Mapping and analyzing innovation club convergence in European Regions

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1. Introduction

This study aims to analyze the patterns of economic convergence or divergence across European NUTS3 regions, focusing on the rural-urban divide within and between clubs - groups of regions/places with similar characteristics that may converge towards better economic conditions (Alexiadis, S., 2013, p. v). Building on literature, the study focuses on the central role of innovation and technological capabilities in influencing economic and social convergence among regions.

Several studies have pointed to the role of inter-regional inequality in determining economic growth (e.g., Bathelt et al. 2024; Boschma and Iammarino 2017) and discuss the role of EU support and network spillovers (e.g. Cappelen et al. 2003; Cortinovis and Van Oort 2019). The Cohesion Report (European Commission 2024) has consistently studied convergence in Europe since 1996 (European commission 1996) and has been fundamental in orienting cohesion policy. It has shown that there is overall regional economic and social convergence led by productivity convergence, but that this has been uneven across EU regions. Such inequalities are related to the observation that convergence has occurred mainly among clubs of similar regions. For instance, Fagerberg and Verspagen (1996) and Verspagen (2010) have shown the existence of innovation clubs among EU countries. More recently, Wirkierman et al. (2023) show that EU regions (NUTS-1) are still divided into different innovation clubs, with innovative clubs benefiting from such differences. Recent evidence also suggests that innovation clubs exhibit a nested structure, with core-periphery patterns replicated at different geographical scales (Wirkierman et al., 2024). However, due to data limitations at highly granular levels, we know less about the role of rural-urban distinctions in participating in different innovation clubs and in the convergence between regions.

Our study addresses this gap by examining the development trajectories of rural areas and their relationship with urban centers within the same and between different innovation clubs. We study whether fractal patterns of regional inequality and dependence exist along the rural-urban dimension. That is, we aim to provide evidence on whether rural and urban regions pertain to different innovation clubs, or if rural regions tend to group with neighboring urban regions. .

We do this in two main steps. First, we map the innovation activity of EU regions, distinguishing between urban and rural ones. Following the Input-Output (I-O) innovation scoreboard framework (OECD 1963; Godin, 2006) we use indicators that relate to different components of the innovation system, distinguishing between enabling conditions, inputs, linkages (Freeman 1995), outputs, and outcomes (Ciarli et al. 2021). In this first output, we distinguish between network-based (linkages) and place-based features of the innovation system. Using hierarchical clustering we distinguish groups of regions based on their centrality in the EU science and innovation network and based on their innovative and employment performance. We study the fractal structure within innovation clubs (clusters of regions) that may reflect urban and rural divides. Specifically, we analyse the extent to which regions at both core and periphery of the innovation network are composed of cores and peripheries in relation to their innovation capabilities. We study how this structure maps into the urban and rural divide.

Second, we analyze patterns of convergence and divergence among rural and urban areas within and across different clubs of regions. This includes examining whether rural regions converge to urban areas within the same club or to rural areas in different clubs. For this, we examine visually sigma convergence (the reduction in the dispersion or variation of GDP per capiat) and beta convergence (the relationship between the initial level of income (or GDP per capita) and the subsequent growth rate of income).

MAIN FINDINGS

At this stage, our results point to the following findings. 1) We confirm the existence of innovation clubs among European regions using network analysis and clustering techniques, revealing that core regions, such as those in Germany, France, and Italy, dominate knowledge exchange, while peripheral clusters are more balanced in their composition. However, in each block we find both cores and peripheries, pointing to evidence of a fractal structure. 2) Regional growth patterns demonstrate beta convergence, with poorer regions, particularly rural ones, growing faster than wealthier ones. 3) However, convergence is not uniform and tends to occur within similar groups (e.g., rural-to-rural or urban-to-urban), with urban regions showing slower growth at very high initial GDP levels. 4) Regional growth dynamics are shaped more by core-periphery structures and geographic factors than by rural-urban differences, as rurality primarily reflects a region's position in innovation networks and its geographic context, with faster rural growth being linked to membership in the Periphery-Periphery club rather than rurality itself. 5) Geographic factors further complicate convergence patterns, as interactions between club membership, rural-urban classifications, and location highlight significant spatial heterogeneity. These findings underscore the need for tailored policies that account for local conditions.

This is research in progress, and we welcome all the suggestions by the JRC. In the next stage of the analysis, we plan to use a wider range of science, technology, and innovation indicators to further understand the role that innovation plays in convergence –distinguishing between inputs, outputs, linkages, outputs, and outcomes. We also plan to explore indicators that allow us to understand technology / innovation convergence. We are also improving the robustness of our study by testing alternative definitions of clubs, including relevant explanatory variables within the national innovation systems framework, examining different model specifications, and exploring more in depth the characteristics of regions associated with being classified as rural, intermediate, or urban.

The rest of the paper is structured as follows. Section 2 describes the data and the methods to following the steps described above. Section 3 illustrates the results of the analysis. And section 4 concludes.

2. Data and methods

2.1 Data

For this deliverable, we have gathered data from the following data sources:

- ARDECO. From Ardeco we have collected information on employment and employment in specific sectors, from 2000 to 2020. We also collected data on population from this database.
- Eurostat. From Eurostat we have collected data on patents per million population and patents per million population in high-tech sectors (available until 2014)
- ESPON: From this database we have collected information to construct the independent variable, GDP per capita (PPS) at the NUTS 3 level from 2000 to 2020.
- OpenAlex. From OpenAlex we have gathered information on publications until 2024. The idea of using OpenAlex was to identify as many links between regions as possible. We also constructed a variable of publications per capita, from 2000 to 2020.
- GISCO. From GISCO we obtained polygon shape files to classify OpenAlex's institutions into NUTS 3 regions.

Our period of study is 2000 to 2020, mainly due to availability of the data in ESPON, but we are exploring to increase it by using ARDECO. As different datasets contained different versions of the NUTS 3 regions (e.g. 2016, 2021), we tried to normalize whenever possible. For this, we used the package "regions" in R, codifying NUTS 3 categories into their 2016 correspondence. Even after doing this codification, we could not get a complete mapping of all NUTS 3 regions, which is an issue that we will continue to explore.

All the data was downloaded and compiled in CSV files, and processed using R.

2.2 Absolute regional convergence

To set the stage we study convergence patterns among EU NUTS-3 regions between 2000 and 2020. We distinguish between urban, rural, and intermediate regions. To distinguish between these tree types of regions we use the rural urban typology, provided by Eurostat (Eurostat undated).

We estimate the following equation:

$$\mathrm{y_i} = \alpha + \beta \cdot \ln\left(GDP_{i,\,2000}\right) + \gamma \cdot Rural_i + \delta \cdot \left(\ln\left(GDP_{i,\,2000}\right) \times R_i\right) + \theta \cdot \left(\ln\left(GDP_{i,\,2000}\right) \times Int_i\right) + \varepsilon_i \qquad (1)$$

Where $\mathrm{Y_i}$ is regional GDP average annual growth rate between 2000 and 2020 $GDP_{2000,i}$ is regional GDP in 2000, $Rural_i$ is a categorical variable (rural, urban, intermediate), δ, captures whether the convergence rate differs for rural areas compared to urban areas and θ captures the difference between intermediate and urban and ε_i is the error term.2.3 Performance and network indicators

In the first step of our analysis, we map the innovation activity of EU regions, distinguishing between urban and rural regions. Following Wikierman, Ciarli, and Savona (2024) we build two main indicators of performance: one based on regional economic and innovation performance (place-based regional groups) and one based on knowledge relations between regions). For economic and innovation performance, we use data on the region's contribution to EU employment, per-capita patent applications, and per-capita scientific publications. In a system with *m* regions, contribution to employment can be defined as:

$$CtEG_r := \frac{\Delta L_r}{\sum_{r=1}^{m} \quad \Delta L_r} \qquad (2)$$

Where L_r is the level of employment during period t (time index suppressed) in region *r,* and *m* is the number of regions. This provides a measure of the proportional contribution of region *r* to the absolute change in EU-wide employment. We also included the same indicator of contribution to employment in high technology sectors from Eurostat:

$$CtEG\mathrm{HT}_r := \frac{\Delta L\mathrm{HT}_r}{\sum_{r=1}^{m} \quad \Delta L_r} \qquad (3)$$

Where $L\mathrm{HT}_r$ is the level of employment in high tech sectors during period t (time index suppressed) in region *r,* and *m* is the number of regions

Patents and publications are calculated as regional per-capita, indicating the regional productive knowledge base (Wikierman, Ciarli, and Savona 2024; Acs et al. 2002). For patents and publications, we operationalize them as:

$$PAT_r \coloneqq \frac{NumPat_r}{Pop_r} \qquad (4)$$

$$PUB_r \coloneqq \frac{NumPub_r}{Pop_r} \qquad (5)$$

Where *r* refers to region, *NumPat to* number of patents, *NumPub* to number of publications, and Pop_r to the population in the region.

