The analysis of stability in the EU convergence clubs by using Poincaré plot features

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This study aims to examine the applicability of the Poincaré plot to economic convergence and demonstrate that the new instability indicator proposed in the study complements the assessment of convergence at average growth rates. We investigate the convergence of NUTS 2 regions over the last decade by applying a novel approach. Using Poincaré plots in the assessment of regional convergence, the analysis goes beyond the speed of GDP growth to include its stability. Cluster analysis is also used to identify groups of regions with similar growth patterns, adding to the empirical illustration. The results reveal that there is convergence, with less prosperous regions generally experiencing higher growth. Further, growth in richer regions is less stable, although it is not statistically significant. The results also reveal that convergence is complex and that its analysis requires a multidimensional approach. The proposed measure of instability (based on the Poincaré plot and related methodology) and the cluster analysis based on growth dynamics can help policymakers to support more stable convergence. The conclusions nuance our knowledge of regional convergence, as obtained using the methodology already employed in previous studies.

Introduction

Economic convergence is a key concept in the growth theory that provides a framework for understanding the process through which poorer economies tend to catch up with richer ones over time. Measuring convergence is not only a "l'art pour l'art" practice in economics but also has been a topic at the forefront of economic policy and academic research in the European Union (EU) for decades. In the ever deepening and growing Europe, whether economic (and social) convergence or coshesion[1] between members is improving has always been an interesting and important practical issue. There is also an explicit policy aimed at reducing disparities in the EU, which used to be called regional policy but is now called cohesion policy.[2]

Although it has been 30 years since the launch of the Single Market project and the strengthening of the regional and cohesion policy and more than 20 years after the 2004 enlargement, the issue of regional disparities is still recurring. The 9th Cohesion Report (EC 2024a) stated that disparities are becoming more persistent: "… many parts of Europe have experienced a remarkable upward economic and social convergence. However, socio-economic disparities persist and a growing number of regions risk facing new challenges" (EC 2024a: p. 13). A document published by the High-Level Group on the Future of Cohesion Policy in February 2024, a few days before the 9th Cohesion Report (EC 2024b), also noted that "This extended period of relative economic underperformance over the last 15–20 years of EU life has been accompanied – and to some extent exacerbated – by increasing polarization within countries. Economic activity has become increasingly concentrated in a few dynamic areas, which tend to coincide with large urban agglomerations and national capitals. However, many regions have been left behind and are often trapped in long periods of underdevelopment from which it is difficult to recover" (EC 2024b: p. 8).

The above findings highlight the challenges of the regional convergence process in the EU. However, how lagging regions can catch up or how best to support their development is still uncertain. Moreover, when and how different regions will react to shocks, especially in the current crisis-prone environment, is unclear. Convergence testing plays a crucial role in determining whether market forces will naturally drive territorial units toward a common path or whether policy intervention is needed to prevent regions from falling into development traps[3]. Therefore, convergence testing

[1] Cohesion is a broader term than convergence. While convergence focuses on economic indicators (e.g., GDP per capita), cohesion includes social and territorial dimensions, such as infrastructure, employment, and quality of life. Cohesion is a broader policy-driven concept that aims to reduce economic, social, and territorial disparities between regions. The EU's Cohesion Policy is one of its main financial and strategic tools to promote balanced development and solidarity between regions.

[2] For a note on the differences between regional policy and cohesion policy, see Nagy–Heil (2013), Sielker et al. (2021), and Fratesi (2025).

[3] Due to the 2008/09 and post-2020 crises, EU Cohesion Policy has often placed greater emphasis on competitiveness than reducing regional disparities (see McCann–Ortega-Argiles 2021).

is essential even in times of external shocks. However, it is challenging for traditional convergence tests to incorporate changing trends and the impact of crises into their methods.

This article aims to use a new method – the Poincaré method – to test whether there is convergence among the EU NUTS 2 regions in this crisis-ridden period and determine the homogeneous groups or convergence clubs that can be identified. The following research questions are answered: (1) is there absolute convergence between the member states of the EU? (2) Is there dynamic convergence between NUTS 2 regions in a country and the EU as a whole? (3) How can the NUTS 2 regions be grouped into more homogeneous convergence clubs?

Theoretical background

Solow (1956) proposed that the convergence of countries to the same level of income is caused by the diminishing marginal product of capital. This phenomenon is called absolute or unconditional convergence (Barro 1991, Barro–Sala-i-Martin 1992), which statistically implies a negative and significant relationship between growth rate and initial income. However, long-run steady-state income depends not only on capital accumulation but also on productivity, which depends on institutions, infrastructure, and human capital (Baumol 1986, Galor 1996). These are the main determinants of long-run economic growth.[4]

Overall, no evidence of *absolute convergence* in income levels has been found around the world[5]; however, some convergence can be observed by considering smaller homogeneous groups, such as the Organisation for Economic Co-operation and Development (OECD) countries or the member states of the United States (Barro 1991). The countries of the EU, especially the regions in a country, can also be considered as homogeneous groups (Sala-i-Martin 1996). The basis for homogeneity can be found in the quality of institutions and economic policies (Mankiw et al. 1992). Countries with different levels of institutional quality converge to different steady-state GDP per capita (Young et al. 2008). This concept is known as *conditional convergence*, and from this logic, it is possible to derive group convergence.

In the literature, two common approaches to analysing this process are β-convergence and σ-convergence. *β-convergence* examines whether less developed regions or countries experience faster growth rates than their wealthier counterparts, thereby reducing income disparities. The widely used technique, "growth-initial level

[4] In this study, the determinants were not discussed in detail. The focus was solely on the change in real GDP per capita, ignoring factors such as GDP per worker, industrial production, convergence in total factor productivity, or nominal convergence in inflation rates, interest rates, budget deficit, and debt-to-GDP ratio. The notion of institutional convergence was also not explained in this study. A comprehensive literature review on all the above convergence processes was conducted by Glawe–Wagner (2021).

[5] There are some exceptions. For example, using the most recent data, some studies have found evidence of absolute convergence at the global level over the last 20 years (see Patel et al. [2021] and Kremer et al. [2022]).

regression", was developed to determine the negative correlation between the base-year income variable and the subsequent growth rate. The name of this convergence was derived from the coefficient of the initial income variable in these regressions (beta [β]) (Islam 2003). However, σ-convergence focuses on the overall dispersion of income levels and assesses whether economic inequality across regions is decreasing.

The β-convergence model is not dynamic. Compared to studying the full dynamics of the convergence process, it is a simplified approach as it uses only the initial and final income of a period (Piras–Arbia 2007). Quah (1996) noted that the β-convergence and σ-convergence models study a relatively static situation, so a dynamic approach is needed.

A review of the convergence literature reveals several different methods used to assess convergence. According to Islam (2003), there are five different methods – informal cross-sectional approach, formal cross-sectional approach, panel approach, time series approach, and distributional approach. Islam (2003) also explained the specifications of the *initial cross-sectional studies*' growth-initial level regressions, which are not formally derived from theoretical growth models. Although these studies were not formally driven, they are linked to growth theories. The most famous initial study on unconditional convergence was by Baumol (1986), who studied 16 OECD countries and found strong evidence of unconditional convergence. An example of the *formal cross-sectional estimation of β-convergence* across subnational regions is the study conducted by Sala-i-Martin (1996). He examined convergence for the regions of the United States (48 contiguous states), Canada (10 provinces), Japan (47 prefectures), and 5 European states (90 regions). Evidence of β-convergence was found among the 90 EU regions (Sala-i-Martin 1996).

