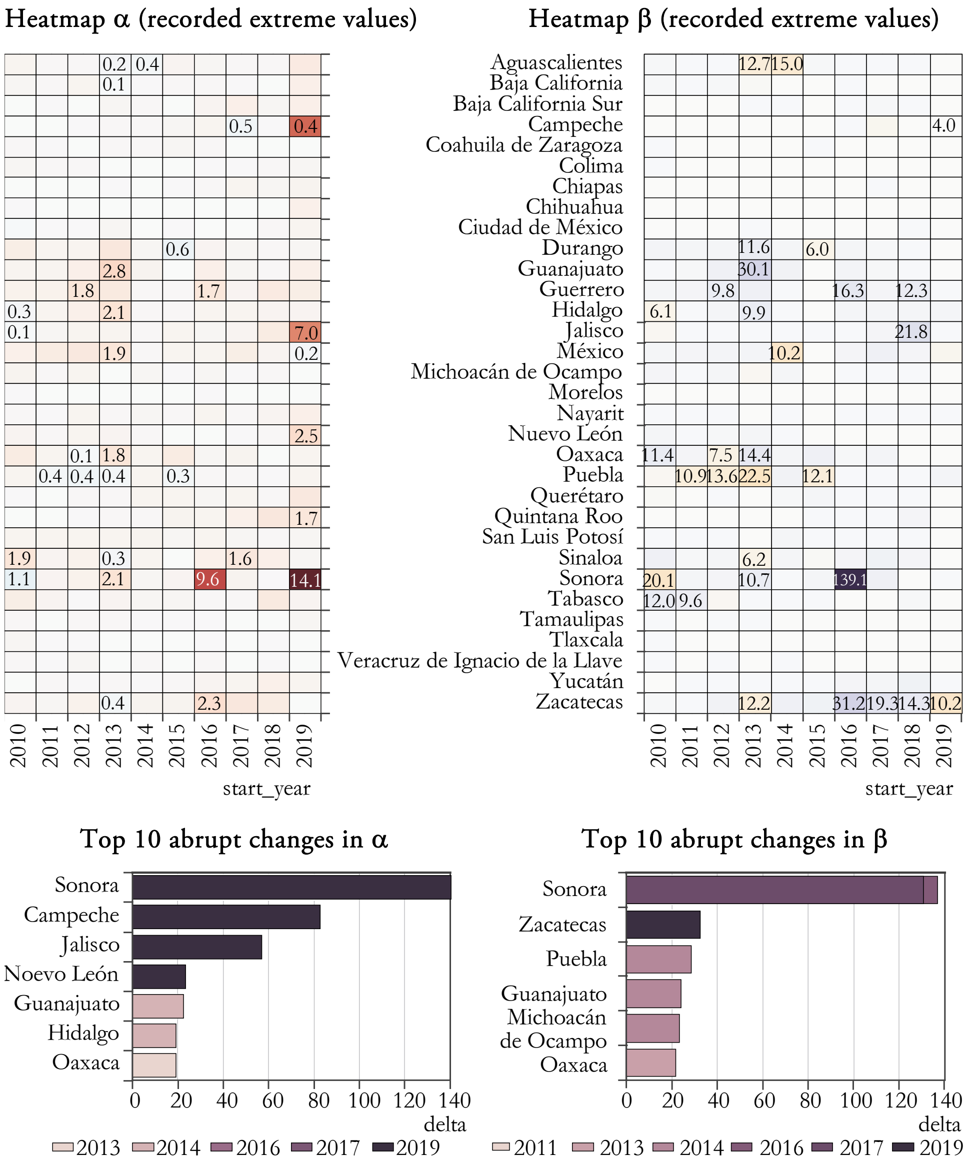
Sensitivity analysis of functional parameters α and β (2010–2019)

