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MAPPING THE SPATIAL DYNAMICS OF INNOVATION-DRIVEN SOCIOECONOMIC INEQUALITY IN THE EUROPEAN UNION

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Abstract

The persistent nature of socioeconomic inequalities across the European Union, despite the institutional and non-institutional efforts given so far for their reduction, motivates this paper investigating the structural characteristics and spatial dynamics of regional inequality across 209 NUTS 2 regions of the European Union, utilizing the most recent harmonized Eurostat data (2023, 2024). A comprehensive four-stage analytical framework is employed, integrating statistical inequality metrics (Gini coefficient and Theil's index), correlation analysis, multivariate techniques (PCA and *k*-Means clustering), and Exploratory Spatial Data Analysis (Global Moran's I and LISA). The results reveal that while social and demographic indicators exhibit strong convergence, economic output and R&D intensity remain highly polarized. The clustering analysis identifies a multi-speed Europe, distinguishing a "Knowledge-Driven Core" in Northern and Western Europe from a vast "Labor-Intensive" cluster in transition economies that relies on manufacturing efficiency rather than endogenous innovation. Furthermore, spatial analysis confirms the existence of significant Spatial Poverty Traps in the Southern and Eastern periphery, while highlighting the phenomenon of capital cities that fail to diffuse prosperity to their hinterlands. The findings suggest that bridging the remaining gap requires a shift in regional policy, prioritizing the diffusion of technological capacity over simple income redistribution.

Keywords: Regional Inequality, Knowledge Economy, Spatial Econometrics, Cluster Analysis, Cohesion Policy.

JEL Classification: R11, R12, R58, O30, O38.

1. Introduction

The existence of pronounced disparities in the levels of economic development between European countries and regions has long constituted one of the greatest challenges to European integration (Lopez-Bazo et al., 1999; Puga, 2002; Polyzos, 2019; Iammarino and Rodriguez-Pose, 2019; Giannakis et al., 2024). These inequalities extend beyond income and production, such as human capital, social participation, and the capacity of regions to benefit from development policies. Given the complex nature of European economies (Pinheiro et al., 2025), multiple crises and external shocks increase the vulnerability of specific areas (Tsiotas and Katsaiti, 2025). As emphasized by the system approach to resilience (Sutton and Arku, 2022; Giannakis et al., 2024), the impact of these shocks depends heavily on the regions' adaptive capacity, specifically, their ability to undergo structural and functional changes to maintain long-term growth. Indeed, recent literature emphasizes that regional development is not solely driven by structural factors but also by behavioral patterns and the emergence of new possibilities within regional systems (Fratesi et al., 2025). Such unequal geographical distribution of resources and opportunities constitutes a serious obstacle to social cohesion, political stability, and the achievement of spatial justice within the EU (Iammarino and Rodriguez-Pose, 2019; Madanipour et al., 2022).

Regional policies often focus on already high-performing regions, investing in sectors with proven growth potential. While this approach can enhance the efficiency of public resources, it frequently leads to widening inequalities, neglecting the needs of less developed regions (Krabokoukis et al., 2024). Indeed, empirical evidence from Greece highlights how unequal geographical concentrations of economic activity, such as tourism, can intensify regional disparities over time, broadening the gap between developed and lagging areas (Krabokoukis and Polyzos, 2021a). As a result, only the most developed European regions have the opportunity to specialize in complex, innovative, high-value-added activities (high-complexity activities), while less developed regions are confined to low-complexity activities, further reinforcing spatial disparities in Europe (Pinheiro et al., 2025).

In addition, these inequalities affect citizens' trust in the EU (Lipps and Schraff, 2021; Ejrnæs et al., 2024) and manifest in various sectors, such as transport (Capello and Cerisola, 2023), tourism (Tsiotas et al., 2021; Krabokoukis and Polyzos, 2023), and innovation (Pinheiro et al., 2025). Structural or redistributive policies, which could substantially support lagging regions, are often considered more complex to implement and have a long-term impact. Consequently, in many cases, an orientation towards strengthening national competitiveness is observed at the expense of internal regional equity and social cohesion (Krabokoukis and Polyzos, 2023; Krabokoukis et al., 2024).

One additional critical aspect, often overlooked in standard convergence analysis, is the role of spatial dependence. Traditional economic approaches tend to treat regions as isolated entities, ignoring the interactions and spillover effects between neighboring areas. However, such perspectives are limited, as traditional measures of inequality are often insensitive to the geographical permutation of data (Cartone et al., 2022). Ignoring these spatial interactions can mask the true extent of disparities, as regional inequality is composed of both a spatial component (inequality influenced by neighbors) and a non-spatial idiosyncratic component. The concept of spatial dependence holds that a region's development trajectory is significantly influenced by the performance of its neighbors, as interregional flows of capital, people, and knowledge create complex patterns of spatial connectivity that can either foster cohesion or reinforce disparities (Tsiotas and Tselios, 2024).

This paper aims to systematically map and analyze socioeconomic inequalities at the NUTS2 regional level in the European Union. To achieve this goal, inequality measures (Gini, Theil), correlation techniques (Spearman, Pearson), Principal Component Analysis (PCA), and Exploratory Spatial Data Analysis (ESDA) are employed. Through these methods, an attempt is made to identify patterns of differentiation and group regions based on their overall performance. The analysis relies on the most recent harmonized Eurostat data (reference years 2023, 2024), incorporating critical indicators of human capital, labor market, social well-being, and demographic characteristics. Beyond traditional statistical metrics, the study introduces an advanced layer of spatial analysis utilizing Global Moran's I and Local Indicators of Spatial Association (LISA) to detect significant spatial clusters. The synthesis of these variables allows conclusions to be drawn about the overall socioeconomic status of the regions and provides significant information for the design of cohesion and sustainable regional development policies.

This study aims to provide empirical evidence on the structural and spatial nature of European disparities by addressing three critical research questions:

[Q_1] ***Does social convergence imply economic convergence?***

Specifically, this research question examines to what extent do inequalities in living standards (social indicators) align with inequalities in economic output and innovation?

[Q_2] ***Which structural factors drive regional polarization?***

This research question examines whether the regional division resulting in polarization is driven by labor market dynamics or by the capacity for innovation and high-value-added production.

[Q_3] ***Do spatial spillover effects mitigate or exacerbate regional inequalities?***

This research question examines whether proximity to wealthy regions fosters regional convergence.