The *distributional approach* to income convergence focuses on how the entire distribution of regional incomes evolves, rather than just measuring average trends (Quah 1996). Unlike traditional β-convergence and σ-convergence, which assess whether poorer regions are catching up with richer ones in aggregate terms, distributional methods analyse the dynamics of income distribution in a larger economic unit (e.g., the EU). Key techniques include Markov chains, which model the probability of regions transitioning between income classes (Le Gallo 2004, Monfort 2020), and stochastic kernels, which visualize how the density function of income levels shifts over time. This approach allows researchers to detect club convergence, where only certain groups of regions converge, persistent inequalities, and polarization trends, which are important insights that are often missed by standard regression-based methods (Eckey–Türck 2006). Club convergence refers to the phenomenon where groups of countries or regions with similar initial conditions or structural characteristics converge to the same steady-state, but different groups converge to different steady states (Quah 1996, Alexiadis 2013, Egri et al. 2024).

A more recent literature used spatial and regional methods in income convergence studies to account for geographic dependencies and spatial autocorrelation among regions. These methods include spatial econometrics, such as spatial lag and spatial error models, which help to capture spillovers and regional interdependencies (Le Gallo–Dall'erba 2008). Some studies measured spatial autocorrelations in income levels (Piras–Arbia 2007, Arbia et al. 2010) and applied spatial panel data models to analyse regional convergence in the EU, highlighting significant spatial heterogeneity (Isla-Castillo et al. 2024).

Regarding club convergence in NUTS 2 regions in the EU, the following authors came to quite different conclusions: Canova (2004), Fischer–Stirböck (2006), Ramajo et al. (2008), Bartkowska–Riedl (2012), Von Lyncker–Thoennessen (2017), Cartone et al. (2021), and Harb et al. (2024). Some demonstrated convergence and others divergence for different periods.[6] Although they recognized the presence of convergence clubs, they did not consider their growth dynamics.

Convergence stability studies are not frequently encountered in the literature on regional growth but can be found in the literature on other economic issues. For instance, Bethlendi (2024) employed the return-risk dimensions of the Markowitz portfolio theory to analyse growth and stability. Growth represents return, and its standard deviation represents instability. The national economy as a whole is obtained as a portfolio of economic sectors. A mean-variance efficient frontier may be constructed, where the chosen position (i.e., the risk-reward trade-off) is a matter of economic policy preference. Our study aims to measure stability, and while it does not examine growth at the sectoral level, it provides an additional dimension of stability or instability by using indicators based on the Poincaré plot.

Others proposed general convergence indicators (GCIs) at national and subnational levels. For example, Kertész (2014) considered the dispersion of GDP data at national and NUTS 3 regional levels. GCIs can be used to quantify the trade-off between national and regional convergence. While Kertész (2014) considered the dispersion across regions in a national economy, our proposed index of instability is primarily designed to describe growth patterns[7].

If a region is experiencing some growth, its growth path may be extremely volatile or flat. This problem has been addressed by calculating all annual growth rates and using the Poincaré method to determine the long- and short-run effects. To the best of the authors' knowledge, the Poincaré (1892) plot has not been used in finance and economics literature in this way, so the primary goal of this study is to examine the applicability of its features. The authors aim to achieve the following theoretical and practical objectives. First, in addition to the average growth rate, the short- and long-

[6] For a more detailed overview of regional disparities in the EU over the last two decades, see the study by Monfort (2020), which was conducted at three geographical levels – country (NUTS 0), NUTS 2, and NUTS 3. Disparities were assessed using various methods and instruments that are often used in the analysis of economic and social inequalities.

[7] Although this article did not consider the trade-off between national and regional convergence in detail, it is worth examining in future research (see footnote 11 for further comments).

term variability as well as the pattern of the temporal dynamics[8] should be calculated for the GDP per capita data of NUTS 2 regions in the EU. Second, the indices (SD1, SD2, and temporal dynamics) should be used to measure convergence in the NUTS 2 regions of the EU. The visualization of stable or unstable growth and the introduction of a new dimension in the measurement of instability are the main advantages of this method.

Method

Poincaré plot

Poincaré plots have been used primarily in cardiology for studying heart rate variability (R–R intervals). The first study was performed by Woo et al. (1992), and many studies have been published afterward (Kamen et al. 1996, Guzik–Piskorski 2007, Che-Hao et al. 2012). Numerous studies in physiology have reported the use of the method to model changes in heart rate induced by environmental stimuli, such as sleeping, exercising, or smoking (Brennan et al. 2002, Mourot et al. 2004, Burgess et al. 2004, Ping et al. 2009). The Poincaré plot was also used in signal processing (Yuen et al. 2004, Goshvarpur et al. 2011, Goshvarpur–Goshvarpur 2012). In a broader sense, the chaos theory is concerned with quantifying complex nonlinear dynamics that exhibit distinct behavior that is not predictable in the long-term. Lorenz (1963) and May (1976) were the first to describe chaotic systems and introduce the chaos theory to science. Poincaré (1892) was the first to study the chaotic motion in certain mechanical systems, paving the way for the creation of the chaos theory. The Poincaré plot is the geometric representation of data in two dimensions so that any two consecutive values in a time series define the coordinates of the point to be plotted. Tulppo et al. (1996) approximated the points of a Poincaré plot by an ellipse, using the semi-minor axis (2SD1) and the semi-major axis (2SD2) as parameters. Kamen et al. (1996) and Brennan et al. (2001) studied and described the two axes in detail and introduced the concepts of point-to-point (SD1) and total variability (SD2). The SD1 and SD2 descriptors are linear statistics and cannot directly measure nonlinear temporal changes in time series (Brennan et al. 2001). The SD1/SD2 statistics were introduced to address this problem, but they gave mixed results for multiple clusters present in the data (Brennan et al. 2001, Karmakar et al. 2009). Karmakar et al. (2009) introduced a novel descriptor for the Poincaré plot that quantitatively captures the temporal information of the plot. The Poincaré plot and its descriptors can also be used to study nonlinear dynamics of the development of longer time series in economics. Its properties enable the simultaneous study of short- and long-term changes by using different lags. For example, the construction of the

[8] For example, Kertész (2014) referred to growth instability as an average and considered how much it deviates from the average in individual years, either upward or downward. These percentages are corrected by the dispersion of GDP per capita in a given region or country, so he considers short-term fluctuations and long-term trends.

Poincaré plot starts with standardized GDP per capita data ($\vec{x}$) for a NUTS 2 region over N years with a lag of 1, as presented below:

$$\vec{x}=(z_1,\ldots z_N) \tag{1}$$

The points of the Poincaré plot are determined by the following set of ordered pairs:

$P_1(z_1,z_2), P_2(z_2,z_3), \ldots, P_i(z_i,z_{i+1}), \ldots, P_{N-1}(z_{N-1},z_N)$, where $P_i(z_i,z_{i+1})$ is a general point (i = 1,…N − 1). If the values from each consecutive year do not differ significantly from each other, the points should be close to the 45-degree identity line. If the point is above or below the identity line, it implies that there has been an increase or decrease in the next year, respectively. To calculate the measures of the Poincaré plot, two auxiliary vectors are defined with $N-1$ elements as follows:

$$\vec{x}_1=(z_1,z_2,\ldots z_{N-1}) \tag{2}$$

$$\vec{x}_2=(z_2,z_3,\ldots z_N) \tag{3}$$

A general point in the Poincaré plot can now be expressed by using the following two vectors: $P_i(x_{1i},x_{2i})$, where i=1, …, N − 1.