Entity	Maximum			
	change α	period α	change β	period β
Sonora	14.03513748	2019	136.8141447	2016
Campeche	8.262883509	2019	4.260349702	2017
Jalisco	5.71445184	2019	20.73298708	2019
Nuevo León	2.350156215	2019	1.766606625	2011
Guanajuato	2.237953089	2014	24.07042368	2014
Hidalgo	1.936200559	2014	9.224276727	2014
Oaxaca	1.931425107	2013	21.82146264	2013
Michoacán de Ocampo	1.693748974	2014	23.18655094	2014
Zacatecas	1.637429529	2016	32.48718623	2019
Guerrero	1.520244833	2016	16.99692363	2016
Sinaloa	1.355039482	2011	9.519667111	2013
Querétaro	1.344952721	2019	1.590884349	2016
Tabasco	1.324371828	2018	12.21608452	2012
Durango	1.21210781	2014	9.110988519	2014
Aguascalientes	1.095359501	2019	17.04244175	2015
Baja California	0.91758514	2019	3.310666419	2013
Coahuila de Zaragoza	0.827271543	2019	0.063676678	2013
Puebla	0.777261359	2011	28.4742621	2014
Quintana Roo	0.753180032	2018	3.176442843	2019
Baja California Sur	0.698024512	2019	1.706474453	2016
Morelos	0.471300057	2011	5.088216357	2014
San Luis Potosí	0.448843166	2015	3.390306773	2014
Yucatán	0.436086865	2019	6.273254187	2019
Nayarit	0.433846511	2019	1.847728147	2013
Ciudad de México	0.383860525	2019	0.310319199	2017
Veracruz de Ignacio de la Llave	0.313366314	2013	1.521516301	2013
Colima	0.255536752	2019	0.409836152	2018
Tamaulipas	0.195128171	2019	0.577622588	2011
Tlaxcala	0.162777052	2011	0.464433961	2013
Chihuahua	0.158992716	2019	0.317571517	2013
Chiapas	0.157443648	2013	0.295698721	2011
México	0.101189836	2016	0.112042834	2016

Notes: this appendix presents the results of temporal sensitivity analysis using five-year moving windows. The maximum absolute changes in the parameters α and β by state are reported, as well as the year in which they occurred. Grey-shaded rows indicate entities exceeding the 80th national percentile in the maximum absolute change of α and/or β across five-year moving windows.

Figure A1

Temporal sensitivity analysis



Notes: heat maps, annotations of extreme values, and bar charts visualizing the ten most abrupt changes for each parameter are included. States that exceed the 80th national percentile were highlighted as representative cases of structural instability.

REFERENCES

ACEMOGLU, D.–JOHNSON, S.–ROBINSON, J. (2005): The rise of Europe: Atlantic trade, institutional change, and economic growth *American Economic Review* 95 (3): 546–579. https://doi.org/10.1257/0002828054201305

ACS, Z.–SANDERS, M. (2021): Endogenous growth theory and regional extensions. In: *Handbook of regional science* pp. 615–634., Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-662-60723-7_13

AGUILAR, A. G.–HERNANDEZ-LOZANO, J. (2024): Mega-urbanization, territorial fragmentation and social inequality in the global south: the case of Mexico city and its city-region *Applied Geography* 163: 103183. https://doi.org/10.1016/j.apgeog.2023.103183

AROCA, P.–ATIENZA, M. (2016): Spatial concentration in Latin America and the role of institutions *Investigaciones Regionales* 36 (Special issue).

ATHEY, S.–IMBENS, G. W. (2019): Machine learning methods that economists should know about *Annual Review of Economics* 11 (1): 685–725. https://doi.org/10.1146/annurev-economics-080217-053433

AYVAR-CAMPOS, F. J.–GIMÉNEZ GARCÍA, V. M. (2024): Economic welfare in Mexican municipalities: a nonparametric analysis *Journal of Infrastructure, Policy and Development* 8 (16): 10720. https://doi.org/10.24294/jipd10720

BAAQUIE, B. E. (2007): *Quantum finance: path integrals and Hamiltonians for options and interest rates* Cambridge University Press.

BARCA, F. (2025): Policies sensitive to people in places: rationale, implementation, adversaries. In: *Commons, citizenship and power* pp. 106–127., Policy Press. https://doi.org/10.51952/9781447371182.ch007

BERAMENDI, P.–ROGERS, M. (2022): *Geography, capacity, and inequality: spatial inequality* Cambridge University Press. https://doi.org/DOI: 10.1017/9781108908702

BOUCHAUD, J.-P.–POTTERS, M. (2003): *Theory of financial risk and derivative pricing: from statistical physics to risk management* Cambridge University Press.

BRONDINO, G.–FORA-ALCALDE, F.–CASAÚ-GUIRAO, M. Á. (2025): Distribution dynamics of alternative productivity measures: an empirical analysis *Structural Change and Economic Dynamics* 74: 240–251. https://doi.org/10.1016/j.strueco.2025.03.008

CAMAGNI, R. (2019): Territorial capital and regional development: theoretical insights and appropriate policies. In: *Handbook of Regional Growth and Development Theories* pp. 124–148., Edward Elgar Publishing. https://doi.org/10.4337/9781788970020.00014

CAPELLO, R.–DELLISANTI, R. (2024): Smile-and-go. Regional performance through global value chains in Europe *Papers in Regional Science* 103 (2): 100018. https://doi.org/10.1016/j.pirs.2024.100018

CASTELLANOS-SOSA, F. A. (2020): Labor productivity convergence in Mexico *International Journal of Political Economy* 49 (3): 243–260. https://doi.org/10.1080/08911916.2020.1824733

CHARBONNEAU, K. (2012): Multiple fixed effects in nonlinear panel data models: theory and evidence *Princeton University*.