For the linkages and knowledge relations between regions (knowledge blocks), we use indicators of interregional knowledge exchange, based on bibliographic citations and patent citations between NUTS3 regions.

Consider a knowledge exchange network where each node is a NUTS3 region and the link between regions is given by the number of citations. We take the matrix of knowledge transactions between regions (citations) and convert it into an undirected weighted graph. The adjacency matrix W of the graph is given by:

$$W = \frac{\frac{1}{2} \cdot (K + K^k)}{1^k K 1} \qquad (6)$$

This means that each element of W is a network link capturing knowledge exchange intensity. The weighted network helps to quantify the strength of knowledge relationships between regions. By assigning weights, the network can reflect how much knowledge exchange occurs between each pair of regions, providing a more detailed and accurate representation of knowledge exchange dynamics. This is computed using the scientific citation network to represent scientific knowledge exchanges.

We then identify knowledge exchange blocks among EU regions, which are based on the scientific connections between them. Additionally, we classify regions into place-based groups according to their innovation and employment performance. We refer to regions with high performance and those that play a central role in the knowledge production network as 'core' regions.

2.4 Identifying core and peripheral regions

To identify core and peripheral regions we cluster regions based on the two above groups of indicators separately for the economic and innovation performance and for the knowledge relations.

2.4.1 Clustering based on knowledge relations

For the clustering based on knowledge relations, we use the weighted network described above and apply the Louvain algorithm to identify "knowledge blocks," which reveal clusters with strong knowledge connections.

To identify the clusters, we analyzed the citation network using a combination of network analysis techniques, including the PageRank algorithm for centrality calculation and the Louvain algorithm for community detection. The methodology aims at transforming raw citation data into meaningful clusters, allowing for the identification of core and peripheral communities (knowledge blocks) within the European research landscape.

Data Preparation and Network Construction

We queried the OpenAlex database snapshot of November 2024 to gain access to all the scientific production in the database. From the scientific production, we extracted all affiliations of authors.

OpenAlex employs a two-step process to accurately parse and match institutional affiliations to scholarly works in its database. This involves using two classification models trained on a large dataset to interpret messy and inconsistent affiliation strings provided by authors, such as “MIT, Boston, USA” and “Massachusetts Institute of Technology,” treating them as the same institution. A deep learning model extracts institutions with high reliability, while a monthly string-matching process corrects common errors. Institutions are linked to works with metadata sourced from Crossref, PubMed, ROR, MAG, and publisher websites. OpenAlex assigns ROR IDs as the canonical external identifier for institutions and collaborates closely with ROR to ensure accuracy (Our Research 2024).

As of 2024, In OpenAlex 94% of institutions have a ROR ID (Our Research 2024). These affiliations have latitude and longitude of the place in which the institution resides, which makes them suitable for matching polygon files and assign NUTS 3 regions and even municipalities.

We calculated the citations from each region identified in OpenAlex to each other region, and aggregated the number of citations received and given between regions.

Data Loading and Filtering

We imported the citation network data. To ensure data integrity and focus, duplicate entries were removed, and the dataset is filtered to include only nodes (regions) from European (EU 27) countries. This filtering process is based on a predefined list of country codes, allowing for a targeted analysis of the European research ecosystem.

Graph Construction

Using the filtered dataset, a directed graph is constructed to represent the citation network. In this graph, nodes represent regions, and edges represent citations between these regions. The edges are weighted based on the total number of citations between each pair of nodes, providing a quantitative measure of the strength of connections within the network.

Centrality Calculation

Adjacency Matrix Creation and Normalization

An adjacency matrix is derived from the citation graph, capturing the structure of connections between nodes. This matrix is then normalized to create a row-stochastic matrix, where each row sums to 1. This normalization step is crucial for the subsequent application of the PageRank algorithm, as it ensures that the matrix represents a valid probability distribution for random walks through the network.

PageRank Algorithm Application

The PageRank algorithm is applied to the normalized adjacency matrix to compute centrality scores for each node in the network. PageRank is chosen for its ability to measure the importance of nodes based on the structure of incoming links, providing a robust metric for identifying influential regions within the citation network.

Knowledge Blocks Detection and Classification

Louvain Algorithm for Community Detection

To identify clusters within the citation network, we employ the Louvain algorithm, a widely used method for community detection in large networks that maximizes modularity. The algorithm is applied to an undirected version of the citation graph, with edge weights considered in the community detection process. The Louvain method is selected for its efficiency in handling large networks and its ability to uncover hierarchical community structures.

Centrality Aggregation

Following community detection, centrality scores are aggregated at the community level (block). This process involves summing the PageRank centrality scores of all nodes within each identified community. Additionally, the percentage of total centrality contributed by each community is calculated, providing a measure of the relative importance of each community within the overall network.

2.4.2 Clustering based on economic and innovative performance

For the clustering based on the economic and innovative performance, we standardize them and calculate the Euclidean distance between regions on:

- Patents per million inhabitants (Eurostat)
- Patents per mitted inhabitants in High-Technology sectors (Eurostat)
- Contribution to employment (ARDECO)
- Contribution to employment in the sectors 'M-N', 'J', 'O-Q': Science and technology professions, Administrative and support service activities, Public administration and defense; compulsory social security, Education, Human health and social work activities, Information and communication[1]
- Publications per capita (OpenAlex)

Data Preparation and Preprocessing

The initial step involved the collection and integration of diverse datasets related to regional characteristics. These datasets included employment contributions in specific sectors, patents per capita, and publications per capita. We merged these individual datasets based on a common identifier, `NUTSCODE`.

Data Scaling

Prior to clustering, we scaled the merged dataset, standardizing all variables to have a mean of 0 and a standard deviation of 1.

Distance Calculation

Following scaling, we calculated the Euclidean distance between all pairs of data points. This distance matrix serves as the foundation for several of the clustering methods employed in this study.

Clustering Methods

We applied multiple clustering techniques to identify place-based clusters, each offering a unique perspective on the data structure:

1. K-means Clustering

We initially employed K-means clustering, a widely used partitioning method. To determine the optimal number of clusters, we utilized the elbow method using the `fviz_nbclust` function from the `factoextra` package.

2. Partitioning Around Medoids (PAM)

To complement the K-means analysis, we applied the Partitioning Around Medoids (PAM) method, which is known for its robustness to outliers. The number of clusters for PAM was determined

[1] our intention is to approximate knowledge-intensive employment, but the current classification does not allow for sector dissaggregation at a granular level

using the silhouette method, which evaluates the quality of clustering by measuring how similar an object is to its own cluster compared to other clusters.

3. Hierarchical Clustering

We conducted hierarchical clustering using two commonly used linkage methods: Ward's method and average linkage. To decide the best method, we computed the cophenetic correlation coefficient to assess how well the clustering preserved the original pairwise distances. Finally, to determine the optimal number of clusters for the hierarchical method, we employed the silhouette method, iterating over a range of cluster numbers (2 to 10) and computing the average silhouette width for each. The number of clusters that maximized the silhouette width was selected as optimal.

4. Louvain Method

Finally, we applied the Louvain method for community detection, which is particularly effective for identifying clusters in network-like structures. We created a graph from an adjacency matrix derived from the distance matrix and computed the membership of Louvain communities.

2.4.2.1 Cluster Analysis and Interpretation

For each clustering method, we computed descriptive statistics of the resulting clusters, including the mean values of the original variables for each cluster. This allowed us to characterize and interpret the clusters based on their distinctive features. We also calculated the number of regions assigned to each cluster to assess the balance and distribution of the clustering solutions.

We applied the k-means clustering algorithm, the Partitioning Around Medoids (PAM), and agglomerative hierarchical clustering, as well as an alternative clustering approach using the Louvain community detection algorithm. This was done using the Euclidean distance matrix of the regions based on the innovation and economic variables. While hierarchical clustering with 2 clusters performed well in terms of internal and stability validation metrics, PAM with 2 clusters offers some advantages that make it a strong alternative. Unlike hierarchical clustering, which is sensitive to noise and outliers, PAM selects actual data points (medoids) as cluster centers, making it more robust in scenarios where the data may contain outliers or when the Euclidean distance matrix may not fully capture the relationships in the data. Additionally, PAM provides more interpretable cluster representatives, as the medoids are actual observations, which can be particularly valuable in studies where the social context or domain-specific knowledge plays a critical role. Compared to k-means, PAM avoids the sensitivity to initialization and ensures more stable results, while hierarchical clustering's reliance on a fixed tree structure can sometimes limit flexibility. Although the Louvain algorithm was explored, it produced too many clusters, most of them with only one observation, and was therefore discarded. Given these considerations, PAM with 2 clusters emerges as a suitable alternative that we used for this draft.