The following notations are introduced for the above vectors:

$$\vec{x}^{+}=\frac{1}{\sqrt{2}}\,|\,\vec{x}_2+\vec{x}_1\,| \text{ and } x_i^{+}=\frac{1}{\sqrt{2}}\,|\,z_{i+1}+z_i\,|\text{, where i = 1, …, N – 1} \tag{4}$$

$$\vec{x}^{-}=\frac{1}{\sqrt{2}}\,|\,\vec{x}_2-\vec{x}_1\,| \text{ and } x_i^{-}=\frac{1}{\sqrt{2}}\,|\,z_{i+1}-z_i\,|\text{, where i = 1, …, N − 1} \tag{5}$$

where x_i^{+} and x_i^{-} represent the coordinates of the i-th point on the Poincaré plot with respect to the rotated axes, that is, the identity line and the line perpendicular to it. Therefore, $\vec{x}^{+}$ and $\vec{x}^{-}$ represent the vectors of the first and second coordinates with respect to the identity line and perpendicular line, respectively.

Using the above vectors, two main values can be calculated to describe the points of the Poincaré plot:

$$SD1^2=\frac{\sum_{i=1}^{N-1}\left[x_i^{-}-m(x^{-})\right]^2}{N-1} \text{ and } SD2^2=\frac{\sum_{i=1}^{N-1}\left[x_i^{+}-m(x^{+})\right]^2}{N-1} \tag{6}$$

where

$$m(x^{-})=\frac{\sum_{i=1}^{N-1}\frac{1}{\sqrt{2}}\,|\,z_{i+1}-z_i\,|}{N-1} \text{ and } m(x^{+})=\frac{\sum_{i=1}^{N-1}\frac{1}{\sqrt{2}}\,|\,z_{i+1}+z_i\,|}{N-1} \tag{7}$$

According to equations (4) and (5), SD1 and SD2 measure the spread of the points on the Poincaré plot along the rotated axes. SD1 is the standard deviation of the points along the line perpendicular to the identity line, and SD2 is the standard deviation of the points along the identity line itself. SD1 represents the *"short-term* *variability*," while SD2 denotes the *"long-term variability"* of time series. A higher SD1 value indicates higher short-term variability and a more flexible and oscillating time series. A higher SD2 value denotes a higher long-term variability. This implies a more stable and resilient time series. Although SD1 and SD2 are two important measures derived from the Poincaré plot, they have not been directly used to assess the fluctuations in the GDP per capita data and the convergence of NUTS 2 regions. Therefore, the present study applied the sliding window concept of Karmakar et al. (2009), which can capture the (non)linear pattern and temporal variability of time series. According to this concept, sliding windows of three consecutive points are taken from the Poincaré plot and the triangular areas defined by these points are calculated and summed. For example, assume that the i^{th} window comprises the following points in the Poincaré plot:

$$P_i(z_i, z_{i+1}), P_{i+1}(z_{i+1}, z_{i+2}), P_{i+2}(z_{i+2}, z_{i+3}), \text{ where } 1 \le i \le N-3 \quad (8)$$

The area of the triangle for the i^{th} window can be calculated by using the following determinant:

$$A(i) = abs\left(\frac{1}{2} \cdot det\begin{pmatrix} z_i & z_{i+1} & 1 \\ z_{i+1} & z_{i+2} & 1 \\ z_{i+2} & z_{i+3} & 1 \end{pmatrix}\right),$$ where *"abs()"* is the absolute value function, and "*det()*" is the determinant function of a matrix. (9)

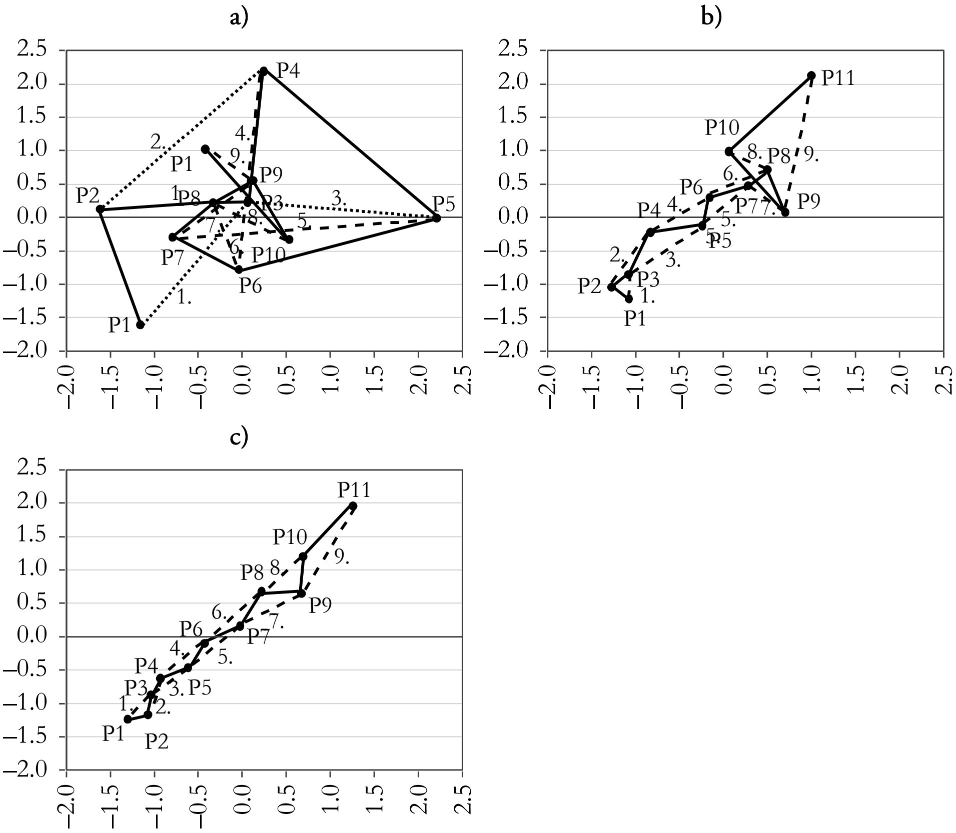
If the time series comprises N years, the Poincaré plot includes $N - 1$ points and the number of triangles is $N - 3$. The total area measure is calculated as the sum of all the individual areas of the triangles as follows:

$$A = \sum_{i=1}^{N-3} A(i) \quad (10)$$

If all the points lie close to a straight trend line near the identity line, then A is close to 0 (Figure 1c). Any deviation from the trend line increases the total area (Figure 1b), measuring fluctuations and instability (i.e., less resistance to change). In extreme situations, there is no clear observable trend, and high fluctuations cause greater instability (Figure 1a). $A(i)$ becomes the instability index. By calculating this area measure, the authors proposed a single number that can measure the convergence of a time series. It is not only the average growth rate that matters but also the changes from year to year and the total variability, both of which are reflected in the new area measure. The authors interpret a positive correlation between the instability index and initial GDP per capita as an indicator of convergence stability, implying that less developed areas tend to have more stable growth. This adds a new dimension to the analysis of convergence.

Figure 1

A visual illustration of the three common patterns of triangle areas on the Poincaré plot



Note: the side that completes the triangle is denoted by a dashed line.