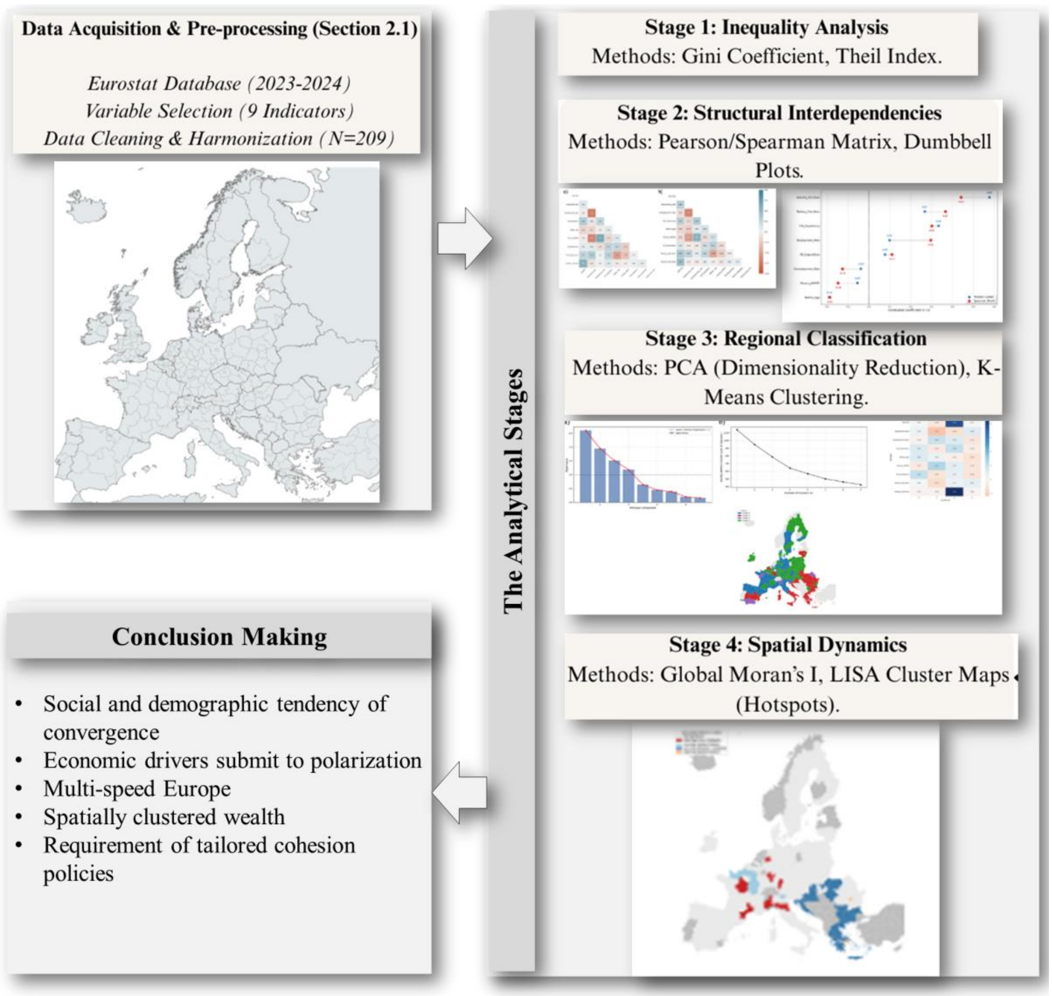
This paper seeks to contribute to identifying NUTS 2 regions in need of support, providing valuable findings for the design of targeted and spatially sensitive development and cohesion policies. The remainder of the paper is organized as follows: Section 2 details the methodological framework, the data harmonization process, and the analytical tools employed. Section 3 presents the empirical results, including the inequality metrics, the multivariate classification of regions, and the spatial cluster analysis. Finally, Section 4 synthesizes the findings, discusses policy implications, and concludes the study.

2. Method

The study examines socioeconomic inequalities across European regions at the NUTS 2 level. The analysis aims to measure the intensity of disparities, determine correlations between variables, identify regional profiles with shared characteristics, and detect geographical patterns of inequality. To achieve these objectives, Figure 1 illustrates the methodological framework.

First, the Data Collection phase (Section 2.1) ensures the creation of a harmonized dataset free of missing values. Subsequently, the analysis includes four stages: Stage 1 quantifies the magnitude of inequality; Stage 2 explores the causal relationships between variables; Stage 3 classifies regions into distinct socioeconomic profiles using PCA, and Stage 4 introduces the geographical dimension, detecting spatial dependencies and clusters of prosperity or deprivation.

Figure 1. Methodological Framework and Analytical Stages.



Source: Own elaboration.

2.1. Data Collection and Sample Specification

In Section 2.1, the empirical analysis relies on a comprehensive dataset derived from Eurostat at the NUTS 2 administrative level, which serves as the primary unit for implementing regional policies in the European Union. The most recent available data were selected for the analysis, as detailed in Table 1.

Table 1. The socioeconomic variables used in the analysis

Dimension	Variable	Description & Rationale	Source	Year
Economic Performance	GDP per capita (PPS)	Gross Domestic Product per capita in Purchasing Power Standards. The primary indicator of regional wealth and living standards, adjusted for price differences.	Eurostat [nama_10r_2gdp]	2023
Economic Structure	Industry Structure (Large Firms' Dominance)	The percentage of total wages in Industry (NACE B-E) generated by large enterprises (250+ employees). Indicates the presence of major industrial players vs. small-scale production.	Eurostat [sbs_sc_ind_r2]	2020
Labor Market	Employment Rate	Percentage of employed persons aged 20-64. Reflects the capacity of the regional economy to utilize its labor resources.	Eurostat [lfst_r_lfe2emprt]	2024
Labor Market	Unemployment Rate	Unemployed persons as a percentage of the labor force (15-74 years). A direct measure of labor market imbalances.	Eurostat [lfst_r_lfu3rt]	2024
Human Capital	Tertiary Education	Percentage of the population (25-64 years) with tertiary education attainment (ISCED levels 5-8). A proxy for the "knowledge economy" potential.	Eurostat [edat_lfse_04]	2024
Innovation	R&D Expenditure	Intramural R&D expenditure (GERD) in Euro per inhabitant. Captures the intensity of investment in innovation and technology.	Eurostat [rd_e_gerdreg]	2023
Social Cohesion	Poverty (AROPE)	People at risk of poverty or social exclusion (% of total population). The headline indicator for monitoring the EU 2030 social inclusion target.	Eurostat [tgs00107]	2024
Demography	Median Age	The median age of the population. Indicates demographic aging, which impacts future growth potential and social security burdens.	Eurostat [demo_r_pjanind2]	2024

Dimension	Variable	Description & Rationale	Source	Year
Quality of Life	Life Expectancy	Life expectancy at birth. A composite indicator of general health conditions, healthcare quality, and environmental factors.	Eurostat [demo_r_mlifexp]	2023

Source: Own elaboration.

The entire analytical pathway, from data acquisition to spatial modeling, was executed using the Python programming language. This computational approach ensured the reproducibility and robustness of the results. Specifically, automated Python scripts were employed to handle the heterogeneity of data availability across different member states. A rigorous data harmonization process was implemented using the intersection method. Through algorithmic filtering, only regions possessing complete datasets across all nine examined variables were retained in the final sample. This approach eliminated the risk of statistical bias in the subsequent multivariate and spatial analyses that could arise from missing values.

The final dataset consists of 209 NUTS 2 regions. Given that the EU-27 comprises 244 NUTS 2 regions according to the 2021 classification, the study achieves a high coverage rate of 85.65%. The sample is geographically broad, ensuring a balanced representation of the distinct European spatial regimes. This extensive coverage allows for a reliable investigation of the North-South and East-West inequalities, as well as the identification of spatial clustering patterns across the continent. To capture the multidimensional nature of regional inequality, nine key variables were selected (Table 1) to reflect not just economic output, but the region's broader systemic capacity. Analyzing the system changes in an economy's structure and function is crucial for understanding its long-term trajectory and resilience type (Krabokoukis and Polyzos, 2021b; Sutton and Arku, 2022; Tsiotas and Katsaiti, 2025; Tsiotas et al., 2025). These variables represent four pillars of regional development: (a) Economic Performance, (b) Labor Market Dynamics, (c) Human Capital and Innovation, and (d) Social Cohesion and Quality of Life.

Particular attention was paid to the construction of specific indicators to ensure comparability. The "Tertiary Education" variable was calculated as a derived indicator. Given that Eurostat does not consistently provide a direct dataset for ISCED levels 5-8 across all regions, this variable was computed by subtracting the percentage of the population with upper secondary and post-secondary non-tertiary education (ISCED levels 3-4) from the aggregate population with upper secondary, post-secondary non-tertiary, and tertiary education (ISCED levels 3-8). This calculation effectively isolates the highly skilled workforce (aged 25–64), providing a precise proxy for human capital potential.

2.2. Inequality Measurement and Statistical Analysis

In Stage 1, the intensity of inequalities for a set of key socioeconomic variables was determined employing the Gini coefficient and Theil's index. The Gini coefficient (Polyzos, 2019) is a widely accepted metric for assessing the relative degree of income (or other variables) inequalities between regions. It calculates the statistical dispersion of a regional variable and is defined as expressed in Equation 1.

$$G = 1 - 2\int_0^1 (ax^2 + bx)dx \tag{1}$$

where, the quotient of the area bounded by the Lorenz curve $y=ax^2+bx$ the line $y=x$, divided by the total area under the diagonal is the second order polynomial formula of the Lorentz curve.

Correspondingly, the Theil's index (Polyzos, 2019) is a statistical entropy function used to measure inequalities. The general form of the Theil's index is given by Equation 2.

$$T = \frac{1}{n}\sum_{i=1}^{n} \frac{x_i}{\mu} \ln\left(\frac{x_i}{\mu}\right) \tag{2}$$

where x_i is the numerical value of the i-th observation of the variable x, and μ is the mean value of the n observations x_i.