However, we continue exploring the best clustering method, as we still need to better assess the balance of the categories with regards to knowledge about the European regions for all the clustering solutions.

2.4.3 Identification of core and peripheral regions

Based on these two clustering approaches, we identified knowledge blocks (from the first clustering based on citation analysis) and place-based regional groups (from the second clustering). On both clusters, we identified cores and peripheries. We defined core as a status derived from high values in characteristics of interest and periphery as a status derived from low values in those characteristics. For each knowledge block identified we summed the total centrality contributed by their nodes. We identified as core blocks those with a higher-than-average total centrality. For the place-based clusters, we explored the different cluster solutions, and examined the averages related to each cluster as well as the balance between the clusters produced. We defined as peripheries those with lower values in their averages. When crossing the two clusters, we identify four clubs: Core-Core, Core-Periphery, Periphery-Core, and Periphery-Periphery.

2.5. Club convergence

In the second part of our analysis, we study patterns of convergence and divergence among rural and urban areas within and across different clubs of regions. We analyze club convergence (convergence within a cluster) and compare different clubs to study under which conditions convergence occurs. We employ cross-sectional approaches using two time periods (t_0 and t_1) to analyze convergence patterns across European regions. We study the patterns visually and we further analyze convergence by identifying clubs and geographic areas (southern, north-western, and southern). We use the following specifications.

Inter-club specification

$$\begin{aligned} y = \beta^0 + \beta^1 \cdot x + \gamma^{(CC)} \cdot Club^{(CC)} + \gamma^{(CP)} \cdot Club^{(CP)} \\ +\gamma^{(PC)} \cdot Club^{(PC)} + \delta^{(CC)} \cdot \left(x \times Club^{(CC)}\right) \\ +\delta^{(CP)} \cdot \left(x \times Club^{(CP)}\right) + \delta^{(PC)} \cdot \left(x \times Club^{(PC)}\right) + \varepsilon \end{aligned} \tag{7}$$

Where y = GDP average annual growth rate, $x = \ln(GDP_{2000})$ = the natural logarithm of GDP in the year 2000, $Club_{CC}$ = 1 if the observation belongs to the Core-Core club; 0 otherwise, $Club_{CP}$ =1 if the observation belongs to the Core-Periphery club; 0 otherwise, $Club_{PC}$ =1 if the observation belongs to the Periphery-Core club; 0 otherwise (The omitted baseline club is Periphery-Periphery)

Within-club specification

For each club (Core-Core, Core-Periphery, Periphery-Core, and Periphery-Periphery), we estimate:

$$
\begin{aligned}
y = \beta^0 + \beta^1 \cdot x + \beta_R \cdot RU_{Rural} + \beta_I \cdot RU_{Intermediate} \\
+\beta_R' \cdot (x \times RU_{Rural}) + \beta_I' \cdot (x \times RU_{Intermediate}) + \varepsilon
\end{aligned}
\qquad (8)
$$

Where y =GDP average annual growth rate, $x = \ln(GDP_{2000})$ the natural of GDP in the year 2000, RU_{Rural} =1 if the area is classified as Rural; 0 otherwise, $RU_{Intermediate}$ = 1 if the area is classified as Intermediate; 0 otherwise (the mitted baseline category for Rural/Urban is Urban)

And

$$
\begin{aligned}
y = \beta^0 + \beta^1 \cdot x + \beta_R \cdot RU_{Rural} + \beta_I \cdot RU_{Intermediate} \\
+\beta_R' \cdot (x \times RU_{Rural}) + \beta_I' \cdot (x \times RU_{Intermediate}) \\
+\theta_{NW} \cdot Region_{NW} + \theta_{Eastern} \cdot Region_{Eastern} + \varepsilon
\end{aligned}
\qquad (9)
$$

Where:

y =GDP average annual growth rate, RU_{Rural} = 1 if the area is classified as Rural; 0 otherwise, $RU_{Intermediate}$= 1 if the area is classified as Intermediate; 0 otherwise (The omitted baseline category for rural / urban is urban), $Region_{NW}$ = 1 if the region is North-western; 0 otherwise, $Region_{Eastern}$= 1 if the region is Eastern; 0 otherwise (The omitted baseline for Region is southern)

3. Results

3.1 Absolute regional convergence

Figure 1 illustrates the relationship between GDP per capita in purchasing power standard (PPS) as a percentage of the EU average in 2000 (x-axis) and the annual average percentage growth of real GDP per capita from 2001 to 2020 (y-axis) for NUTS 3 regions in the EU. It shows a negative relationship between initial GDP per capita and GDP percentage growth, for regions that were below the EU average in 2000. Regions with lower GDP per capita in 2000 with respect to the EU average (on the left side of the x-axis) tend to have higher annual average GDP growth rates, exceeding the average growth rate (indicated by the red dashed line) (higher points on the y-axis), suggesting economic convergence. Regions with GDP per head above 200% of the EU average in 2000 (on the far right of the x-axis) generally show lower growth rates below the average, which is expected of developed regions. However, regions that in 2000 were close to the EU average or above follow similar increases in GDP, suggesting divergence.

Table 1 shows that regions that have experienced GDP convergence are concentrated in Eastern European countries, which have experienced significant economic catch-up since the 2004 EU enlargement (Cohesion Report, 2024?).

Nine regions with a very high GDP per head (above 200% of the EU average in 2000) show moderate growth rates, suggesting that some highly developed regions sustain higher than average growth. Of these, six are in Germany (Ingolstat, Coburg, Erlangen, Braunschweig, Wolfsburg, Emden), one in Ireland (Dublin), one in the Netherlands (Groot-Amsterdam), and Luxemburg.

Figure 1. GDP growth vs GDP per head

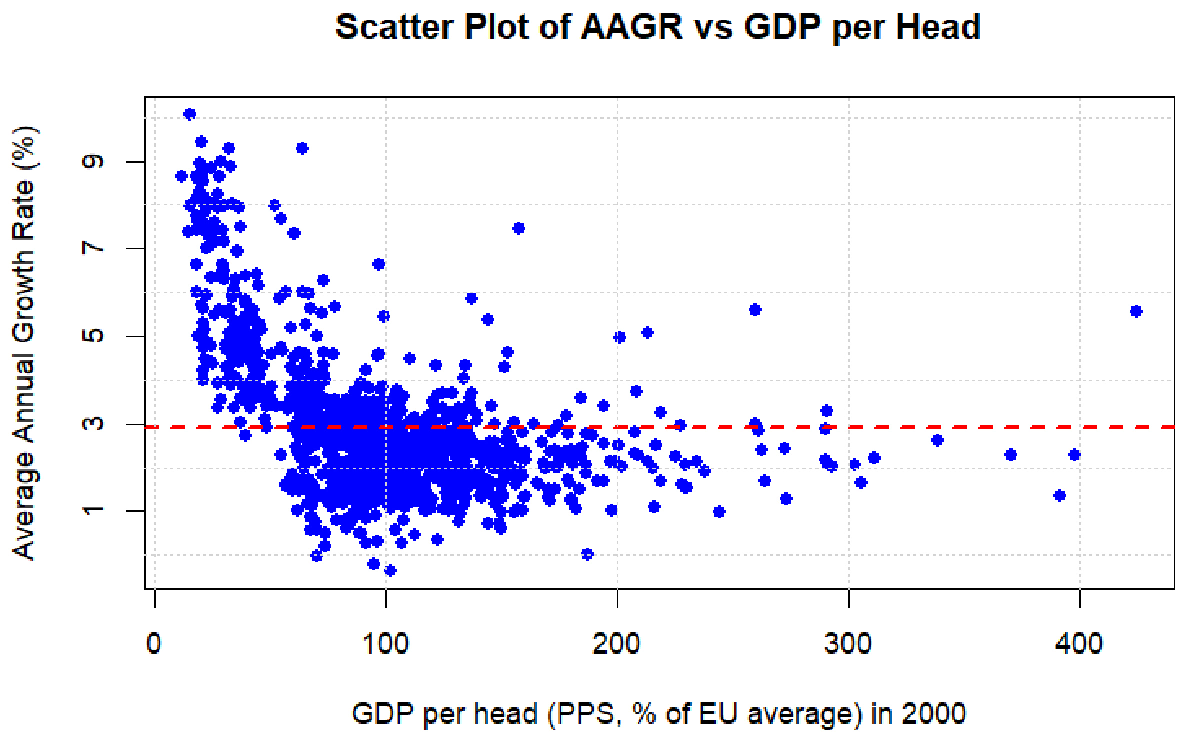


Table 1. Top 10 Countries by Regional GDP Growth and Above-Average Performing NUTS 3 Regions

Country	Number of regions	AAGR
Romania (RO)	42	8%
Latvia (LV)	6	7%
Lithuania (LT)	10	7%
Estonia (EE)	5	6%
Ireland (IE)	5	6%
Bulgaria (BG)	28	5%
Poland (PL)	73	5%
Croatia (HR)	17	4%
Slovakia (SK)	8	4%
France (FR)	2	4%

Figure 2 breaks down the convergence plot by rural-urban typology. Urban regions generally have higher initial GDP per head (clustered on the right side of the x-axis) and lower growth rates compared to rural and intermediate regions. However, some urban regions with lower initial GDP per head (closer to the left) exhibit relatively high growth rates.