Clustering

To identify the typical patterns of growth and convergence, a cluster analysis of the NUTS 2 regions was conducted using the annual GDP growth rates in the research period. Several clustering algorithms were tried, all of which produced similar groups of regions. The *k*-means method (MacQueen 1967) was chosen mainly for its simplicity and interpretability. *K*-means clustering produced clear centroids that represent the average characteristics of each cluster, which helps to better understand the growth characteristics of each cluster of regions. The clustering process involved initializing a predefined number of clusters, assigning each data point to the nearest cluster mean (centroid), and iteratively updating the centroids until convergence (i.e., when the centroids no longer change) or a predefined number of maximum iterations is reached. The *k*-means implementation of the scikit-learn machine learning library (Varoquaux et al. 2015) in Python was used with the classical Lloyd's (1982) algorithms. The clusters were initialized using greedy *k*-means++, which favors centroids that are far from each other. The clustering variables (i.e., the annual growth rates) were standardized by subtracting the mean and dividing the result by the standard deviation. A total of eight clusters were created using the elbow method (Thorndike 1953). The resulting clusters were described by the clustering variables (growth rates) and other characteristics such as the proposed measures of growth and instability.

Results

Results of the Poincaré method

To give a better insight into the method used and the characteristics of the Poincaré plots, the authors have presented three examples (see Figure 2). The regions were chosen to represent three situations – low growth rate with high fluctuations, medium growth rate with some stability (there is only one dip in the trend), and high growth rate with strong stability. The data are taken from the Eurostat database (Eurostat 2025a, 2025b). In this database, GDP per capita (PPS) data were available for all 242 NUTS 2 regions of the 27 EU member states from 2011 to 2022. GDP per capita data were standardized to make the results easier to interpret and to make the cases more comparable.

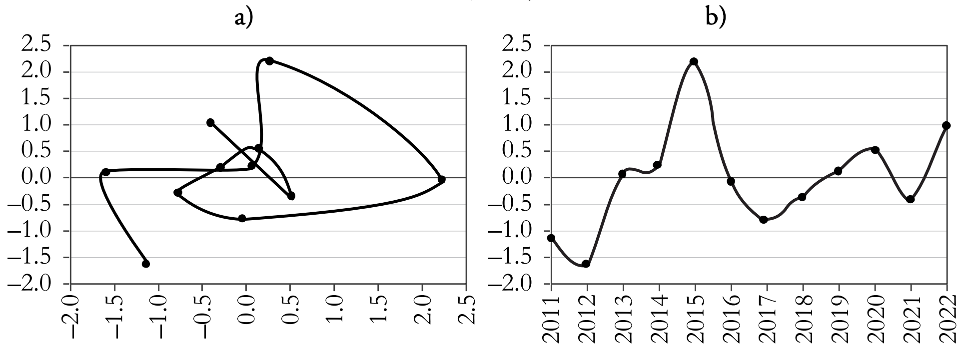
Higher fluctuations were observed in the standardized GDP per capita data for the Slovak region SK01.[9] There are three rising periods – from 2012 to 2015, from 2017 to 2020, and from 2021 to 2022. The Poincaré plot (part a) had a spiral pattern; the instability was high (9.98); and the short-term variability (0.77) and the average growth rate were low (0.41%). The Portuguese region PT18 had a different pattern, with a reasonable average growth rate of 3.22% and a much lower SD1 (0.12) and instability (1.47). During the Covid-19 crisis, there was a drop in GDP per capita, but apart from this period, a steady increase along a remarkable trend line was observed. The third region (RO32) in Romania had a high growth rate of 6.01%, with a minimum SD1 of 0.03 and an instability of 0.65. The reason for this is a straight increase along a trend line with no major shocks or fluctuations.

[9] In the context of the Slovak data, there are some problems of GDP time series stability due to the insecurity of Slovak purchasing power parity calculations (for details see Dujava–Žúdel 2023).

Figure 2

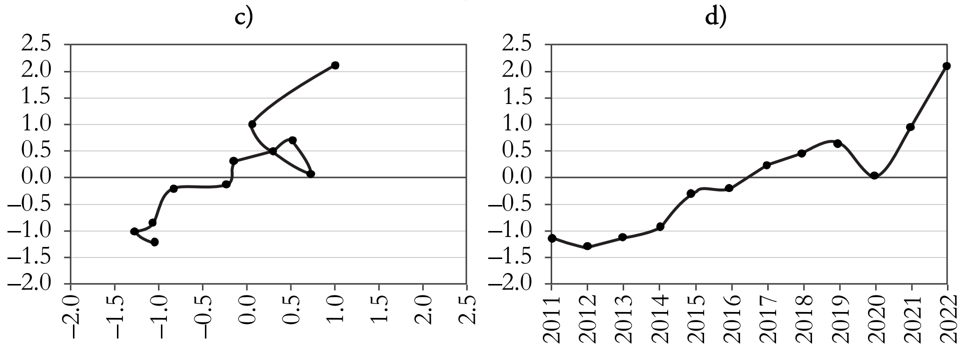
Poincaré plots and standardized GDP per capita data from 2011 to 2022

Bratislavský kraj (SK01)



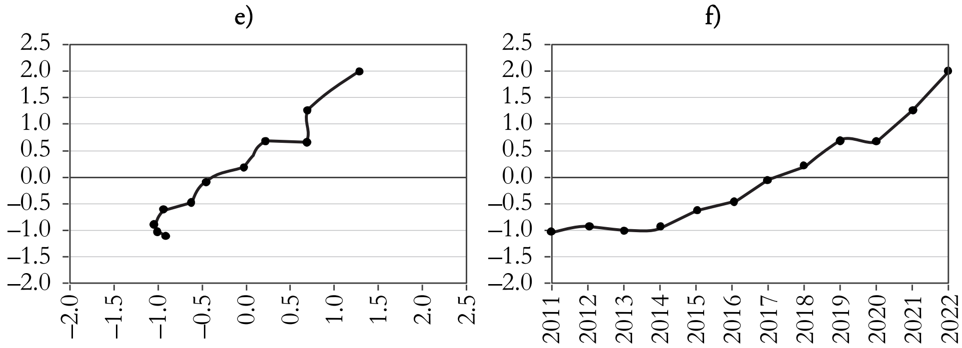
Average growth rate: 0.38%; SD1: 0.77; SD2: 1.18; instability: 9.98

Alentejo (PT18)



Average growth rate: 2.95%; SD1: 0.12; SD2: 1.46; instability: 1.47

Bucureşti–Ilfov (RO32)



Average growth rate: 5.50%; SD1: 0.037; SD2: 1.62; instability: 0.65

Note: graphs a), c), and e) represent the Poincaré plots, while b), d), and f) are the standardized GDP per capita values.

Source: own elaboration using Eurostat (tgs00005) data (Eurostat 2025a).

In this article, the authors have examined the average growth rate of 242 NUTS 2 regions in the EU27 member states and have calculated the Poincaré plot measures (SD1, SD2, SD1/SD2, and instability) for the regions of the EU countries. The results demonstrate that this novel instability measure can enhance and complement the assessment of convergence beyond the capabilities of the average growth rate.