The combined utilization of these two measures is methodologically critical to ensure the robustness of the findings. While the Gini coefficient is most sensitive to inequalities around the median of the distribution, the Theil's index exhibits greater sensitivity to the upper and lower tails (Cowell, 2011). Given the presence of significant economic outliers in the European context, this dual approach provides a more comprehensive capture of the spatial dispersion patterns, ensuring that the inequality metrics reflect both the general trend and the influence of extreme values.

2.3. Correlation Analysis

In Stage 2, the interdependencies between primary socioeconomic factors were examined to highlight the relationship between regional productive bases and key well-being indicators. Correlations between the variables listed in Table 1 were analyzed using both Pearson (r) and Spearman (ρ) coefficients. The dual application of these metrics allows for the detection of both linear and non-linear monotonic relationships. This distinction is crucial for identifying threshold effects, particularly in cases where variables may trigger disproportionate economic growth only after surpassing a critical level.

2.4. Multivariate Classification of Regions

In Stage 3, European regions were classified to identify clusters with similar socioeconomic profiles. The process began with Principal Component Analysis (PCA), implemented via the Scikit-learn library, to reduce the dimensionality of the dataset while retaining the maximum variance. As demonstrated in recent regional science literature (Tsiotas et al., 2020), this technique effectively extracts dominant patterns of variation and has been successfully applied to classify regions into distinct groups based on their structural characteristics, facilitating the identification of meaningful typologies. The optimal number of clusters was determined using the Elbow Method, which balances within-cluster homogeneity and between-cluster heterogeneity. Subsequently, the *k*-means clustering algorithm was applied to the principal components to classify regions into distinct typologies. This clustering approach has been successfully employed in regional analysis to categorize areas based on their distinct structural characteristics (Krabokoukis et al., 2021a), enabling the identification of structural inequalities.

2.5. Spatial Dynamics and Cluster Detection

In Stage 4, the analysis expands to the spatial dimension using Exploratory Spatial Data Analysis (ESDA) to detect geographical patterns of inequality. To ensure accurate spatial calculations, the dataset was harmonized with the Eurostat NUTS 2024 boundary files using the GeoPandas library. To model spatial interactions, a K-Nearest Neighbors spatial weights matrix was constructed employing the PySAL (Python Spatial Analysis Library) package. This approach ensures that island regions and isolated areas are effectively integrated into the spatial analysis. Advanced spatial econometric techniques are increasingly recognized as essential tools for testing conceptual assumptions about regional disparities and uncovering localized patterns of development (Fratesi et al., 2025). Based on this matrix, the Global Moran’s I statistic was calculated, determining whether the spatial distribution of wealth and poverty is random or clustered. Finally, Local Indicators of Spatial Association (LISA) were employed to generate regional clusters, identifying significant "Hotspots", "Coldspots", and spatial outliers. This stage provides critical insights into the formation of convergence clubs and the spatial spillover effects of inequality.

3. Results and Discussion

3.1. Stage 1: Inequality Analysis using Gini coefficient and Theil’s index

The results of the inequality analysis, as summarized in Table 2, reveal a distinct dichotomy in the spatial structure of the European Union. The values of the Gini coefficient and Theil’s index highlight that regional disparities are not uniform across all dimensions. They are strongly driven by economic performance and innovation capacity, while social and demographic indicators exhibit significantly higher levels of convergence. The most pronounced inequalities are observed in the variables related to economic output and technological intensity. GDP per capita (PPS) exhibits the highest degree of spatial concentration among all examined variables, with a Gini coefficient of 0.5147 and a Theil's index of 0.4834. This indicates a sharp polarization of wealth, likely driven by strong agglomeration effects in metropolitan hubs and capital regions compared to peripheral areas. Crucially, R&D Expenditure mirrors this extreme inequality (Gini: 0.5129; Theil: 0.4670), confirming that the "knowledge economy" remains highly centralized. This near-perfect alignment between GDP and R&D disparities suggests that innovation potential is the primary dividing line between the European core and the periphery. Similarly, Industry Structure shows a high level of inequality (Gini: 0.4454), suggesting that the industrial base of Europe is unevenly distributed, with large enterprises clustering in specific industrial corridors.

Table 2. Gini and Theil inequality measures for key socioeconomic variables across European NUTS2 regions

No.	Variable	Gini	Theil	No.	Variable	Gini	Theil
1	GDP per capita (PPS)	0.5147	0.4834	6	R&D Expenditure	0.5129	0.4670
2	Industry Structure (Large Firms' Dominance)	0.4454	0.3482	7	Poverty (AROPE)	0.2015	0.0647
3	Employment Rate	0.0532	0.0050	8	Median Age	0.0379	0.0023
4	Unemployment Rate	0.2983	0.1472	9	Life Expectancy	0.0167	0.0005
5	Tertiary Education	0.1708	0.0460				

Source: Own elaboration.

A notable contrast emerges within the labor market indicators. While the Employment Rate appears remarkably balanced across regions (Gini: 0.0532), the Unemployment Rate displays moderate-to-high inequality (Gini: 0.2983). This discrepancy implies that while participation in the labor market is relatively high across the EU, the incidence of joblessness –and particularly structural unemployment– remains spatially concentrated in specific "lagging" regions, predominantly in Southern and Eastern Europe. Regarding social cohesion, Poverty (AROPE) and Tertiary Education show moderate dispersion levels (Gini: 0.2015 and 0.1708, respectively). This indicates that while educational attainment and social inclusion policies have achieved some level of territorial cohesion, significant gaps persist, particularly in the geographic distribution of human capital. Finally, the analysis at the first stage identifies a strong convergence in demographic and health outcomes. Life Expectancy registers the lowest inequality among all variables (Gini: 0.0167; Theil: 0.0005), reflecting the universal coverage and effectiveness of European healthcare systems and the high standards of living across the continent. Similarly, the very low dispersion of Median Age (Gini: 0.0379), combined with a high sample mean of 45.2 years compared to the global median of ~30.5 years, identifies demographic aging as a pan-European phenomenon.

From a literature standpoint, the finding that regional inequalities appear more pronounced in the economic sphere of knowledge- and innovation-intensive production mechanisms, as compared to social and demographic indicators –which seem to exhibit a higher degree of convergence– appears to further advance the discussion introduced by Tsiotas and Tselios (2024) regarding the lower level of cohesion and the higher degree of spatial asymmetry of knowledge flows in the EU, as identified through the study of interregional flows of goods and services, capital, people, and knowledge. Moreover, evidence drawn from the review paper by Polyzos and Tsiotas (2025) corroborates the levels of convergence achieved in the social pillar relative to the EU’s economic model. From a theoretical perspective, grounded in the endogenous growth theory of Romer (1999) and Lucas (1988), according to which the production factor of labor generates increasing returns to scale that lead to knowledge- and innovation-based economies (Capello, 2015; Polyzos, 2019), economic performance –and, by extension, the path toward achieving economic cohesion in the EU– appears to be more sensitive to mechanisms of knowledge and innovation accumulation which, through increasing returns, operate multiplicatively on interregional inequalities.