Rural regions are more concentrated on the left side of the x-axis, indicating lower initial GDP per head in 2000. These regions show a wide range of growth rates, with many achieving high growth, reflecting the potential for rural areas to catch up economically. However, most rural regions exhibit stagnation or low growth.

Intermediate regions are distributed across the x-axis, with a mix of low and high initial GDP per head. These regions tend to have moderate growth rates, with fewer extreme outliers compared to rural or urban regions. Overall, rural regions show strong growth potential but with high variability, while urban regions show slower growth and intermediate are more balanced.

Figure 2. GDP growth vs GDP per capita by Rural – Urban Typology

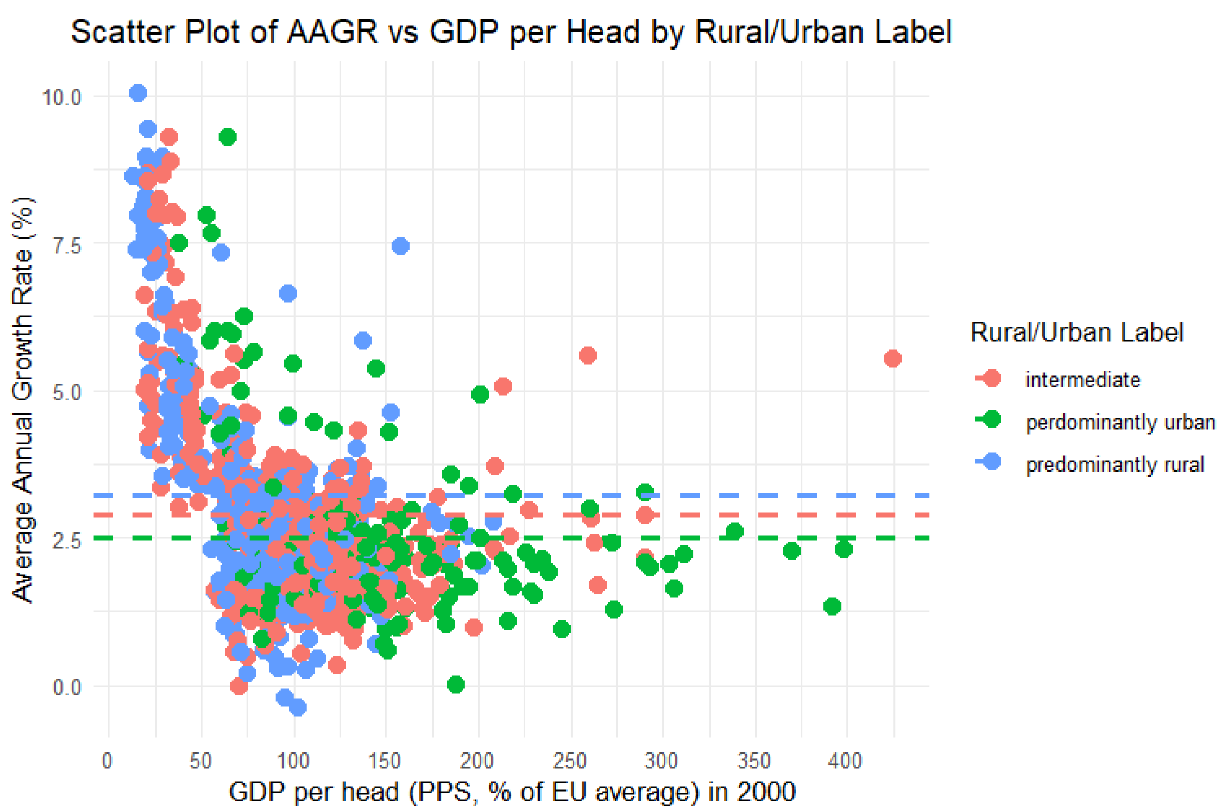


Figure 3 shows the GDP per capita (PPS, as a percentage of the EU average) for predominantly urban, intermediate, and predominantly rural regions over time. Urban regions lead consistently in GDP per head, while rural regions lag behind with modest improvements over time. Intermediate regions remain closer to the EU average. The figure suggests that despite the signs of convergence, there is still a large gap between the two types of regions. It also suggests that the convergence observed in Figure 1 may relate to each type of region: e.g. poorer urban (rural) regions may be converging towards richer urban (rural) regions.

Figure 3. GDP (PPS) over time by rural – urban typology, as a percent of EU average

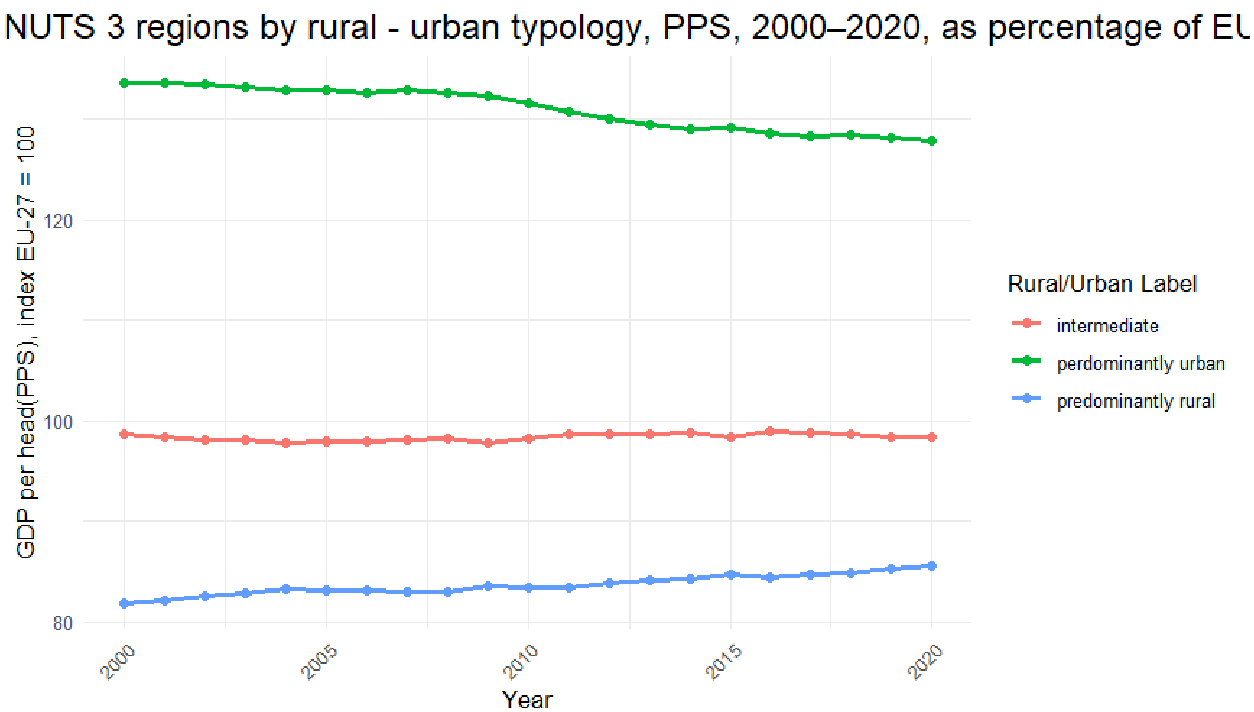
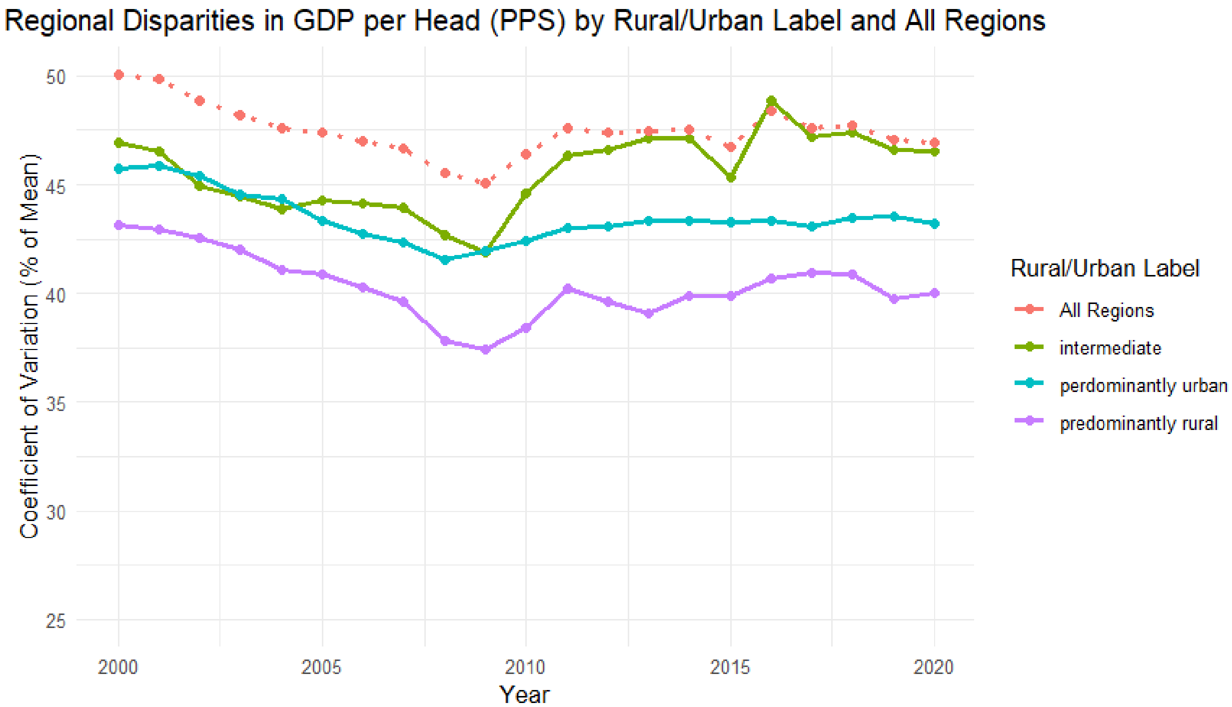