Table 1

Regional mean values of the studied indicators and convergence from 2011 to 2022 per each NUTS 2 region in a given country

Country	Average growth rate of the given countries' regions (%)	Poincaré plot measures				Initial standardized GDP (2011) per capita (PPS) of the given countries' regions	Spearman's correlation with initial GDP per capita (PPS) (2011)	
		SD1	SD2	SD1/SD2	instability		average growth rate (%)*	instability measure**
Austria	2.69	0.13	1.31	0.10	1.39	0.81	**−0.494**	**0.733**
Belgium	2.77	0.08	1.44	0.06	1.12	0.49	0.218	−0.127
Bulgaria	5.40	0.09	1.39	0.06	0.67	−1.46	0.429	**0.600**
Croatia	4.26	0.09	1.47	0.06	1.17	−0.80	NA	NA
Cyprus	2.48	0.12	1.63	0.07	1.23	0.05	NA	NA
Czech Republic	3.14	0.05	1.66	0.03	0.85	−0.28	0.405	−0.143
Denmark	2.92	0.04	1.61	0.02	0.59	0.59	0.900	−0.821
Estonia	4.23	0.02	1.62	0.01	0.56	−0.63	NA	NA
Finland	1.86	0.20	1.47	0.13	2.04	0.68	**−0.900**	**0.900**
France	2.05	0.12	1.50	0.08	1.54	−0.18	0.171	0.070
Germany	2.26	0.06	1.56	0.04	0.90	0.64	**−0.476**	**0.572**
Greece	1.75	0.47	1.04	0.45	4.50	−0.81	0.091	0.327
Hungary	3.94	0.06	1.55	0.04	0.78	−0.86	**−0.643**	**0.762**
Ireland	7.79	0.06	1.53	0.04	0.66	0.57	NA	NA
Italy	2.04	0.21	1.32	0.16	2.04	0.24	0.186	−0.116
Latvia	5.01	0.02	1.54	0.01	0.36	−1.05	NA	NA
Lithuania	5.21	0.03	1.60	0.02	0.56	−0.53	NA	NA
Luxembourg	2.15	0.11	1.40	0.08	1.34	4.75	NA	NA
Malta	4.58	0.07	1.57	0.04	1.14	−0.30	NA	NA
Netherlands	2.33	0.11	1.46	0.07	1.10	0.81	0.021	**0.420**
Poland	4.35	0.04	1.54	0.02	0.56	−0.90	0.263	0.061
Portugal	3.01	0.17	1.37	0.12	1.66	−0.50	**−0.500**	**0.893**
Romania	5.90	0.03	1.63	0.02	0.48	−1.09	**−0.643**	**0.310**
Slovakia	1.98	0.26	1.37	0.19	3.53	−0.03	NA	NA
Slovenia	3.26	0.05	1.62	0.03	0.68	−0.27	NA	NA
Spain	2.01	0.31	1.37	0.22	3.57	−0.15	−0.065	0.271
Sweden	2.12	0.10	1.41	0.07	1.28	0.75	0.263	**0.934**
EU 27 NUTS 2 regions		0.13	1.45	0.11	1.55		−0.339	0.175

Note: NA: not applicable – cannot be calculated due to the small number of regions (<5); *: bold highlights indicate strong convergence in case of negative correlation; **: bold highlights indicate strong convergence in case of positive correlation.

Source: own elaboration using Eurostat (tgs00005) data (Eurostat 2025a).

Table 1 presents the national averages of the annual average growth rates of individual regions of the given countries, the initial standardized GDP per capita, and the Poincaré plot measures for the NUTS 2 regions in each country (the same measures for national level data are presented in Table 2). The highest average annual growth rates were observed in the Irish[10], Romanian, Bulgarian, Lithuanian, Latvian, Maltese, Polish, and Estonian regions. Regarding the initial standardized year (2011) GDP per capita, the regions of Bulgaria and Romania had the lowest values, while the regions of Sweden, Austria, and, particularly, Luxembourg had the highest initial GDP per capita values. SD1 values and instability were highest in Greece, Spain, Italy, and Finland and lowest in Latvia, Romania, Lithuania, Poland, Denmark, Ireland, and Bulgaria. Moreover, countries with higher average regional growth rates tend to have lower SD1 and instability values and higher SD2 values, that is, lower SD1/SD2 values[11]. The instability index provides a more nuanced analysis of convergence than the SD1/SD2 measure; for example, Belgium, Bulgaria, and Croatia had the same SD1/SD2 measure but a different instability. The regions of Finland, Romania, Hungary, Austria, Germany, and Bulgaria had the greatest convergence in the correlation between the initial GDP per capita values and average growth. There was no convergence at all in the Czech Republic, Denmark, and Italy. The negative correlation between GDP per capita and average growth rates indicates convergence, as the less developed regions grew more than the well-developed ones. Regarding the correlation between initial GDP per capita and instability, the greatest convergence was in the regions of Sweden, Finland, Portugal, Hungary, and Austria. Denmark, the Czech Republic, and France experienced divergence in their regions. The mean values of all EU27 NUTS 2 regions reveal that both the average growth rate method ($r = -0.339$, $p < 0.001$) and the instability measure ($r = 0.175$, $p = 0.006$) demonstrated convergence.

[10] In the Irish case, there are some distortions in the Irish GDP calculations, which stem from the activities of multinational corporations that shift profits and intangible assets to Ireland to benefit from its low corporate tax rates. This inflates GDP figures without corresponding increases in actual domestic economic activity, leading to a disconnect between GDP and the real economy (Khder et al. 2020). The Central Statistics Office Ireland has acknowledged these distortions (see Honohan 2021).

[11] When the convergence of a national economy accelerates, the more developed regions in the country grow faster, while the less developed regions grow slower. This results in the dispersion of per capita income increasing, that is, the difference between the more and less developed regions becomes even greater (EC 2024a, Kertész 2014). In summary, in certain countries, the most developed regions demonstrate the highest rate of growth, thus resulting in a larger income inequality between its regions (see the rows in Table 1 for Denmark and the Czech Republic). Conversely, in other countries, the richest regions exhibit the slowest rate of growth, leading to a convergence of income in these countries (Austria, Finland, and Slovakia).

Table 2

National mean values of the studied indicators from 2011 to 2022

Country	Growth rate (%)	Poincaré plot measures				Initial standardized GDP (2011) per capita (PPS)
		SD1	SD2	SD1/ SD2	instability	
Austria	2.51	0.11	1.33	11.81	1.17	0.66
Belgium	2.79	0.08	1.40	18.60	0.82	0.47
Bulgaria	5.60	0.03	1.56	51.71	0.42	−1.19
Croatia	4.20	0.08	1.52	20.02	1.15	−0.83
Cyprus	2.90	0.12	1.56	13.45	1.07	−0.04
Czech Republic	3.30	0.02	1.73	77.44	0.50	−0.31
Denmark	3.23	0.05	1.50	31.91	0.55	0.68
Estonia	4.29	0.02	1.61	80.06	0.49	−0.61
Finland	1.97	0.05	1.59	30.58	0.59	0.44
France	1.90	0.09	1.56	17.15	1.22	0.24
Germany	2.29	0.05	1.55	30.23	0.74	0.61
Greece	1.96	0.33	1.08	3.27	2.99	−0.54
Hungary	4.07	0.04	1.55	37.47	0.66	−0.72
Ireland	8.01	0.05	1.58	32.95	0.79	0.75
Italy	2.20	0.18	1.34	7.58	1.67	0.15
Latvia	5.01	0.02	1.59	82.16	0.53	−1.00
Lithuania	5.38	0.02	1.61	98.52	0.46	−0.74
Luxembourg	2.13	0.10	1.40	13.78	1.26	3.92
Malta	4.65	0.04	1.67	43.87	0.81	−0.30
Netherlands	2.74	0.08	1.40	17.29	0.79	0.84
Poland	4.31	0.02	1.63	91.04	0.44	−0.73
Portugal	2.83	0.13	1.41	10.92	1.17	−0.47
Romania	5.46	0.02	1.67	72.12	0.42	−0.99
Slovakia	2.33	0.07	1.45	19.49	1.14	−0.51
Slovenia	3.44	0.05	1.59	33.08	0.68	−0.34
Spain	2.35	0.27	1.35	5.02	3.15	−0.12
Sweden	1.91	0.08	1.52	19.74	1.41	0.67