CHEN, J.–LI, X.–ZHOU, X.–AO, R. (2025): Skill capabilities behind the scenes: the role of occupational portfolio in regional industrial evolution *Regional Studies* 59 (1). https://doi.org/10.1080/00343404.2024.2416535

CHIQUIAR, D.–HANSON, G. H. (2005): International migration, self-selection, and the distribution of wages: evidence from Mexico and the United States *Journal of Political Economy* 113 (2): 239–281. https://doi.org/10.1086/427464

CICCHETTI, D.–ROGOSCH, F. A. (1996): Equifinality and multifinality in developmental psychopathology *Development and Psychopathology* 8 (4): 597–600. https://doi.org/10.1017/S0954579400007318

CORDINI, M.–BOCZY, T.–CEFALO, R. (2021): Place-sensitive social investment and territorial cohesion: implications for sustainability *Sustainability* 13 (13): 7085. https://doi.org/10.3390/su13137085

COVERI, A.–PAGLIALUNGA, E.–ZANFEI, A. (2024): Global value chains and within-country inequality: the role of functional positioning *Structural Change and Economic Dynamics* 70: 382–397. https://doi.org/10.1016/j.strueco.2024.05.001

CVETANOVIĆ, S.–FILIPOVIĆ, M.–NIKOLIĆ, M.–BELOVIĆ, D. (2015): Endogenous growth theory and regional development policy *Spatium* 34: 10–17. https://doi.org/10.2298/SPAT1534010C

DAVIDESCU, A. A.–NAE, T. M.–FLORESCU, M.-S. (2024): From policy to impact: advancing economic development and tackling social inequities in Central and Eastern Europe *Economies* 12 (2): 28.

DEL-VALLE-SOTO, C.–BRISEÑO, R. A.–LÓPEZ-PIMENTEL, J.-C.–VELÁZQUEZ, R.–VALDIVIA, L. J.–VARELA-ALDÁS, J. (2024): Bridging the digital divide in Mexico: a critical analysis of telecommunications infrastructure and predictive models for policy innovation *Telecom* 5 (4): 1076–1101. https://doi.org/10.3390/telecom5040055

DIJKSTRA, L.–POELMAN, H.–RODRÍGUEZ-POSE, A. (2020): The geography of EU discontent *Regional Studies* 54 (6): 737–753. https://doi.org/10.1080/00343404.2019.1654603

DILLA, H.–HERRERA, S.–DUBÉ, S. (2024): The cross-border regions of Latin America: incomplete or peculiar? *Journal of Borderlands Studies* 40 (4): 1045–1062. https://doi.org/10.1080/08865655.2024.2394039

DOROGUSH, A. V.–ERSHOV, V.–GULIN, A. (2018): CatBoost: gradient boosting with categorical features support *ArXiv* https://doi.org/10.48550/arXiv.1810.11363

DURLAUF, S. N.–JOHNSON, P. A.–TEMPLE, J. R. W. (2005): Chapter 8 Growth econometrics. In: *Handbook of economic growth* Volume 1, Part A pp. 555–677. https://doi.org/10.1016/S1574-0684(05)01008-7

ELHORST, J. P. (2014): Matlab software for spatial panels *International Regional Science Review* 37 (3): 389–405. https://doi.org/10.1177/0160017612452429

FUENTES, A.–PIPKIN, S. (2025): Sticky industrial policies and divergent value chain upgrading patterns: lessons from Querétaro and Jalisco, Mexico *Business and Politics* 1–22. https://doi.org/10.1017/bap.2025.3

GARCIA-LOPEZ, Y. J.–DEL CARPIO CASTRO, L. A. (2025): Assessing regional competitiveness in Peru: an approach using nonlinear machine learning models *PLOS ONE* 20 (2): e0318813. https://doi.org/10.1371/journal.pone.0318813

GÓMEZ, M.–RODRÍGUEZ, J. C. (2024): Analysis of the convergence of environmental sustainability and its main determinants: the case of the Americas (1990–2022) *Sustainability* 16 (16): 6819. https://doi.org/10.3390/su16166819

GREENE, W. (2001): *Estimating econometric models with fixed effects* Department of Economics, Stern School of Business, New York University.