Figure 4 provides a partial answer to that question. It shows the coefficient of variation (CV) of GDP per head across urban, rural, intermediate, and all regions. From 2000 to 2008, disparities declined within regions in all three categories, with rural regions experiencing the most significant reduction, indicating economic convergence and catch-up of poorer rural areas. However, after the 2008 financial crisis, disparities stagnated or slightly increased, particularly in rural and intermediate regions, reflecting uneven recovery patterns, and suggesting that the convergence may be within groups of regions (rural, urban and intermediate) rather than between groups. Urban regions maintained relatively stable disparities, showing resilience to divergence. Overall, intermediate regions consistently had the highest disparities, while rural regions showed the lowest disparities, reflecting more uniform but lower economic performance.

Figure 4. Coefficient of variation of GDP per capita (PPS) over time – overall and by rural – urban typology



The scatter plot in Figure 5 shows the beta convergence for NUTS 3 regions in the EU from 2000 to 2020. It plots the log of initial GDP per capita in 2000 (x-axis) against the annual average growth rate of GDP per capita between 2000-2020 (y-axis). The red regression line represents the overall trend of convergence. The negative slope confirms the presence of beta convergence: regions with lower initial GDP per head in 2000 (on the left side of the x-axis) tend to exhibit higher average growth rates (higher points on the y-axis), while regions with higher initial GDP per head (on the right side) grow more slowly. However, there is significant variation in growth rates across regions, even for those with similar initial GDP per capita.

Figure 6 plots the same relation for different types of regions. We observe within group convergence for all three groups of rural, intermediate, and urban regions. Rural regions show the steepest negative slope (strongest convergence), and urban the flattest (weakest convergence). Again, this may be because higher income rural regions have grown less.

Figure 5. Overall Beta convergence for EU 27 NUTS 3 regions

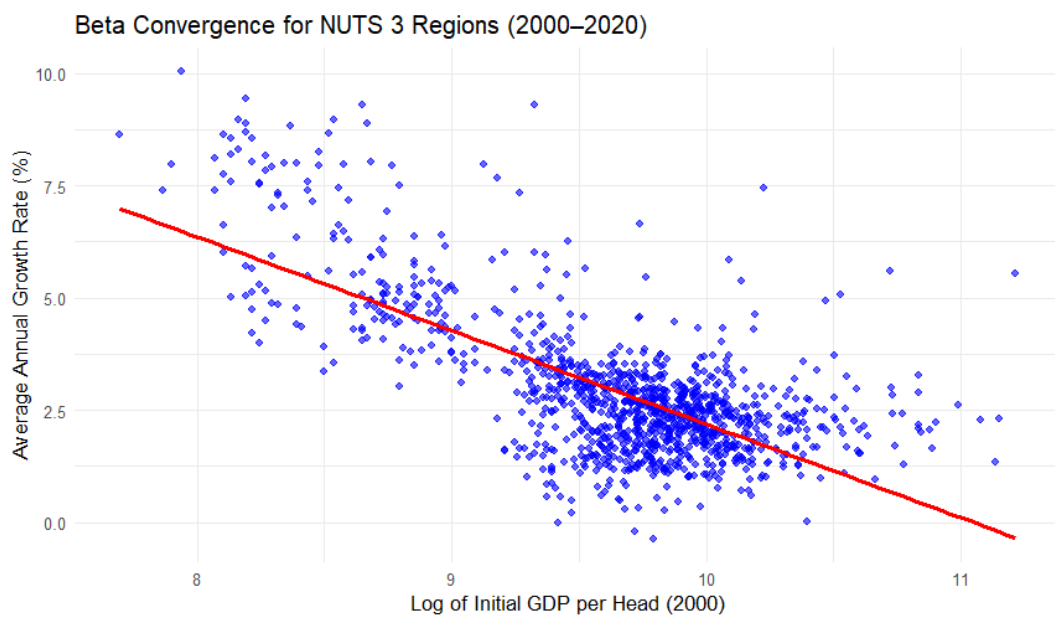


Figure 6. Beta convergence for EU 27 NUTS 3 regions by rural – urban typology

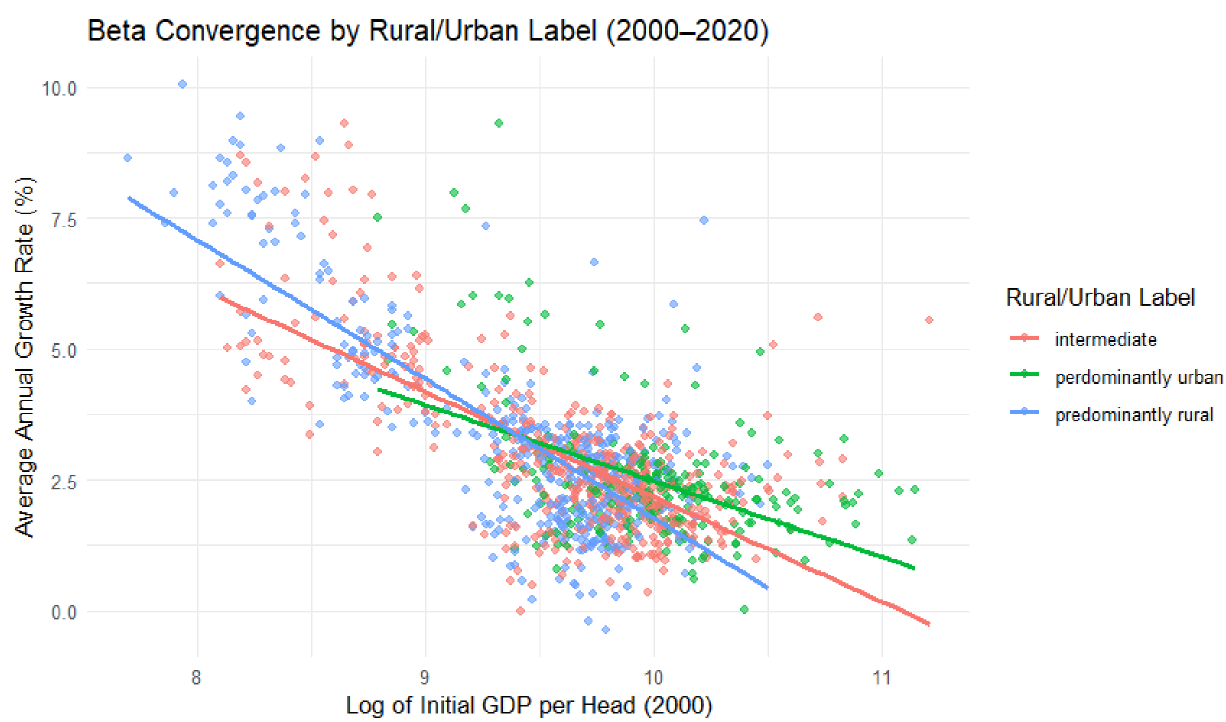


Table 2 reports results for the absolute regional convergence regression. The regression tests the relationship between average annual GDP growth (AAGR) and the log of initial GDP per capita (log_initial_gdp), accounting for rural/urban typologies, with urban regions as the reference category. The model explains 51.28% of the variation in GDP growth (Adjusted R-squared = 0.5128) and confirms beta convergence: regions with lower initial GDP grow faster. For urban regions, a 1% higher in initial GDP per capita is associated with a 1.45 percentage point decrease in growth (log_initial_gdp coefficient = -1.4476, p < 0.001). Intermediate regions grow 5.23 percentage points faster than urban regions (coefficient = 5.2269, p = 0.009), while predominantly rural regions grow 11.34 percentage points faster (coefficient = 11.3431, p < 0.001). Interaction terms reveal that the negative relation between initial GDP and GDP growth is stronger for intermediate regions by 0.55 percentage points (coefficient = -0.5529, p = 0.006) and for predominantly rural regions by 1.21 percentage points (coefficient = -1.2052, p < 0.001). These results suggest that urban regions experience weaker diminishing returns and therefore weaker convergence, while poorer rural regions grow faster but face stronger diminishing returns, and therefore faster convergence.