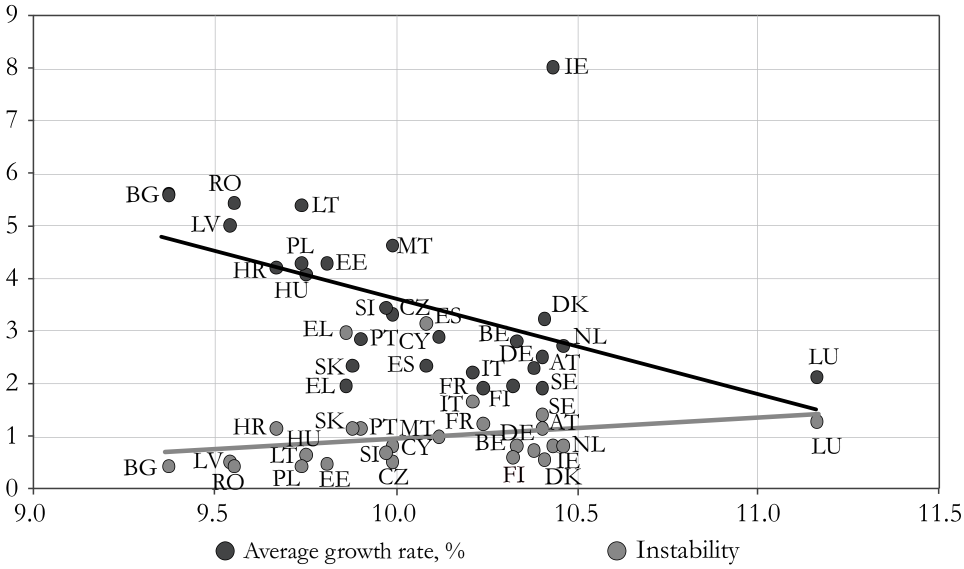
Source: own elaboration using Eurostat (nama_10_pc) data (Eurostat 2025b).

The two methodological approaches produced similar results but with some differences. The regions of Greece, Bulgaria, the Netherlands, and Sweden had convergence only when the instability measure was considered. To compare the two methodological approaches, the relationship between average growth rate or instability and initial GDP per capita is presented for the regions of the EU countries in Figure 3.

As depicted in Figure 3, the two methodological approaches were significantly correlated ($r = -0.725$, $p < 0.001$). The negative correlation indicates that countries with more stable NUTS 2 regions grow more than those with less stable NUTS 2 regions. When all EU27 member states are considered, both the average growth rate method ($r = -0.550$, $p < 0.003$) and the instability measure ($r = 0.456$, $p = 0.016$) had convergence.

Figure 3

Relationship between the average growth rate/instability and the GDPPC 2011



Notes: GDPPC denotes the initial GDP per capita. AT: Austria, BE: Belgium, BG: Bulgaria, CY: Cyprus, CZ: Czech Republic, DE: Germany, DK: Denmark, EE: Estonia, EL: Greece, ES: Spain, FI: Finland, FR: France, 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.

Source: own elaboration using Eurostat (nama_10_pc) data (Eurostat 2025b).

Results of the cluster analysis

Table 3 presents the results of the clustering. A total of eight clusters were formed based on the standardized annual percentage GDP per capita changes, and the number of NUTS 2 regions is given in parentheses. The number of clusters was chosen partly using the elbow method (based on inertia) and partly for practical reasons (larger cluster numbers would make interpretation and use of the clusters more difficult). There is a single-member cluster with the outlier Southern Ireland region, and there are two small clusters (with 4 and 6 members) and five clusters with over 28 members. SD1 and SD2 represent the short- and long-term variances, respectively. Based on this, an instability index was calculated. Finally, in the last two columns, we applied Spearman's correlation of GDP per capita (2011) with the average growth rate and the instability index.

Table 3

Mean values of the studied indicators and convergence from 2011 to 2022 per each cluster

Cluster (size)	Growth rate (%)	Poincaré plot measures				Initial standardized GDP (2011) per capita (PPS)	Spearman's correlation with initial GDP (2011) per capita (PPS)	
		SD1	SD2	SD1/ SD2	instability		average growth rate (%)*	instability index**
1 (37)	2.14	0.36	1.22	0.33	3.76	−0.41	0.053	**0.296**
2 (55)	2.36	0.12	1.41	0.09	1.30	0.69	−0.054	0.050
3 (68)	2.29	0.08	1.57	0.06	1.15	0.19	**−0.200**	−0.029
4 (1)	6.23	0.11	1.53	0.07	1.14	0.53	-	-
5 (4)	6.70	0.03	1.62	0.02	0.59	−0.08	0.800	−0.400
6 (28)	2.35	0.19	1.36	0.14	1.94	0.16	0.025	−0.073
7 (6)	6.03	0.03	1.63	0.02	0.43	−1.38	**−0.429**	**0.200**
8 (43)	4.25	0.04	1.55	0.03	0.63	−0.74	**−0.308**	**0.268**

Note: * bold highlights indicate strong convergence in case of negative correlation; ** bold highlights indicate strong convergence in case of positive correlation.

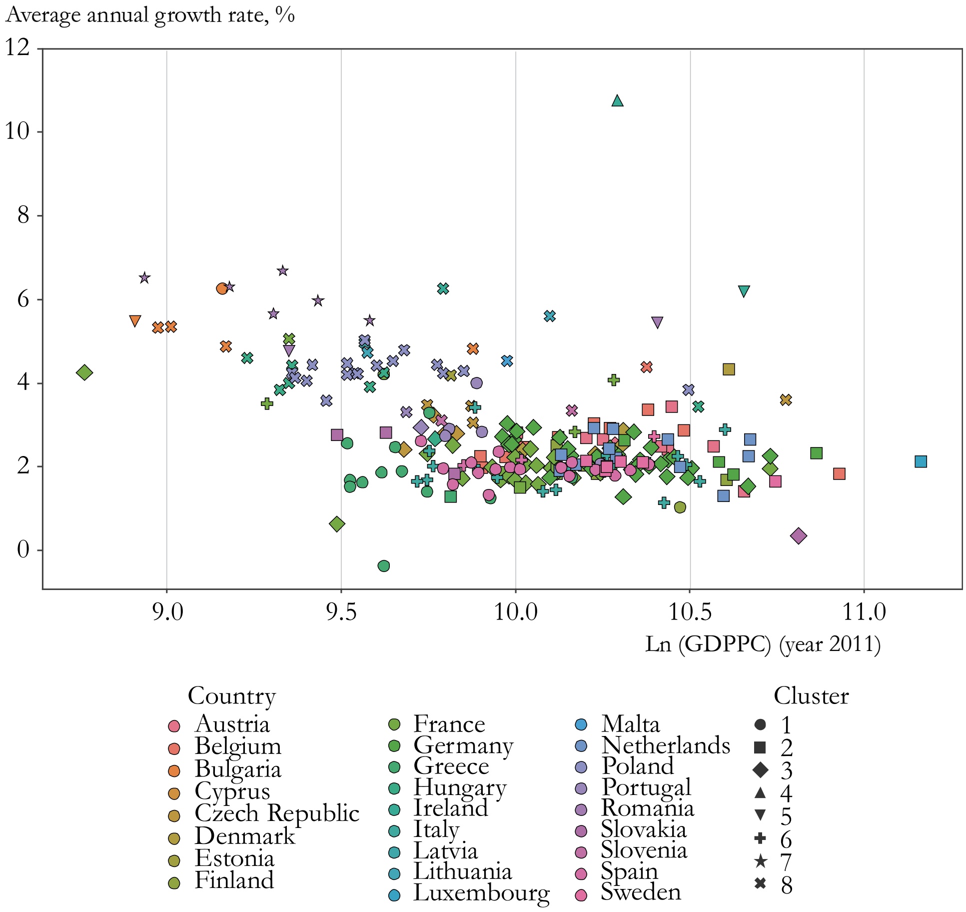
Source: own elaboration using Eurostat (tgs00005) data (Eurostat 2025a).