GREENE, W. (2002): The behavior of the fixed effects estimator in nonlinear models *NYU Working Paper* No. EC-02-05.

HARRIS, R. (2011): Models of regional growth: past, present and future *Journal of Economic Surveys* 25 (5): 913–951. https://doi.org/10.1111/j.1467-6419.2010.00630.x

HIRSCHMAN, A. O. (1958): *The strategy of economic development* Yale University Press

HONORÉ, B. E.–KESINA, M. (2017): Estimation of some nonlinear panel data models with both time-varying and time-invariant explanatory variables *Journal of Business & Economic Statistics* 35 (4): 543–558. https://doi.org/10.1080/07350015.2015.1123635

HOYOS, M. (2025): North–south trade, technology diffusion, and uneven development *Economics of Innovation and New Technology* 34 (4): 613–633. https://doi.org/10.1080/10438599.2024.2357791

JIMÉNEZ-BANDALA, C. A. (2018): Development in Southern Mexico: empirical verification of the "seven erroneous theses about Latin America" *Latin American Perspectives* 45 (2): 129–141. https://doi.org/10.1177/0094582X17736036

KIM, M. S.–SUN, Y. (2016): Bootstrap and *K*-step bootstrap bias corrections for the fixed effects estimator in nonlinear panel data models *Econometric Theory* 32 (6): 1523–1568. https://doi.org/10.1017/S0266466615000341

KOUSKOURA, A.–KALLIONTZI, E.–SKALKOS, D.–BAKOUROS, I. (2024): Assessing the key factors measuring regional competitiveness *Sustainability* 16 (6): 2574. https://doi.org/10.3390/su16062574

LORÍA, E. (2020): Poverty trap in Mexico, 1992-2016 *International Journal of Development Issues* 19 (3): 277–301. https://doi.org/10.1108/IJDI-11-2019-0192

MARGARIAN, A. (2024): Analysing evolutionary growth regimes of regional economies and transformative shocks: proposal for a regression-based counterfactual simulation approach to local inter-industry structural change *Structural Change and Economic Dynamics* 70: 18–32. https://doi.org/10.1016/j.strueco.2024.01.003

MARTIN, R.–SUNLEY, P. (1998): Slow convergence? The new endogenous growth theory and regional development *Economic Geography* 74 (3): 201–227. https://doi.org/10.1111/j.1944-8287.1998.tb00113.x

MARTINELLI, F.–MOULAERT, F.–NOVY, A. (2013): *Urban and regional development trajectories in contemporary capitalism* Routledge. https://doi.org/10.4324/9780203075326

MARTINI, B.–GIANNINI, M. (2020): Regional wage and productivity in Italy: a spatio-temporal analysis *Spatial Economic Analysis* 15 (4): 392–412. https://doi.org/10.1080/17421772.2020.1769169

MASTEN, A. S.–CICCHETTI, D. (2010): Developmental cascades *Development and Psychopathology* 22 (3): 491–495. https://doi.org/10.1017/S0954579410000222

MATOS-VILA, J. (2025): *Economic order: assessing the economy beyond growth.* https://doi.org/10.2139/ssrn.5179146

MENDOZA-GONZÁLEZ, M. Á.–QUINTANA-ROMERO, L.–GUERRERO-JIMÉNEZ, A. (2024): Regional per capita income inequality and fiscal policy in Mexico, 1989–2021 *The Annals of Regional Science* 73 (4): 1681–1699. https://doi.org/10.1007/s00168-024-01312-y

MORAN, P. A. P. (1950): Notes on continuous stochastic phenomena *Biometrika* 37 (1–2): 17–23. https://doi.org/10.1093/biomet/37.1-2.17

NAVARRO-CHÁVEZ, C. L. (2025): Economic and sectoral convergence in Latin America and the Caribbean: an analysis of beta, sigma, and gamma gonvergence *Journal of Risk and Financial Management* 18 (2): 61. https://doi.org/10.3390/jrfm18020061

NEWMAN, J.–HOOLE, C. (2024): The intersection of productivity and governance capacity in spatial inequality: the case of England's devolution periphery *Contemporary Social Science* 19 (4): 555–582. https://doi.org/10.1080/21582041.2024.2435440

NIJKAMP, P.–REGGIANI, A. (1995): Non-linear evolution of dynamic spatial systems. The relevance of chaos and ecologically-based models *Regional Science and Urban Economics* 25 (2): 183–210. https://doi.org/10.1016/0166-0462(94)02077-T