Table 2. Beta convergence model conditional on rural – urban typology

Variable	Estimate	Std. Error	t-value	p-value	Significance
(Intercept)	16.9567	1.7505	9.687	< 2e-16	***
log_initial_gdp	-1.4476	0.1753	-8.258	4.11e-16	***
Intermediate	5.2269	1.9846	2.634	0.00856	**
Predominantly rural	11.3431	2.0096	5.644	2.09e-08	***
log_initial_gdp: Intermediate	-0.5529	0.2003	-2.761	0.00586	**
log_initial_gdp: Predominantly rural	-1.2052	0.2040	-5.909	4.54e-09	***

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.14 on 1131 degrees of freedom
Multiple R-squared: 0.5149
Adjusted R-squared: 0.5128
F-statistic: 240.1 on 5 and 1131 DF, p-value: < 2.2e-16

3.2 Core and peripheral regions

As mentioned in the methodology, we identified clusters representing knowledge blocks based on between and within regions citations and place-based regional groups. Using those clusters, we build a 2X2 matrix that allows us to identify different regional clubs, and to identify the rural – urban typology within each club.

3.2.1 Knowledge blocks

We identified seven knowledge blocks applying the Louvain algorithm to citations. Table 3 shows the block identifiers, and their total contributed centrality. We defined as core the blocks with total centrality above 0.14, which is the average centrality.

The analysis shows regional clusters and varying levels of centrality and concentration. Core blocks (1, 6, 5) have higher centrality scores and are often dominated by a single country, with the exception of block 3: Block 1 is predominantly German regions (91.5%), Block 5 is French-centric (93.8%), while Block 6 features a more diverse Southern-Eastern European cluster led by Italy (55.7%). In contrast, periphery blocks are more balanced in their regional distributions, such as the Nordic-Baltic focus of Block 4 (Sweden-Finland-Denmark) and the Netherlands-Belgium link in Block 7. The composition of the blocks shows that core blocks tend to be dominated by one or two influential countries (e.g., Germany, France). Periphery blocks are slightly more balanced in terms of the percentage of regions from each represented country. As expected, this structure highlights the dominance of larger, higher income countries in core blocks producing and using more knowledge and innovation, while smaller countries cluster in periphery groups.

Table 3. Knowledge blocks identified through citations between NUTS 3 regions, using the Louvain community algorithm

Knowledge block	Total Centrality	Number of countries	Number of NUTS 3 regions	Composition of the block	Classification
1	0.26732032	4	76	DE (91.5%), AT (8%), BE (0.3%), HU (0.3%)	Core
6	0.1782618	14	183	IT (55.7%), EL (20.8%), HR (8.7%), BG (7.1%), DE (1.1%), FR (1.1%), HU (1.1%), LT (1.1%), BE (0.5%), CY (0.5%), EE (0.5%), ES (0.5%), FI (0.5%), MT (0.5%)	Core
5	0.16956059	4	96	FR (93.8%), BE (3.1%), DE (2.1%), PL (1%)	Core
7	0.1138985	6	79	NL (49.4%), BE (40.5%), DE (6.3%), BG (1.3%), HU (1.3%), LU (1.3%)	Periphery
4	0.10649912	12		SE (29.2%), FI (25%), DK (13.9%), IE (11.1%), DE (5.6%), EE (4.2%), IT (2.8%), PL (2.8%), AT (1.4%), BG (1.4%), LV (1.4%), RO (1.4%)	Periphery
2	0.088573	7	85	ES (62.4%), PT (28.2%), BG (2.4%), DE (2.4%), FR (2.4%), BE (1.2%), HR (1.2%)	Periphery
3	0.07588667	11	167	PL (41.3%), RO (16.8%), HU (9.6%), CZ (8.4%), SI (7.2%), SK (4.8%), LT (4.2%), LV (3%), DE (2.4%), BG (1.2%), HR (1.2%)	Periphery
Total	**1**	27	1,058		

* AT = Austria; BE = Belgium; BG = Bulgaria; CY = Cyprus; CZ = Czechia; DE = Germany; DK = Denmark; EE = Estonia; ES = Spain; FI = Finland; FR = France; GR = Greece; HR = Croatia; HU = Hungary; IE = Ireland; IT = Italy; LT = Lithuania; LU = Luxembourg; LV = Latvia; MT = Malta; NL = Netherlands; PL = Poland; PT = Portugal; RO = Romania; SE = Sweden; SI = Slovenia; SK = Slovakia. Core = above 0.14 centrality

3.2.2 Place-based clusters

Table 5 reports the result of the PAM clustering using the innovation and economic performance indicators. Regions in cluster 2 are high performers in both employment and innovation. They have higher employment contributions overall and in knowledge-intensive sectors, as well as significantly higher innovation output (patents and publications). Cluster 1 is more geographically diverse, encompassing a larger number of regions and countries, while Cluster 2 is more concentrated, with German regions dominating the cluster.

Table 5. Clusters and averages in their variables

Cluster	Contribution to employment	Contrib to Employment in specific sectors	Patents per million pop	Pubs per capita	Patents per million p in High-Tech	Number of NUTS 3 regions	Number of countries	Composition of the cluster
1	0.000475593	0.000590853	45.87128	0.02818113	3.724841	866	26	DE (20.3%), IT (11.8%), FR (9.9%), PL (8.3%), ES (6.7%), EL (6%), RO (4.8%), BE (4.3%), BG (3.2%), NL (3.2%), PT (3%), HR (2.4%), HU (2.3%), AT (2.1%), CZ (1.6%), FI (1.6%), SE (1.6%), SI (1.4%), LT (1.2%), SK (0.9%), IE (0.8%), DK (0.7%), LV (0.7%), EE (0.6%), MT (0.3%), CY (0.1%)
2	0.001873046	0.001551854	345.69703	0.10561333	23.279008	314	14	DE (71.7%), AT (5.7%), FR (4.8%), NL (4.1%), IT (2.9%), BE (2.5%), SE (2.5%), DK (1.9%), FI (1.9%), ES (0.6%), HU (0.3%), IE (0.3%), LU (0.3%), PL (0.3%)

3.2.3 Urban-rural representation in regional clubs

Based on the two clustering exercises, we identify four clubs of regions.

Core-Core regions: these are regions at the core of the knowledge network, and which have a stronger innovation and economic performance. I.e. regions that produce and/or source scientific knowledge to/from others and capture the benefits of those exchanges.

Core-Periphery regions: these are regions at the core of the knowledge network, but which have weaker innovation and economic performance. I.e. regions that produce and/or source scientific knowledge to/from others, but do not capture the benefits of those exchanges (e.g. they produce knowledge for others).

Periphery-Core regions: these are regions at the periphery of the knowledge network, but which have a stronger innovation and economic performance. I.e. regions that produce and/or source little scientific knowledge to/from others, but which have their own capabilities to innovate and generate employment in high tech sectors.

Periphery-Periphery regions: these are regions at the periphery of the knowledge network, and which also have a weaker innovation and economic performance. I.e. regions that produce and/or source little scientific knowledge to/from others, and do not have their own capabilities to innovate and generate employment in high-tech sectors.

Table 6 reports the urban-rural composition of those four regional clubs. Core-Core regions concentrate 37% of urban areas, 22.3% of intermediate areas, and 10.6% of rural areas, while Core-Periphery regions are more balanced, concentrating 28% of urban areas, 36.4% of intermediate areas, and 36.9% of rural areas. Periphery-Core regions concentrate 10.6% of urban areas, 6.3% of intermediate areas, and 3.8% of rural areas, whereas Periphery-Periphery regions concentrate 24.3% of urban areas, 35% of intermediate areas, and 48.7% of rural areas.

Urban areas are primarily concentrated in Core-Core and Periphery-Core clusters, intermediate areas act as bridges across clusters, and rural areas dominate the least integrated and lowest-performing clusters, suggesting disparities in access to knowledge networks and innovation opportunities.