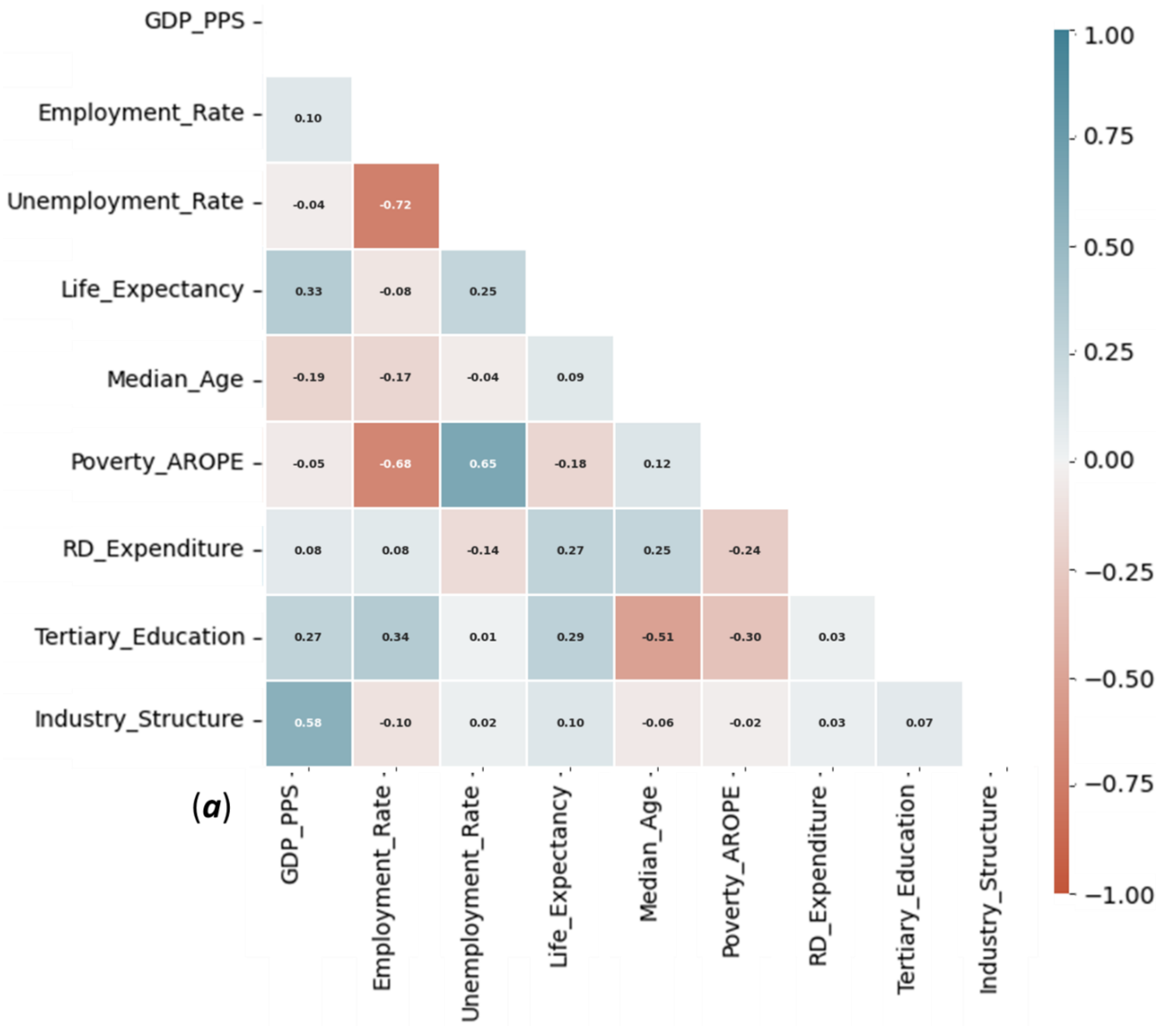
The literature on “learning regions” (Florida, 1995) and regional innovation systems (Chung, 2002; Asheim et al., 2011) suggests that the high spatial concentration of the knowledge economy reinforces self-sustaining growth processes, confirming the importance of innovation ecosystems (Thomas et al., 2021) and knowledge networks (Kratke, 2010) within the objectives of EU cohesion policy (Cappellin, 2004). Furthermore, the finding of strong GDP polarization confirms that the established spatial development patterns in the EU (Blue Banana, Mediterranean Arc, Atlantic Arc, and Eastern Arc) (Tsiotas and Polyzos, 2025) exhibit persistence, indicating the presence of path dependence and lock-in mechanisms (Martin and Sunley, 2006; Levinson and Xie, 2011), as well as their significance in economic geography (Krugman, 1998) for the achievement of territorial, social, and economic cohesion. With regard to the concentration of structural unemployment in “lagging” regions of Southern and Eastern Europe, the relevant literature (Tsiotas and Polyzos, 2025) indicates that unemployment in these areas is associated with lower productivity, structural constraints, and weak innovation mechanisms.

Overall, the findings at this stage of the analysis provide indications that reinforce the view (Farole et al., 2011) that, although convergence in the EU may be relatively easier to achieve at the institutional level (e.g., through the implementation of policies), its realization in the sphere of production constitutes the greatest challenge.

3.2. Stage 2: Interdependencies of Socioeconomic Variables and Productive Sectors

In the second stage of the analysis, the focus shifts to understanding the structural interdependencies that shape regional disparities. Figure 2 presents the correlation matrices employing both Pearson (r) and Spearman (ρ) coefficients to detect linear and monotonic relationships, respectively.

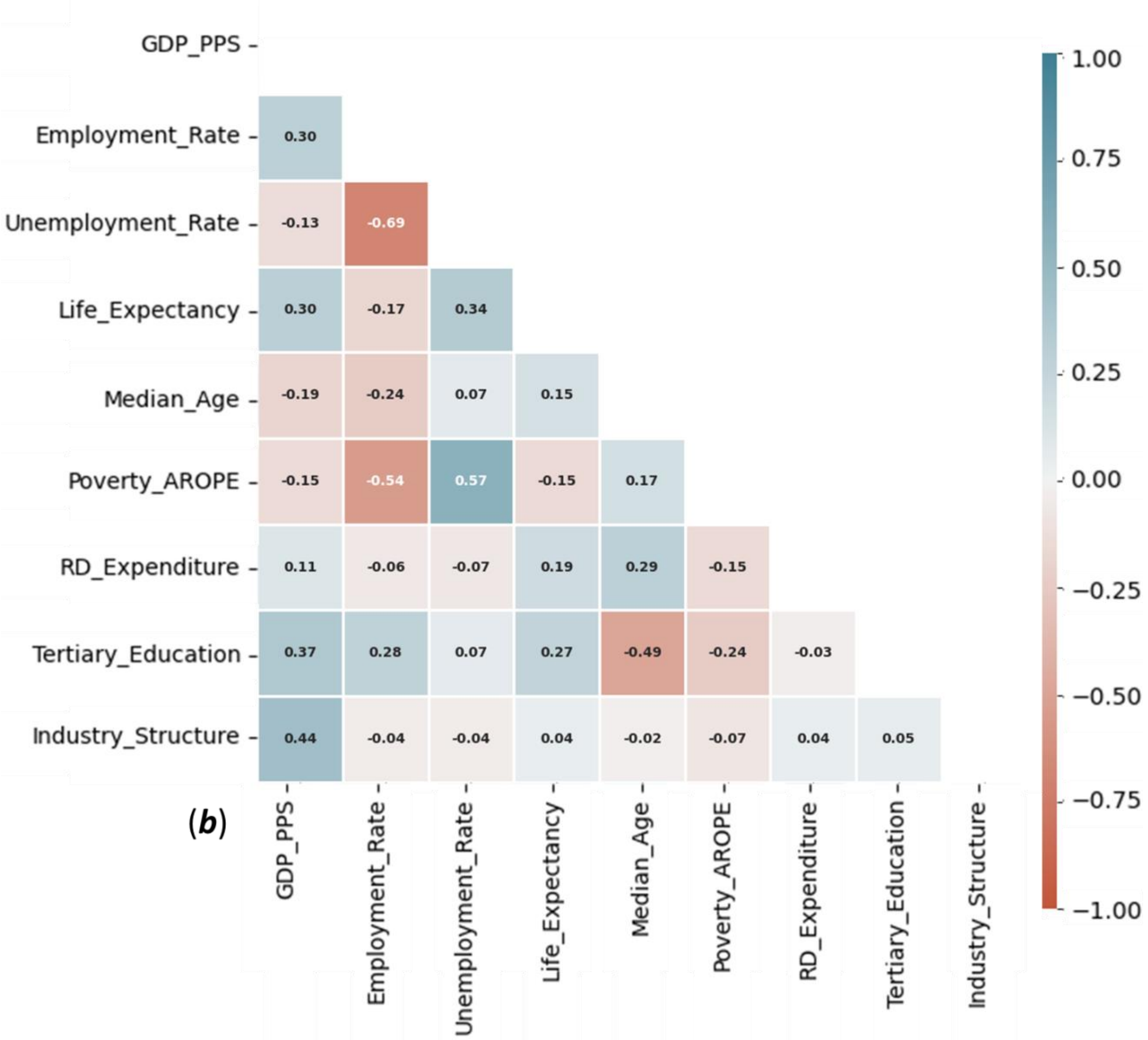
Figure 2. Heatmap of a) Pearson (linear) and b) Spearman (rank-based) correlations among the available variables.