Higher growth rates were present in clusters 4, 5, 7, and 8. The most stable regions were in clusters 5, 7, and 8. Regions in clusters 1 and 6 were the least stable, having the highest short-term variability (SD1) and the lowest long-term variability (SD2). Correlating the initial value with both the average growth rate and the instability revealed convergence in the NUTS 2 regions in clusters 7 and 8. In clusters 2 and 6, no clear pattern was identified. Regarding clusters 1 and 3, convergence was demonstrated by only one method. Regions in cluster 1 with lower initial GDP per capita value also experienced convergence using the instability index. In general, the regions that experienced convergence had a relatively low initial GDP per capita value (clusters 7 and 8), but some regions also experienced convergence, apart from the relatively high initial GDP per capita value (cluster 3).

The authors used Kruskal–Wallis's analysis to determine whether the new instability measure discriminates better between the clusters. The analysis revealed a significant difference between the clusters for both measures – average growth rate ($H = 112.04$; $p < 0.001$) and instability ($H = 143.28$; $p < 0.001$). However, when only the clusters with lower growth rate regions (clusters 1, 2, 3, and 6) were selected, there was only a significant difference between the clusters in terms of instability ($H = 90.89$, $p < 0.001$), and growth rate was not significantly different ($H = 7.25$, $p = 0.064$). When only the clusters with no clear pattern were selected, the Kruskal–Wallis analysis also revealed a significant difference only for instability ($H = 21.92$, $p < 0.001$), while the average growth rate was not significant ($H = 1.28$, $p = 0.258$). Figure 4 depicts the NUTS 2 regions by the natural logarithm of initial GDP per capita and the average annual GDP growth rate. The shape of the dots indicates the cluster, and the color indicates the country of the region.

Figure 4

NUTS 2 regions by the logarithm of the initial GDP per capita and average annual growth rates



Notes: GDPPC denotes the initial GDP per capita. The color of the dots indicates the country, and the shape indicates the cluster.

Source: own elaboration using Eurostat (tgs00005) data.

The first cluster is called "crisis and recovery regions" and includes regions that were hit hard by Covid-19 but have had a strong rebound. The cluster indicates the largest average GDP per capita decline from 2019 to 2020 (−11.55%). However, the following year brought a strong rebound (+11.97%). The cluster is characterized by a moderate initial GDP per capita (20,446). The average annual growth rate of this cluster is 2.14%, and it has the highest instability index (3.76). This cluster contains 37 regions – 12 in Greece and 17 in Spain. The second cluster is called the "stable economies". This cluster is characterized by small growth in most years. The 2019–2020 contraction was mild (−2.42%) with a decent recovery in 2020–2021

(+9.03%). Overall, it results in a 2.36% average annual growth rate, with a moderate instability index (1.30). The constituents are mature economies that experienced a steady economic expansion with some resilience during downturns. It is the second-largest cluster, comprising 55 wealthier Western European regions (8 in Austria, 10 in Belgium, 10 in the Netherlands, and 7 in Sweden). This cluster has the highest initial GDP per capita (31,071). The third cluster is called the "moderate growth industrial hubs". This is the largest cluster, with 68 members, a steady growth with a relatively mild Covid-19 contraction (−2.45%), and a moderate next year recovery (+5.30%). The average annual growth rate of this cluster is 2.29, and the instability index is 1.15. These regions represent structurally sound economies with consistent economic performance, comprising 34 regions in Germany, 22 in France, and 4 out of 5 Danish regions.

The fourth cluster is not really a group of regions, but a single outlier region, Southern Ireland. In 2015, the Irish economy experienced extreme growth. This growth did not result from an increase in employment or accumulation of new physical capital, rather the relocation of intangible assets by multinational companies (as mentioned earlier in the footnote, see also Khder et al. 2020). The fifth cluster is referred to as "emerging high-growth regions". It is a small cluster with 2 Romanian, 1 Bulgarian, and 1 Irish regions, characterized by high growth, especially from 2016 to 2018 (nearly 10% per year) and post-2020 (12.64% and 11.13%). Overall, the average annual growth rate is the highest (6.70%). This cluster has the second-lowest instability index (0.59). It is also characterized by large intra-cluster variability. The Eastern European regions likely benefit from EU integration, foreign investment, and economic catch up. The sixth cluster, entitled "recovering lagging regions", experienced a negative growth in early years (2011–2014), then a gradual recovery (~3%–4%), a significant contraction in 2019–2020 (−6.45%), and a strong rebound (+11.97%). Its average annual growth rate of 2.35% is moderate; however, its instability index (1.94) is the second-highest of all clusters. Of the 28, 21 regions are in Italy, with other members from France (3), Spain (2), Cyprus (1), and Sweden (1). These regions likely struggled post-2008 global financial crisis.

The seventh, "rapidly developing low-GDP regions", cluster has the lowest initial GDP per capita (11,100), a relatively large average annual growth rate (6.03%) (excluding the outlier Southern Ireland), and the lowest instability index (0.43). It experienced very high early growth (14.06% in 2011), followed by a negative growth of 4.03%, and a sustained high growth until 2019. All the six member regions in this cluster are in Romania. The eighth cluster, which is called the "high-growth converging economies", has a small average initial GDP per capita (17,240), a large average annual growth rate (4.25%), and a small instability index (0.63). These regions experienced sustained high growth (>5% in multiple years), mild contraction in 2019–2020, and a strong post-2020 recovery (+9.73%). This cluster has 43 members, most are from Poland (17) and Hungary (7), but Bulgaria and the Czech Republic also have 4 members each. Table 4 and Figure 5 summarize the cluster members.