Table 6. A typology of regions to identify clubs

		Rural Urban typology				
Knowledge blocks	Place-based regional groups	Predominantly rural	intermediate	Predominantly urban	Not in a knowledge block	Total
Core	Core	42	113	87	0	242
Core	Periphery	146	184	66	17	413
Periphery	Core	15	32	25	0	72
Periphery	Periphery	193	177	57	26	453
Total		396	506	235	43	1180

3.3 Club convergence

3.3.1 Within club convergence

Figures 7 and 8 illustrate the relationship between GDP per capita (as a percentage of the EU average in 2000) and the Average Annual Growth Rate (AAGR) across regions conditional a region pertaining to one of the four knowledge block and place-based “clubs.” This is superimposed to the absolute convergence (grey dots). The scatter plots reveal distinct economic growth patterns based on rural, urban, and intermediate classifications, by club.

First, as expected, we observe convergence among regions in the periphery place-based clusters, but not in the core ones, which are the higher performing regions.

Second, we also observe that among those more performing regions there is a wider difference among regions with respect to their GDP in 2000. The cluster of regions with lowest dispersion is the Periphery-periphery.

Third, combining the first two points, differences among the high performing regions tend to widen. As the rural regions are those with lowest GDP per capita in 2000, this also suggests that the few rural, high performing regions do not use the higher innovation capabilities and employment in high tech sectors to produce/consume more. This result may be related to the pattern of specialization of these different regions and indeed to the population.

Fourth, although rural regions in Periphery-Periphery areas show the highest growth rates, many remain below the EU average GDP per capita. Intermediate regions exhibit a mix of characteristics, often bridging the gap between urban and rural areas. They are more dispersed in terms of GDP per capita and growth rates. It can also be seen that belonging to a club affects the growth patterns of regions by their rural / urban characteristics.

Fifth, in the mixed clubs (Core-Periphery and Periphery-Core) there is no difference between the rural and urban regions in terms of growth performance between 2000 and 2020 observed in Figure 1. That is, regions' potential to growth is more homogenous. To understand why this is the case needs further investigation

Figure 7. GDP growth vs GDP per capita by clubs and rural urban typology

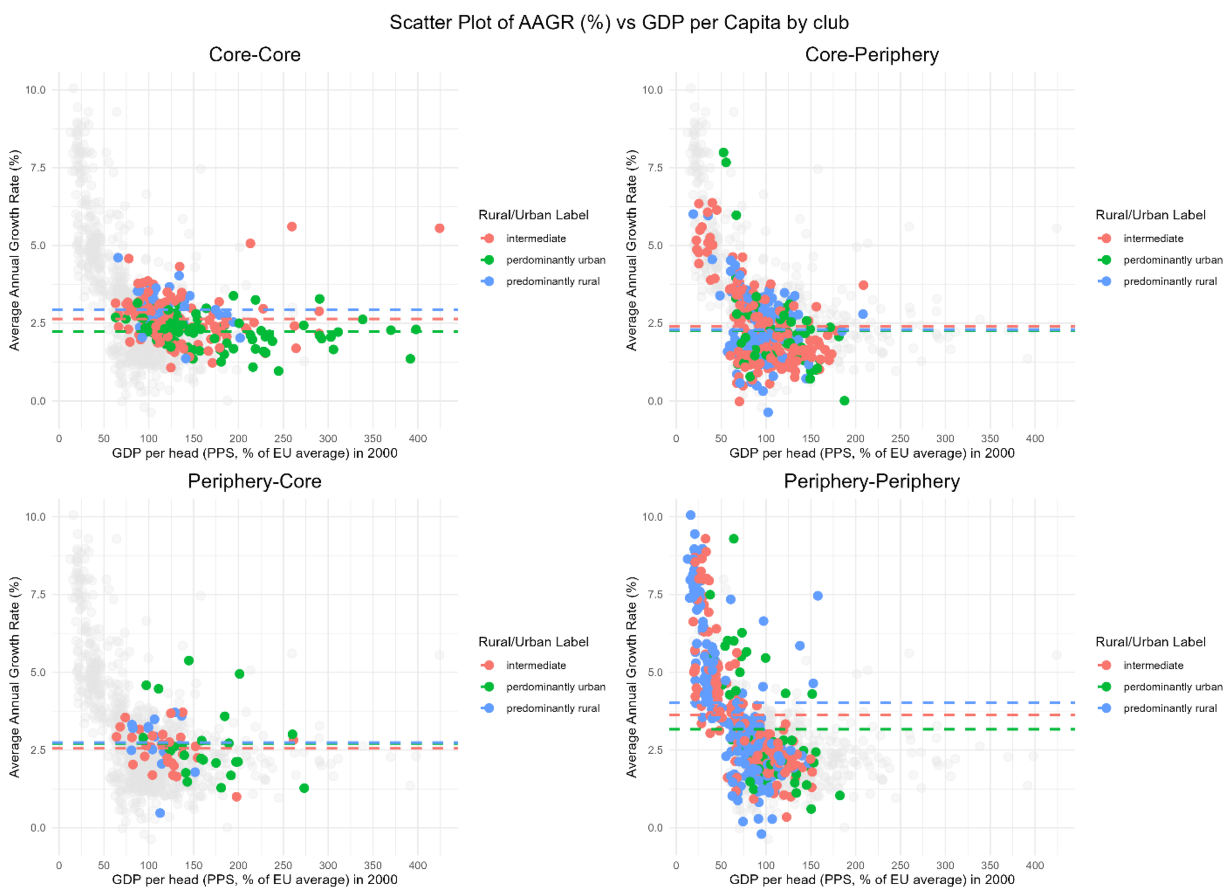
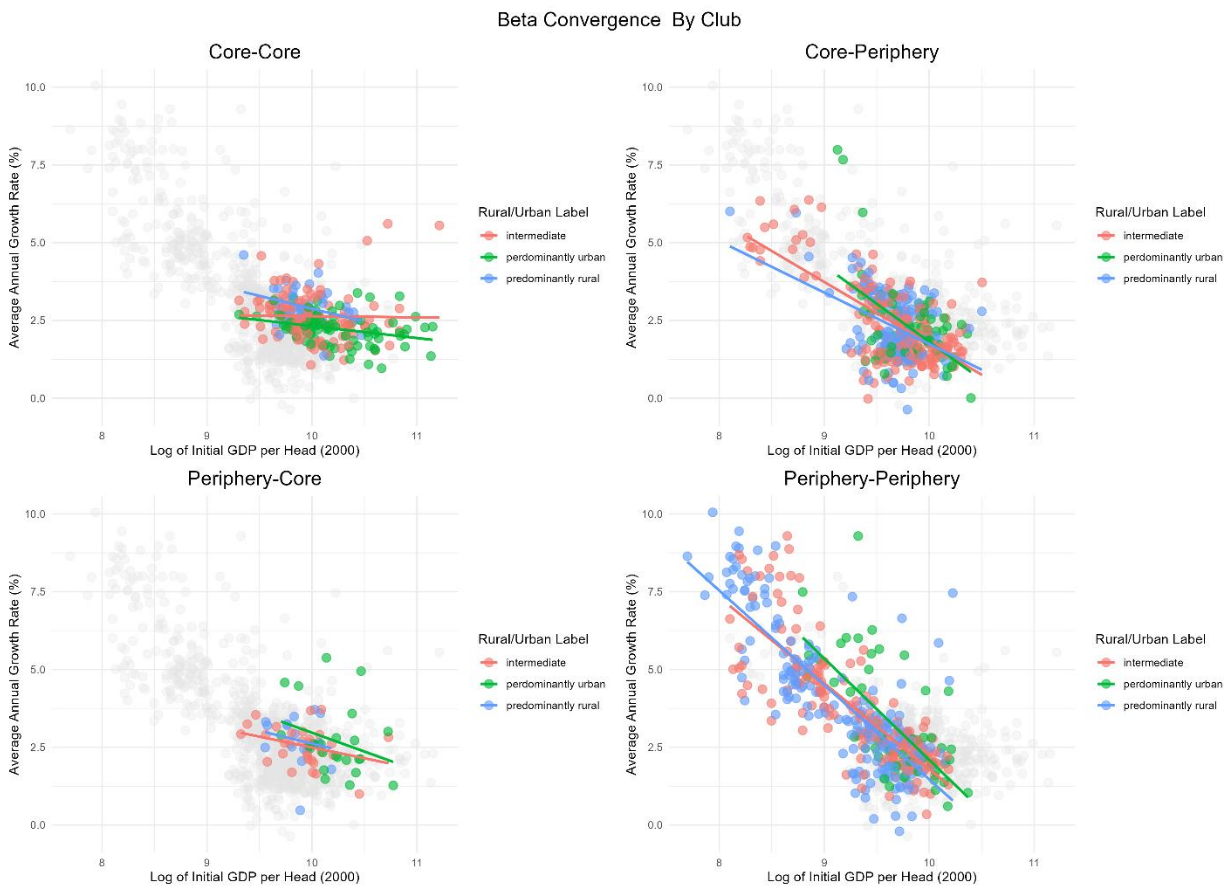


Figure 8. Beta convergence by club



3.3.2. Inter-club and within-club convergence models

Annexes 1, 2, and 3 have the regression results for:

(1) overall inter-club convergence.