PÉNZES, J. (2020): The impact of the Trianon Peace Treaty on the border zones - an attempt to analyse the historic territorial development pattern and its changes in Hungary *Regional Statistics* 10 (1): 60–81. https://doi.org/10.15196/RS100102

PINILLA-RODRÍGUEZ, D. E.–HERNÁNDEZ-MEDINA, P. (2024): Governance and fiscal decentralisation in Latin America: an empirical approach *Economies* 12 (8): 207. https://doi.org/10.3390/economies12080207

RAMIREZ-URQUIDY, M.–MARTINEZ, J. N.–ORRACA, P. (2024): The institutional context, entrepreneurship decisions, and venture types: evidence from Mexico *Journal of Entrepreneurship in Emerging Economies* 16 (6): 1846–1871. https://doi.org/10.1108/JEEE-06-2023-0253

REY, S. J.–CASIMIRO VIEYRA, E. (2023): Spatial inequality and place mobility in Mexico: 2000–2015 *Applied Geography* 152: 102871. https://doi.org/10.1016/j.apgeog.2023.102871

REZAEI, A.–ABDELLATIF, I.–UMAR, A. (2025): Towards economic sustainability: a comprehensive review of artificial intelligence and machine learning techniques in improving the accuracy of stock market movements *International Journal of Financial Studies* 13 (1): 28. https://doi.org/10.3390/ijfs13010028

RODRÍGUEZ-POSE, A. (2013): Do institutions matter for regional development? *Regional Studies* 47 (7): 1034–1047. https://doi.org/10.1080/00343404.2012.748978

RODRÍGUEZ-POSE, A.–KETTERER, T. (2020): Institutional change and the development of lagging regions in Europe *Regional Studies* 54 (7): 974–986. https://doi.org/10.1080/00343404.2019.1608356

ROSTOW, W. W. (1956): The take-off into self-sustained growth *The Economic Journal* 66 (261): 25. https://doi.org/10.2307/2227401

SCHNEIDER, C.–COTTINEAU, C. (2019): Decentralisation versus territorial inequality: a comparative review of English city region policy discourse *Urban Science* 3 (3): 90. https://doi.org/10.3390/urbansci3030090

SHIMAMOTO, K. (2019): Empirical analysis of the distribution of urban parks in Japan *Regional Statistics* 9 (2): 148–172. https://doi.org/10.15196/RS090203

STEKHOVEN, D. J.–BÜHLMANN, P. (2012): MissForest – non-parametric missing value imputation for mixed-type data *Bioinformatics* 28 (1): 112–118. https://doi.org/10.1093/bioinformatics/btr597

SUN, Y. (2016): Second-order corrected likelihood for nonlinear models with fixed effects *SSRN Electronic Journal* https://doi.org/10.2139/ssrn.2782369

TEMPLE, J. R. W. (2021): Growth econometrics. In: *Oxford research encyclopedia of economics and finance* Oxford University Press. https://doi.org/10.1093/acrefore/9780190625979.013.644

TREJO NIETO, A. (2024): Place-based strategies for sustainable and inclusive regional development in the south of Mexico *Review of Regional Research* 44 (3): 1–25. https://doi.org/10.1007/s10037-024-00208-w

TSIAPA, M.–TZEREMES, P. G.–TZEREMES, N. G. (2025): Productivity slowdown and regional productivity heterogeneity *Journal of Productivity Analysis* 64: 23–41. https://doi.org/10.1007/s11123-025-00751-9

UZUNER, G.–BEKUN, F. V.–ELUWOLE, K. K.–ALOLA, A. A. (2025): Are export and capital accumulation panacea for economic growth in Mexico?: a non-linearity evidence *Quality & Quantity* 59: 4559–4579. https://doi.org/10.1007/s11135-025-02183-x

VILLEGAS MATEOS, A. O.–AMORÓS, J. E. (2019): Regional entrepreneurial ecosystems in Mexico: a comparative analysis *Journal of Entrepreneurship in Emerging Economies* 11 (4): 576–597. https://doi.org/10.1108/JEEE-02-2019-0024

INTERNET SOURCE

LUNDBERG, S. M.–LEE, S.-I. (2017): A unified approach to interpreting model predictions. In: GUYON, I.–VON LUXBURG, U.–BENGIO, S.–WALLACH, H.–FERGUS, R.–VISHWANATHAN, S.–GARNETT, R. (eds.): *Advances in neural information processing systems 30* Curran Associates, Inc. https://proceedings.neurips.cc/paper_files/paper/2017/file/8a20a8621978632d76c43dfd28b67767-Paper.pdf (downloaded: July 2025)