Source: Own elaboration.

In contrast, Figure 3 isolates the correlation of all variables with GDP per capita (PPS), identifying the primary drivers of economic prosperity and the structural barriers to growth. The analysis reveals a strong, positive clustering among the variables associated with the "Knowledge Economy”. R&D Expenditure and Tertiary Education exhibit the strongest positive correlations with GDP per capita (Figure 3). A critical observation from the comparative analysis is that the Spearman coefficient for R&D (ρ=0.75) is consistently higher than the Pearson coefficient. This discrepancy suggests a non-linear, cumulative relationship. Beyond a certain threshold of investment in innovation, regional wealth accelerates disproportionately. This confirms that the most developed European regions function as "innovation hubs”, where high concentrations of human capital and technological investment create a self-reinforcing cycle of prosperity.

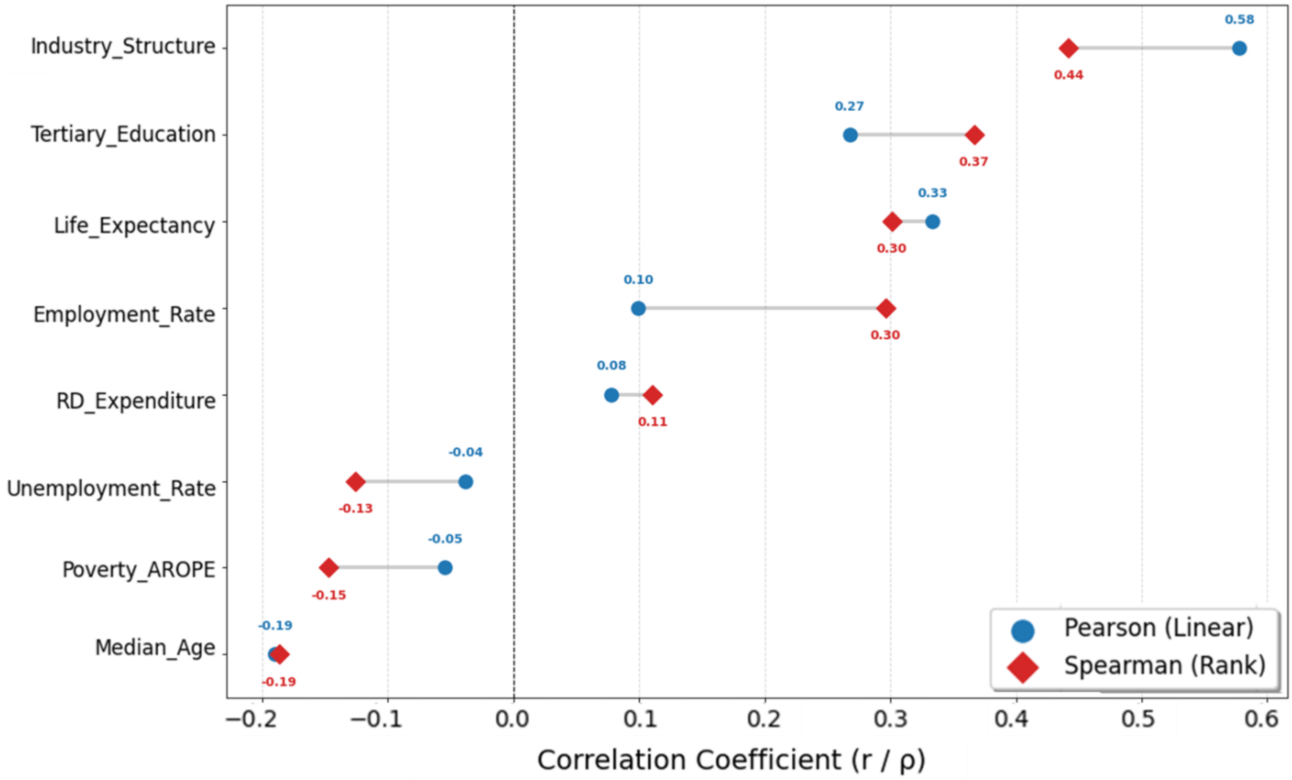
Figure 2. Heatmap of (a) Pearson (linear) and (b) Spearman (rank-based) correlations among variables (continued).



Source: Own elaboration.

Conversely, Poverty (AROPE) and Unemployment Rate display strong negative correlations with GDP, acting as the primary "forces of divergence". The Dumbbell plot in Figure 3 clearly illustrates this inverse relationship, with coefficients approaching -0.60. The robust rank-based correlation (Spearman) indicates that regions with high unemployment rates are those with the lowest income levels. This highlights that cohesion problems in Southern and Eastern Europe are structural, where labor market rigidities and social exclusion act as persistent barriers to convergence.

Figure 3. Correlation with GDP per capita (PPS): Pearson vs Spearman.



Source: Own elaboration.

The relationship between Industry Structure and regional wealth is positive but moderate (ρ = 0.45). This suggests that while a robust industrial base acts as a pillar of economic resilience (particularly in Central Europe), it is not the sole determinant of wealth. Finally, Median Age shows a weak correlation with economic performance. This aligns with the findings of Stage 1 (low Gini), reinforcing the conclusion that demographic aging is a generalized, pan-European phenomenon. It affects both affluent and lagging regions with similar intensity.

The empirical findings at this stage of the analysis confirm that European economic development is characterized by strong processes of spatial concentration of knowledge and human capital (Stirbock, 2001; Marrocu et al., 2013), while at the same time socio-economic factors such as unemployment and poverty operate as key mechanisms of divergence across regions (Polyzos and

Tsiotas, 2025). First, the strong positive correlation among knowledge economy variables suggests that the most developed European regions function as innovation hubs (De Groot, 2009; Marrocu et al., 2013; Polyzos, 2019). The concentration of highly skilled human capital, investments in research and development, and technological activities generates significant knowledge externalities and agglomeration economies (Marrocu et al., 2013). This process leads to a self-reinforcing growth cycle, whereby innovation attracts further investment and specialized labor (De Groot, 2009; Polyzos, 2019). These findings are consistent with empirical studies (Kratke, 2007; Iammarino and McCann, 2013; Chica and Marmolejo, 2016), which recognize that the knowledge economy is primarily concentrated in large metropolitan areas with strong universities, research institutions, and entrepreneurial ecosystems.

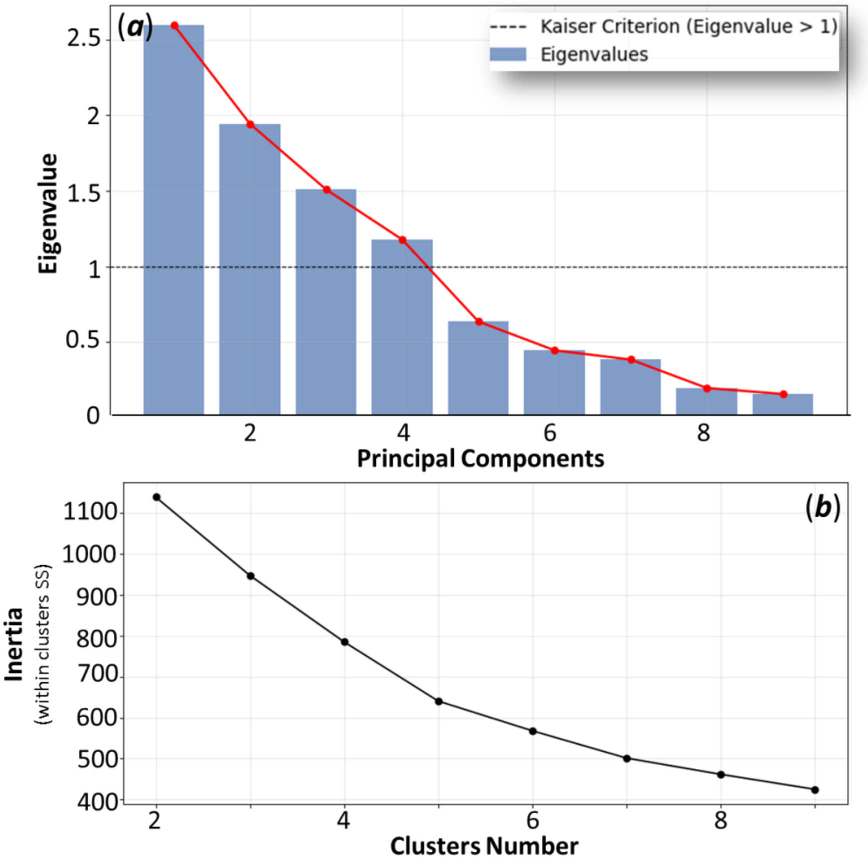
Second, the negative correlation between GDP and indicators such as poverty (AROPE) and unemployment rates indicates that these variables act as fundamental drivers of divergence among European regions (Polyzos, 2019; Polyzos and Tsiotas, 2025), highlighting the risk that less developed regions may enter a vicious cycle of low productivity, limited investment, and high unemployment (Basile and De Benedictis, 2008; Polyzos, 2019; Dobrzanski et al., 2024; Tsekeris, 2025). Furthermore, the results suggest that cohesion challenges in the regions of Southern and Eastern Europe have a deeper structural character (Polyzos, 2019), as –despite substantial funding through EU cohesion policies– these areas continue to face persistent constraints (Polyzos, 2019; Di Caro and Fratesi, 2022; Tsiotas and Polyzos, 2025), including high structural unemployment, lower productivity, and limited integration into knowledge-intensive activities, which may trap (Diemer et al., 2022; Rodriguez-Pose et al., 2024) certain regions in states of developmental lag.