(2) within-club convergence (4 regressions) for each of the four clubs examining convergence between rural, intermediate and urban.

(3) within-club convergence, examining rural urban typology and regional area (southern, north-western, and eastern).

The model in (1) confirms patterns of absolute convergence across European regions, as evidenced by the negative and statistically significant coefficient for initial GDP (-0.028***). This indicates that poorer regions tend to grow faster than richer ones. However, this convergence rate varies significantly between the defined clubs: Core-Core, Core-Periphery, Periphery-Core, and Periphery-Periphery. The Periphery-Periphery regions exhibit the fastest convergence, benefiting from the strongest catch-up effects, while the Core-Core regions converge the slowest. Specifically, the coefficients for the club categories show that, relative to the Periphery-Periphery regions (the omitted category), Core-Core regions have a significantly lower growth rate (-0.230***), as do Core-Periphery (-0.090***) and Periphery-Core (-0.214***) regions. Additionally, the interaction terms between initial GDP and these club categories reveal interesting differences in how convergence unfolds. For example, the positive and statistically significant interaction term for Core-Core regions (0.024***) indicates that convergence is slower for richer Core-Core regions compared to poorer ones, reflecting the diminishing returns to growth in these highly developed areas. Similarly, Core-Periphery (0.009***) and Periphery-Core (0.022***) regions also show slower convergence for richer areas.

The second set of models in (2) examines the convergence dynamics within each club by distinguishing between urban, intermediate, and rural regions. Across all clubs, absolute convergence remains, as indicated by the negative and statistically significant coefficients for initial GDP: -0.004** for Core-Core, -0.024*** for Core-Periphery, -0.012* for Periphery-Core, and -0.033*** for Periphery-Periphery. These coefficients confirm that poorer regions grow faster than richer ones, with the fastest convergence occurring in the Periphery-Periphery club and the slowest in the Core-Core club. However, when differentiating between rural, intermediate, and urban classifications, the results show no significant differences in growth rates within the clubs.

The third set of models in (3) incorporates geographic areas such as Eastern EU and North-Western Europe into the analysis, providing additional insights into how location influences convergence dynamics within each club. Absolute convergence remains, with negative and statistically significant coefficients for initial GDP in most clubs: -0.004** for Core-Core, -0.014*** for Core-Periphery, and -0.026*** for Periphery-Periphery, though it is not significant in Periphery-Core (-0.007). These results confirm that poorer regions grow faster than richer ones, with the Periphery-Periphery club again exhibiting the fastest convergence and the Core-Core club the slowest. The inclusion of geographic variables reveals important regional effects. In the Core-Periphery club, Eastern EU regions grow faster than others (0.032***), as do Eastern EU regions in the Periphery-Core (0.024***) and Periphery-Periphery (0.013***) clubs, highlighting catch-up effects in these regions. Similarly, North-Western Europe shows significant positive effects in Core-Core (0.010***) and Core-Periphery (0.011***) clubs, reflecting advantages of these regions. Despite these geographic effects, the differentiation between urban, intermediate, and rural regions continues to show no significant differences in growth rates within clubs. For example, in the Periphery-Core and Periphery-Periphery clubs, the coefficients for intermediate (-0.003 and -0.056, respectively) and predominantly rural regions (0.011 and -0.025, respectively) are not statistically significant. In the Core-Periphery club, intermediate (-0.090***) and rural (-0.072*) regions grow slower than urban ones, but the interaction terms between initial GDP and rural or intermediate classifications are insignificant, indicating that convergence rates do not meaningfully differ by rural-urban classification.

4. Conclusions and future work

In this document we have provided an analysis of innovation clubs in Europe with a focus on the rural / urban classification at the NUTS 3 level. Some of the key results are:

Innovation Club Structures

The analysis identifies innovation clubs among European regions using a combination of network analysis and clustering techniques. After identifying core and periphery regions based on i) cluster variates measuring region's economic contribution and ii) centrality of regions in knowledge exchange networks, we created four clubs reflecting the affiliation of regions across the two possible core-periphery classifications. This resulted in four innovation clubs: Core-Core, Core-Periphery, Periphery-Core, and Periphery-Periphery.

Core regions—often dominated by economically powerful countries such as Germany, France, and Italy—exhibit high centrality in knowledge exchange, while peripheral clusters tend to be slightly more balanced in their composition. However, in all clubs there are one or two countries that dominate in terms of their percentage of regions included.

Evidence of convergence with heterogeneity

Overall regional growth patterns demonstrate beta convergence: regions with lower initial GDP per capita (mainly rural areas) tend to grow faster than richer regions.

However, convergence is not uniform. Urban regions with very high initial GDP tend to show lower growth rates, and convergence seems to occur primarily within similar "clubs" (e.g., rural to rural or urban to urban) rather than across all regions. Along the core-periphery axis, Core-Core regions do not show convergence. Strongest convergence dynamics tend to emerge in regions that are peripheral in terms of economic performance, but not for regions at the periphery of the knowledge network.

Core-Periphery Structures and Geography Outweigh Rural-Urban Differences in Shaping Regional Growth

Aggregate analyses reveal that poorer rural regions grow faster and encounter stronger diminishing returns compared to urban regions. On the other hand, within-club convergence regressions show that the rurality of regions ceases to explain regional growth dynamics after accounting for the core-periphery club membership of regions, indicating that rurality has a strong connection to the centrality of regions in innovation networks and are affected by the European area in which networks are located. These findings suggest that, within each club, convergence dynamics are largely uniform across rural, intermediate, and urban regions and are instead more influenced by structural and geographic factors. The faster growth of rural and intermediate regions observed in aggregate analyses is likely driven by the predominance of rural areas in the Periphery-Periphery club, rather than by their rurality itself.

Spatial Heterogeneity and the Role of Geography

When geographical areas (e.g., Northern, Southern, Eastern, North-Western Europe) are taken into account, the convergence patterns become more nuanced.

The interactions between club membership, geographic location, and rural–urban classification indicate that regional dynamics are spatially heterogeneous—underscoring the need for policies that are tailored to local conditions.

Robustness and Future Directions

Our results are preliminary, and we are in the process of increasing their robustness through testing alternative definitions of clubs, different convergence indicators, and various model specifications (including the inclusion/exclusion of control variables and geographical area dummies).

Future work

We will focus on further improving the measurement of place-based innovation capabilities by extending the analysis to include all dimensions of the Input–Output (I–O) framework and exploring indicators to understand technology/innovation convergence. As our aim is to characterize regions based on a comprehensive Input-Output framework, distinguishing between rural and urban regions, we seek to assemble a variety of indicators at the NUTS3 level to identify each component of the I-O framework. We have identified suitable indicators in 1) the Ardeco database, a comprehensive database that offers indicators on regional GDP, Capital formation, Capital stock, Domestic product, Employment, Labour costs, Labour productivity, Population, and vital statistics. 2) the JRC Rural Observatory, which offers similar indicators and adds energy and climate, infrastructure and accessibility, and tourism. 3) Eurostat, which adds indicators on agriculture, forestry, and fisheries, Industry, trade, and services, population and social conditions, science and technology, and transport. 4) REGPAT offers information on the number of patent applications to EPO by NUTS3. 5) Meta's social connectedness index, which is a calculation of Facebook exchanges between NUTS3.Because some of these indicators take more time to get access to, we have constructed our main variables on indicators that are available and that we can work with to aggregate at the NUTS3 level. However, we expect to include all the data sources listed here to increase the comprehensiveness of our identification of the input-output framework and how it relates to convergence.

Finally, the preliminary results included in this draft have highlighted a strong analogy between urban-rural and core-periphery dynamics. In further steps of the analysis, we will explore more in depth the core-periphery dynamics of rural and urban regions separately (including analyzing more in depth the characteristics of rural vs urban NUTS 3 regions), in order to assess the extent to which core-periphery dynamics emerge also within rural or urban groups, and to evaluate its usefulness to further qualify the innovation potential of rural regions.

7. References

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Annexes

model 1. https://drive.google.com/file/d/1Ifi3u6BobtrZuFlDlTlb0_oqa7cy6oOJ/view?usp=sharing

model 2.
https://drive.google.com/file/d/19afq1zqk9v6BegAkQzAirFL_1AcMOWcV/view?usp=drive_link

model 3.
https://drive.google.com/file/d/1AJP842aUPxlbE8JuEeHdmtWMIQ9jLFMo/view?usp=sharing