Table 4

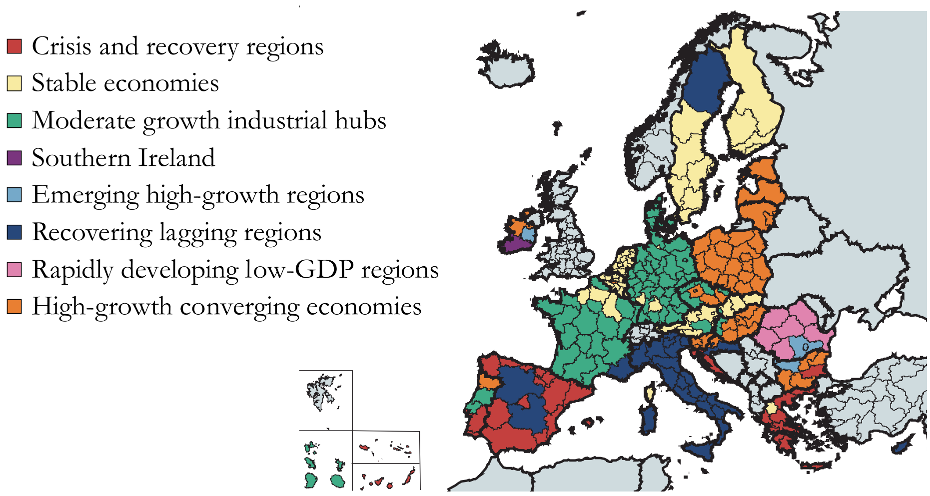
Cluster members

Cluster	Members
1	BG34, FI20, HR03, EL63, EL65, EL51, EL30, EL64, EL42, EL62, EL61, EL54, EL52, EL41, EL43, PT30, PT17, PT15, PT18, PT20, ES21, ES24, ES62, ES61, ES43, ES23, ES12, ES64, ES11, ES52, ES22, ES51, ES63, ES30, ES53, ES70, ES13
2	AT34, AT12, AT11, AT21, AT32, AT33, AT13, AT31, BE23, BE35, BE10, BE34, BE24, BE25, BE32, BE21, BE33, BE22, DK01, FI1C, FI1B, FI1D, FI19, FRE2, FRD2, FRM0, FRF2, DEB3, DE50, DE60, DE11, EL53, LU00, NL42, NL12, NL23, NL13, NL31, NL22, NL32, NL41, NL21, NL34, NL33, NL11, SK04, SK03, SK02, SE22, SE11, SE32, SE23, SE12, SE21, SE31
3	AT22, CZ03, CZ05, CZ04, CZ08, DK04, DK05, DK02, DK03, FRJ1, FRY3, FRG0, FRI3, FRE1, FRJ2, FRY5, FRY1, FRK2, FRF3, FRI2, FRY4, FRY2, FR10, FRH0, FRB0, FRC1, FRD1, FRC2, FRK1, FRI1, FRF1, DE80, DEC0, DE93, DE14, DED4, DE26, DE72, DEA3, DE94, DEE0, DE91, DE40, DE30, DE21, DE24, DE23, DEA5, DE25, DEG0, DEB2, DE73, DE92, DE13, DEA1, DE12, DEB1, DEA2, DE22, DEF0, DED5, DE27, DED2, DE71, DEA4, HU22, PT16, SK01
4	IE05
5	BG31, IE06, RO32, RO31
6	CY00, HR02, FRL0, HR05, ITF4, ITG1, ITI2, ITI1, ITH1, ITC2, ITH3, ITH2, ITG2, ITF1, ITF6, ITF3, ITF2, ITC4, ITI3, ITF5, ITH5, ITI4, ITC1, ITH4, ITC3, ES42, ES41, and SE33
7	RO11, RO21, RO12, RO42, RO22, RO41
8	BE31, BG41, BG42, BG33, BG32, CZ06, CZ07, CZ01, CZ02, EE0, HR06, HU12, HU11, HU33, HU31, HU21, HU23, HU32, IE04, LV00, LT01, LT02, MT00, PL51, PL62, PL91, PL41, PL42, PL71, PL84, PL82, PL72, PL61, PL63, PL92, PL81, PL43, PL21, PL22, PL52, PT11, SI04, SI03

Source: own elaboration using Eurostat (tgs00005) data.

Figure 5

Cluster members



Note: Small islands on the bottom left corner of the map are: upper left islands: NO0B – Jan Mayen and Svalbard (non-EU); lower left islands: FRY – Régions Ultrapériphériques Françaises/Outermost Regions of France, FRY1 Guadeloupe, FRY2 Martinique, FRY3 Guyane, FRY4 La Réunion, FRY5 Mayotte; upper right: PT20 Região Autónoma dos Açores, PT30 Região Autónoma da Madeira; lower right: ES70 Canarias.

Source: own elaboration using Table 4 data and mapchart.net.

Discussion

As very few recent studies have addressed similar research questions for EU NUTS 2 regions, it is difficult to compare our results to many studies. However, our results can best be compared with those of Simionescu (2015), who conducted a similar study for 1995–2012 and concluded that convergence clubs can be distinguished and that poorer regions are developing faster than richer ones. She performed clustering, distinguishing four clusters for countries and five clusters for NUTS 2 regions. In their 2017 study, von Lyncker–Thoennessen (2017) examined a more extensive period (1980–2012) and created four clubs (north vs. south) and a high-income cluster for capital cities.

Harb et al. (2024) claimed that the absence of a single equilibrium in favor of multiple equilibria is due to the heterogeneity of regional economies. In the absence of such a unique equilibrium, subgroups with similar transition paths are identified endogenously. They did not find divergence but rather found club convergence clustered around different steady-state levels. They identified 20 convergence clubs and only one diverging club.

Egri–Lengyel (2024) looked at NUTS 3 regions, and found that convergence among 185 regions was weak. Based on the EU regional typology, they found that it was initially strong among capital cities and moderate in intermediate and rural areas, while divergence was observed in urban areas. Although the level of our analysis and the period are different, our conclusion is quite similar. Fischer–Stirböck (2006) looked at 256 regions in the EU15 and new member states from 1995 to 2000. Although this is an older study, it also found that convergence clubs can be formed based on spatial location.

Conclusion

This study examines the dynamics of convergence of NUTS 2 regions in the EU from 2011 to 2022. Absolute convergence was tested with β-convergence, while conditional convergence was tested using cluster analysis of EU NUTS 2 regions, creating homogeneous groups or clubs.

There has been absolute convergence between countries over the period, with poorer countries growing significantly faster than richer countries. Convergence between NUTS 2 regions in a country has been uneven, with some countries converging and others experiencing increasing disparities between regions. At the EU level, convergence between NUTS 2 regions is evident, although weaker. This is why cluster analysis was necessary.

The novel application of the Poincaré method in this study is capable of dynamically capturing long- and short-term variability, and the resulting instability index adds a new dimension to the analysis of convergence. Using Poincaré plots and their numerical descriptors, we have examined not only the magnitude but also the stability of GDP growth in the European Union.

Instability is positively but not significantly correlated with initial GDP per capita, indicating that poorer countries have more stable growth patterns. Clustering the regions based on growth patterns alone resulted in fairly geographically distinct groups, indicating that regions in a country tend to have similar growth characteristics. The instability index was able to distinguish between clusters with similar growth rates, indicating that it can be a useful indicator for quantifying the nature of convergence. The results imply that the Poincaré plot has a place in the economist's toolbox. Policymakers should consider the specific characteristics of clusters when developing funding strategies.

NUTS 2 regions are relatively large units and cannot be considered homogeneous. Future research can examine the convergence of NUTS 3 regions. To look at the issue from a different perspective, it may be useful to use the Gini index to measure income inequality between and within regions. Due to the short time series and limited data, the correlation is not significant. In the future, we would like to use longer time series to analyse the dynamics of convergence.

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