Finally, the findings indicate that a strong industrial (secondary-sector) base is not the sole determinant of economic growth and development in the EU (Polyzos, 2019); rather, its contemporary growth model increasingly depends on knowledge- and innovation-intensive activities, as well as high value-added services (Van Exel et al., 2002; Crescenzi, 2005; Todtling et al., 2006).

3.3. Stage 3: Classification of European Regions

In the third stage, a multivariate classification was performed to construct a typology of 209 examined European regions based on their shared socioeconomic characteristics. Specifically, Principal Component Analysis (PCA) was first applied to reduce the dimensionality of the dataset (as shown in Figure 4a), followed by *k*-Means clustering. The application of the Elbow Method (Figure 4b) indicated that a solution with k=4 clusters offers the optimal balance between within-cluster homogeneity and between-cluster heterogeneity.

Figure 4. a) Scree plot: Eigenvalues of Principal Components and b) Elbow method for optimal k



Source: Own elaboration.

The complete sample of 209 regions was classified into four distinct groups. The average characteristics of these clusters are presented in Table 3, and their profiles are visualized in Figure 5. The analysis reveals the following distinct regional typologies, as illustrated in Figure 6.

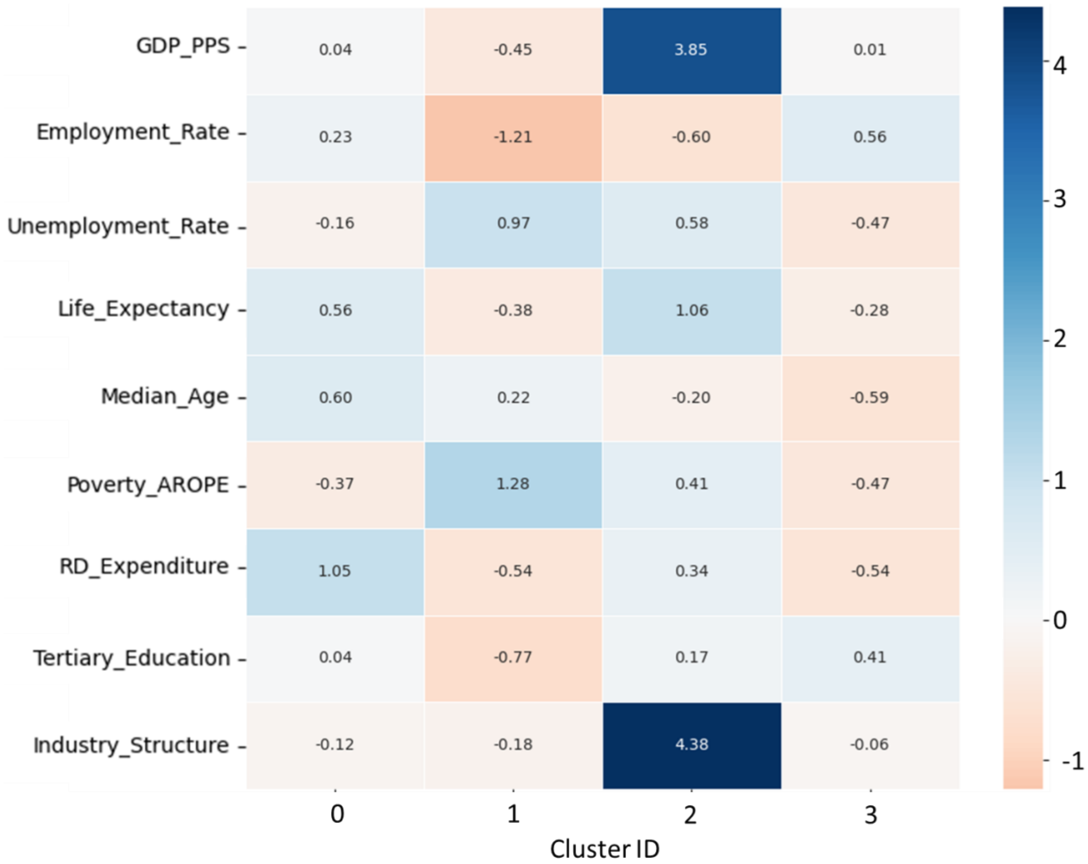
Table 3. Average characteristics of clusters

Cluster	GDP PPS	Employment Rate	Unemployment Rate	Life Expectancy	Median Age	Poverty AROPE	R&D Expenditure	Tertiary Education	Industry Structure	Count
0	79.32	72.34	5.41	82.57	47.07	18.16	607.15	34.82	89.47	68
1	33.29	62.38	9.38	80.26	45.90	30.94	154.57	26.42	82.62	50
2	437.16	66.60	8.00	83.80	44.60	24.20	403.79	36.20	540.40	5
3	76.99	74.60	4.34	80.50	43.41	17.37	154.32	38.70	95.63	86

Source: Own elaboration.

Cluster 2: Specialized Industrial Hubs (*n*=5). This small cluster represents the extreme outliers of the European economy (Andalucia, Ile de France, Pays de la Loire, Lombardia, and Nord-Est). These regions exhibit an exorbitant GDP per capita (437.16 PPS) and a massive Industry Structure index (540.40). They function as global financial or industrial command centers, operating on a scale completely different from the rest of the continent.

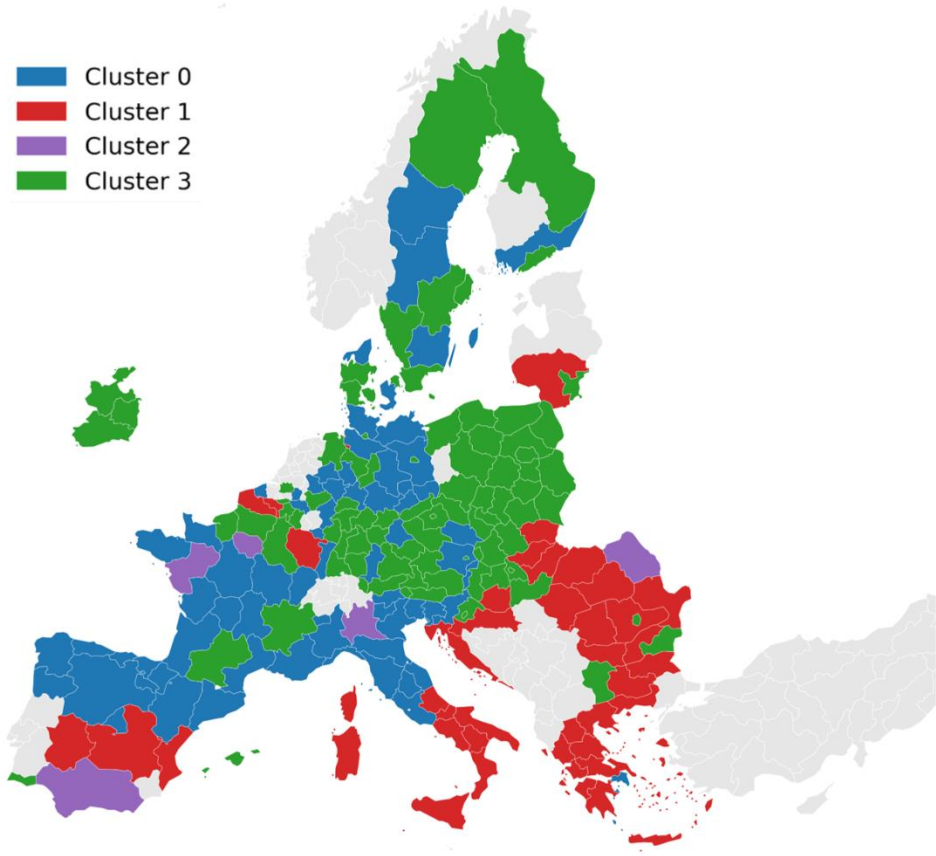
Figure 5. Heatmap of Socioeconomic Profiles by Cluster (Normalized Z-scores).



Source: Own elaboration.

Cluster 0: The Innovation-Driven Core (n=68). This cluster represents the developed "knowledge economy" of Europe. With a high GDP per capita (79.32) and the highest R&D expenditure among the main groups (607.15), these regions base their competitiveness on technology and human capital. Geographically, this grouping closely mirrors the established 'Blue Banana' spatial pattern, extending from Northern Italy through Germany to the UK, which is historically recognized as the industrial and technological backbone of the EU (Tsiotas and Polyzos, 2025). However, they also exhibit the highest Median Age (47.07), suggesting that the European innovation core is facing significant demographic aging challenges.

Figure 6. Spatial distribution of socioeconomic clusters.



Source: Own elaboration.

Cluster 3: Labor-Intensive and Transition Economies (n=86). This is the largest and perhaps most interesting cluster, comprising 41% of the sample. These regions have a GDP per capita (76.99) comparable to the "Innovation Core" (Cluster 0) and boast the lowest unemployment rate (4.34) and the highest employment rate (74.6). Furthermore, they have the youngest population (Median Age 43.4). However, a critical structural weakness is evident. As visualized in the heatmap of Figure 5, the contrast in innovation intensity between Cluster 0 and Cluster 3 is stark, despite their comparable employment rates. While Cluster 0 exhibits high R&D intensity, Cluster 3 lags significantly, with R&D expenditure (154.32) being four times lower. This suggests a growth model driven by labor intensity and manufacturing efficiency rather than endogenous innovation. This cluster largely corresponds to the "Eastern Arc", a region characterized by a dynamic yet uneven transition from centrally planned to market economies, often relying on lower labor costs to attract investment (Tsiotas and Polyzos, 2025).

Cluster 1: Structurally Lagging Regions (*n*=50). Geographically concentrated in the Southern and Eastern periphery, this cluster faces the most acute challenges. It records the lowest GDP (33.29), the highest unemployment rate (9.38), and the highest risk of poverty (30.94). With low tertiary education attainment (26.4) and minimal R&D investment, these regions appear trapped in a cycle of low productivity and social exclusion. Structural analyses of Southern European economies further support this, highlighting that limited cross-industry linkages and reliance on low-multiplier sectors hinder their ability to recover from asymmetric shocks and converge with the core (Polyzos et al., 2024). Especially for the Mediterranean regions within this cluster, this structural weakness is often exacerbated by a high reliance on seasonal tourism models (3S), which tend to generate spatial asymmetries and limit the diversification of the local productive base (Krabokoukis et al., 2024).

3.4. Stage 4: Spatial Dynamics and Cluster Detection

To empirically validate the geographical patterns observed in the previous stages and to quantify the extent of spatial dependence, Exploratory Spatial Data Analysis (ESDA) was performed using GDP per capita (PPS) as a primary proxy for regional economic development. The Global Moran's I index has a positive value of 0.0923, which is statistically significant (ρ=0.0210 < 0.05). This result rejects the null hypothesis of spatial randomness, confirming that wealth in the European Union is not randomly distributed. However, the relatively low magnitude of the index suggests a more complex and fragmented spatial structure. While there is a general tendency for high-income regions to cluster together (and vice versa), the spatial continuity appears to be interrupted. This indicates a "mosaic" pattern where islands of high prosperity (e.g., metropolitan hubs) often emerge within less developed surroundings, rather than forming vast, continuous homogeneous zones. To identify specific local patterns and spatial anomalies, the Local Indicators of Spatial Association (LISA) regional clusters' layout was generated (Figure 7). Advanced spatial econometric techniques are increasingly recognized as essential tools for testing conceptual assumptions about regional disparities and uncovering localized patterns of development (Fratesi et al., 2025). The analysis classified the 209 regions into five categories based on their relationship with their neighbors. As shown in the summary table below, the majority of regions (163) do not exhibit significant spatial dependence, further highlighting the fragmented nature of European development. However, significant clusters emerged, revealing distinct "Hotspots" and "Coldspots".

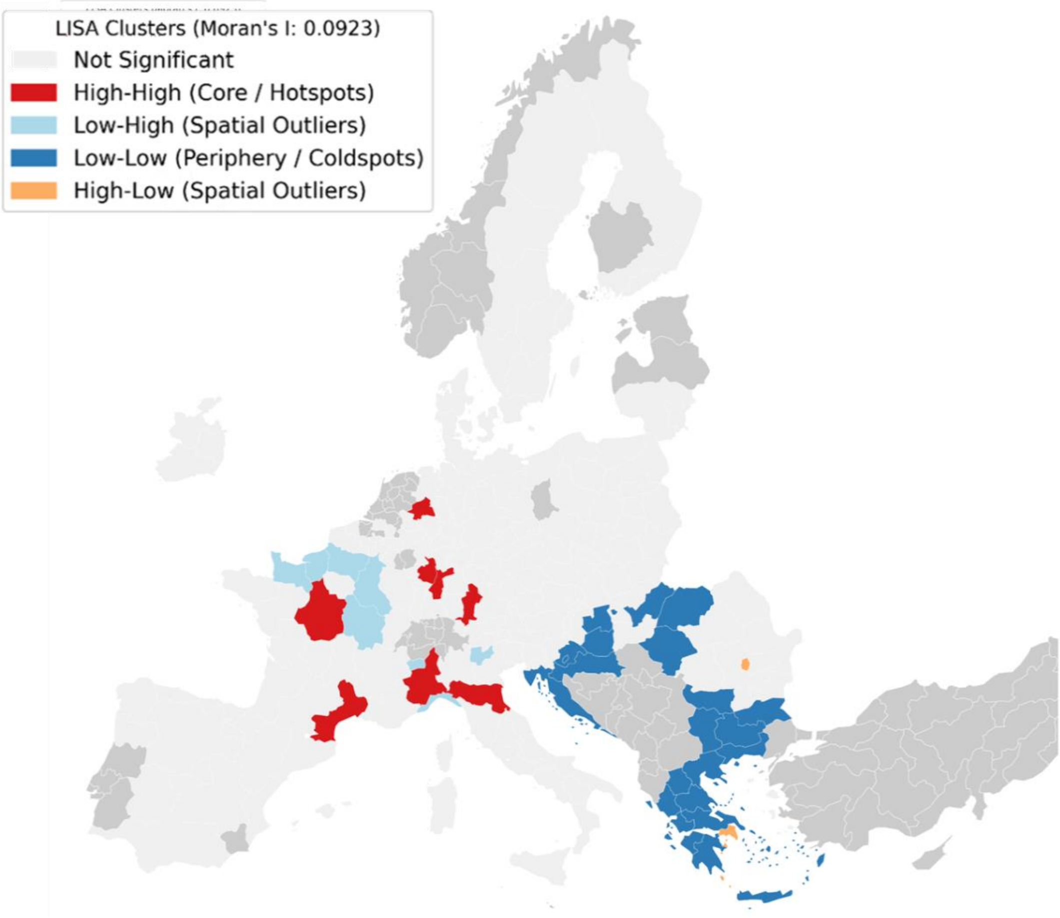
Table 4. Classification of Regions based on Spatial Association (LISA) of GDP per capita.

LISA Category	Count	Description
Not Significant	163	Random spatial distribution.
Low-Low (Periphery)	27	Low-income regions surrounded by low-income neighbors.
High-High (Core)	9	Wealthy regions surrounded by wealthy neighbors.
Low-High (Spatial Outlier)	8	Lower-income regions adjacent to wealthy hubs.

High-Low (Spatial Outlier)	2	Wealthy islands (capitals) in poorer hinterlands.

Source: Own elaboration.

Figure 7. LISA Clusters Layout of Regional GDP (Spatial Dynamics)



Source: Own elaboration.

The High-High Clusters (red) identify the established powers of the European economy. This zone is geographically concentrated in Southern Germany (Karlsruhe, Münster, Rheinhessen-Pfalz, Schwaben), Northern Italy (Veneto, Emilia-Romagna, Piemonte), and parts of France (Centre - Val de Loire, Languedoc-Roussillon). In these areas, wealthy regions are surrounded by equally wealthy neighbors, creating a powerful agglomeration of economic activity. This proximity fosters positive spatial spillovers, such as shared labor markets, integrated supply chains, and knowledge diffusion, reinforcing a cycle of cumulative causation.

The Low-Low Clusters (blue) dominate the southern and eastern periphery, highlighting regions that are in spatial poverty traps (Argyropoulou et al., 2019). This cluster includes: a) Greece: Almost the entire country falls into this category, as Thessalia, Sterea Elláda, Peloponnisos, Dytiki Elláda, Anatoliki Makedonia & Thraki, Notio Aigaio, Ipeiros, Dytiki Makedonia, Ionia Nisia, and Kriti are included in this cluster. b) The Balkans & Eastern Europe: Regions in Bulgaria

(Severozapaden, Yugoiztochen, Yuzhen tsentralen), Romania (Nord-Vest, Vest), Croatia (Jadranska Hrvatska, Panonska Hrvatska, Sjeverna Hrvatska, and notably the capital area Grad Zagreb), as well as parts of Hungary (Közép-Dunántúl, Észak-Alföld, Dél-Alföld, Dél-Dunántúl, and Budapest) and Slovakia (Východné Slovensko). The classification of capital regions like Budapest and Zagreb as LL (in this specific spatial weight configuration) underscores the severity of the regional depression in their broader vicinity, where the lack of dynamic neighboring markets exacerbates economic isolation and hinders convergence.

The analysis also highlights significant spatial outliers that disrupt regional homogeneity. The High-Low (HL) Outliers (orange): Two capital regions, Attiki (Greece) and Bucureşti-Ilfov (Romania), are classified as "wealthy regions" surrounded by significantly poorer hinterlands. This shows that capital cities connect to global networks but fail to diffuse their prosperity to their immediate neighbors. The Low-High (LH) Outliers (light blue): Eight regions located near wealthy hubs but recording lower economic performance. These include French regions (Haute-Normandie, Picardie, Bourgogne, Basse-Normandie, Champagne-Ardenne), Liguria in Italy, and the autonomous regions of Trento and Valle d'Aosta. These cases illustrate that proximity to a core does not automatically guarantee spillover benefits; in some cases, the core may even drain resources from its immediate neighbors.

The aforementioned findings primarily underscore the importance of spatial proximity and the development of networks of economic activity in shaping positive externalities that enhance regional development through mechanisms of knowledge diffusion, labor mobility, and the interlinkages of productive activities. Spatial proximity facilitates the exchange of information and innovation (De Groot et al., 2009; Iammarino and McCann, 2013; Thomas et al., 2021), fostering the emergence of positive spillovers that lead to a self-reinforcing core–periphery growth cycle, in line with the theory of cumulative causation (Myrdal, 1957; McCann and Van Oort, 2019). On the other hand, the presence of strong metropolitan centers may create the conditions for their operation as gateways to the global economy and their transformation into growth poles (Perroux, 1955). On the other hand, this situation further reinforces mechanisms of spatial concentration and the emergence of backwash effects (Polyzos, 2023), which undermine the diffusion of benefits to the wider periphery and lead to processes of spatial underdevelopment, such as brain drain or agglomeration shadow effects (Partridge et al., 2009; Zhen et al., 2023). Overall the results highlight both the dual nature of spatial spillovers (Polyzos, 2019) and the critical importance of place-based development strategies (Barca et al., 2012; Méndez et al., 2021) within the European Union.

4. **Conclusion**

This study employed a comprehensive, multi-stage analytical framework to investigate the spatial dynamics of socioeconomic inequality across 209 European NUTS 2 regions. By integrating inequality metrics, multivariate classification, and spatial econometrics, the analysis provides empirical evidence.

The results reveal that while social and demographic indicators (such as life expectancy and median age) show strong signs of convergence across the continent, economic drivers, specifically R&D expenditure and GDP per capita, remain highly polarized. The classification analysis identified a multi-speed Europe. On the one hand, a technologically advanced "Innovation Core" centered in Northern and Western Europe, on the other hand, a "Labor-Driven" cluster in transition economies that relies on manufacturing efficiency rather than endogenous innovation. The lack of innovation capacity in this cluster suggests that these regions risk relying on "engineering resilience", bouncing back to established low-value activities, rather than developing the "evolutionary resilience" required for structural adaptation and long-term competitiveness (Sutton and Arku, 2022; Tsiotas and Katsaiti, 2025). The spatial analysis (LISA) confirmed that wealth is not randomly distributed but is spatially clustered, creating Spatial Poverty Traps (Argyropoulou et al., 2019) in the southern and eastern periphery, where negative spillovers hinder development.

These findings suggest that cohesion policies are insufficient. Tailored strategies that consider specific sectoral dynamics and local economic landscapes are essential to drive sustainable and inclusive growth (Krabokoukis et al., 2024). The clear distinction between the "Innovation Core" (Cluster 0) and the "Transition/Labor" group (Cluster 3) implies that policy interventions must be place-based. For the transition regions (Cluster 3), the focus has to shift aggressively towards R&D and higher education. Furthermore, reliance on traditional tourism models may lead to saturation points that hinder long-term growth, and affect regional economic resilience, necessitating a strategic shift towards more sustainable and diversified economic activities (Krabokoukis et al., 2021b; Tsiotas et al., 2025). For lagging regions (Cluster 1), the priority should remain on basic infrastructure and social inclusion (poverty reduction).

Despite the robust methodology, this study is subject to certain limitations. First, the analysis relies on cross-sectional data for the period 2023-2024. While this provides a detailed snapshot of the current state of inequalities, it does not capture the dynamic evolution of these disparities over time. Future studies could employ panel data analysis to investigate whether the identified clusters are stable or if regions are effectively migrating from lower to higher performance groups over the last decade. Second, the use of NUTS 2 regions as the unit of analysis, while standard for EU policy, may contain significant intra-regional inequalities. For instance, the wealth of a capital city can obscure poverty in its immediate rural hinterland. Indeed, recent empirical evidence at the finer NUTS 3 level suggests that while broad spatial inequality may be decreasing, the idiosyncratic (local) component of inequality often remains stable or increases, highlighting the need for more granular analysis (Cartone et al., 2022). A granular analysis at the NUTS 3 level could unveil these micro-spatial disparities. Third, the variable selection, although covering four key pillars of development, did not include environmental indicators. Future research could integrate variables related to carbon emissions and green transition readiness to assess whether environmental sustainability acts as a new driver of regional inequality.

In conclusion, while the EU has achieved notable success in social harmonization, the "Geography of Innovation" remains deeply unequal. Addressing this structural divide requires a shift in regional policy, moving from simple income redistribution to the strategic diffusion of knowledge and technological capacity to the periphery. Without integrating high levels of research and technological knowledge into their production processes, less developed regions will struggle to close the gap with the European core (Polyzos and Tsiotas, 2025).

Data and Code Availability

The harmonized dataset comprising 209 NUTS 2 regions (reference years 2023, 2024) and the Python scripts employed for the Principal Component Analysis (PCA), k-Means clustering, and Spatial Analysis (Global Moran's I, LISA) are available upon reasonable request.

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