

Review

UDC: 330.101.541:519.237(4-67EU)

DOI: <https://doi.org/10.32676/n.11.1.9>

MULTIVARIATE ANALYSIS OF MACROECONOMIC HETEROGENEITY AMONG EUROPEAN UNION COUNTRIES IN 2024

univ. spec. Zlatko Čehulić¹
univ. spec. Rajka Hrbić, PhD²

ABSTRACT

The aim of this study was to examine macroeconomic heterogeneity among European Union countries in 2024 and to identify latent economic patterns and country groups with similar characteristics. The analysis employed hierarchical and non-hierarchical cluster analysis, discriminant analysis, principal component analysis (PCA), and factor analysis of macroeconomic variables: gross domestic product, unemployment rate, inflation (HICP), public debt, and budget surplus. The results reveal the existence of four clearly separated clusters of countries, differing in terms of economic growth, inflation, employment, fiscal balance, and public debt, with noticeable geographical and development-based distinctions among clusters. Discriminant analysis confirmed the stability of the identified groups, while PCA and factor analysis allowed for reducing the complexity of the data into key dimensions, such as fiscal stability, labour market performance, and public debt. The study concludes that the EU remains divided into distinct macroeconomic profiles, highlighting the importance of continuously monitoring heterogeneity and its implications for economic policies. The findings suggest that targeted fiscal coordination and cohesion policy interventions could support economic convergence and stability across member states.

KEYWORDS: macroeconomic indicators, cluster analysis, discriminant analysis, factor analysis, regional disparities

JEL CLASSIFICATION: C38, E02, F15, O47, R11

1. Introduction

Macroeconomic heterogeneity among European Union countries represents a significant challenge for the implementation of a common economic and monetary policy. Differences in economic growth, inflation, unemployment, fiscal balance, and the level of public debt shape the diverse economic profiles of the member states and affect the stability of the Union. To address this challenge, this study employs harmonized 2024 macroeconomic data and applies

¹ Croatian National Bank, e-mail: zlatko.cehulic@hnb.hr.

² Croatian National Bank, e-mail: rajka.hrbic@hnb.hr.

© 2025 Zlatko Čehulić & Rajka Hrbić. This is an open access article licensed under the Creative Commons Attribution- NonCommercial-NoDerivatives 4.0 International License (CC BY-NC-ND 4.0). For more information, see <https://creativecommons.org/licenses/by-nc-nd/4.0/>.

a multivariate clustering framework to uncover updated patterns of economic heterogeneity across EU countries. Recognizing and understanding these differences enables a more accurate evaluation of policies, better risk forecasting, and the promotion of economic cohesion among countries. This analysis is grounded in the Optimal Currency Area (OCA) theory (Mundell, 1961; McKinnon, 1963; Bilas, 2005) and the concept of convergence clubs, providing a theoretical lens to interpret the observed macroeconomic clusters and their policy relevance. Recognizing and understanding these differences enables a more accurate evaluation of policies, better risk forecasting, and the promotion of economic cohesion among countries. Identifying these clusters contributes to understanding the potential effectiveness of fiscal coordination, cohesion policies, and monetary policy transmission within the EU.

The aim of this study is to examine macroeconomic heterogeneity among EU countries in 2024 and to identify latent economic patterns and clusters of countries with similar characteristics. Special attention is given to analysing the factors that shape economic strength, fiscal stability, and labour market conditions, with an emphasis on their impact on economic cohesion. The study hypothesizes that EU countries can be grouped into several clearly distinct clusters based on a combination of macroeconomic indicators, reflecting both geographical and developmental differences within the Union.

The structure of the paper includes a review of the relevant literature, the presentation of the results of the conducted analyses, including cluster, discriminant, PCA, and factor analysis, followed by a discussion of the findings and conclusions. Finally, the implications and policy recommendations derived from the results are presented, along with guidelines for future research.

2. Literature review

Macroeconomic heterogeneity within the European Union has been the subject of numerous empirical studies aiming to understand the differences in growth, inflation, fiscal policies, and other key indicators among member states. For this purpose, quantitative methods provide effective tools for identifying patterns and latent relationships among variables (Jolliffe & Cadima, 2016; Hair et al., 2019). Cluster methods and dimensionality reduction techniques, such as principal component analysis (PCA) and factor models, are particularly useful, as they enable the systematic grouping of countries according to their economic characteristics and the discovery of hidden structures within the data (MacQueen, 1967; Ward, 1963).

Empirical studies show that convergence processes in the EU exhibit heterogeneous dynamics. Alcidi et al. (2018) highlight the “two-speed” phenomenon, where Central and Eastern European countries experience accelerated economic growth, while some Western European member states progress more slowly or occasionally lag behind. Similar conclusions are drawn by Borsi and Metiu (2015) and Forgó and Jevčák (2015), emphasizing the differentiated adjustment rhythms within the Union. Analyses of convergence clubs indicate that certain groups of countries share long-term economic trajectories, allowing for a more precise understanding of EU heterogeneity (Gligor & Ausloos, 2006; Monfort et al., 2012).

Multivariate methods allow for further clarification of these patterns. Corrado, Martin, and Weeks (2004) employ statistical models to identify clusters, emphasizing the importance of

latent structures in macroeconomic data. Onuferová et al. (2020) extend these analyses by incorporating indices such as the Global Competitiveness Index, the Global Innovation Index, and the Human Development Index, demonstrating how the combination of institutional and economic factors influences the diverse trajectories of EU countries.

Data sources for such analyses typically come from official statistical databases, most commonly Eurostat, including indicators such as unemployment rates, HICP, fiscal balance, public debt, current account, and GDP per capita in purchasing power parity (Eurostat, 2024a-e). These data allow for comparisons across countries and over time, which is essential for rigorous analyses of heterogeneity and convergence.

Recent studies also emphasize the sensitivity of European economies to external shocks. The 2008 financial crisis and the COVID-19 pandemic significantly affected the pace of adjustment and heterogeneity among member states (Dräger et al., 2023; Licchetta & Mattozzi, 2023; Glavaški et al., 2023). For instance, the pandemic slowed down the convergence of per capita income in the Eurozone, while fiscal adjustments exhibited a high degree of differentiation across countries.

Lungu (2024) examines the economic convergence of EU member states through ten key macroeconomic indicators, using descriptive statistics, multiple regression, and ANOVA analysis. The results indicate overall convergence trends among the member states, but with significant variations in individual countries, particularly in GDP per capita, inflation, unemployment, and trade balances. The author emphasizes the importance of coordinated policies between member states and the EU to achieve faster and more effective absolute convergence. Despite the extensive empirical research on EU macroeconomic heterogeneity, several gaps remain. Most studies focus on historical datasets prior to 2020, often neglecting the updated economic conditions following recent shocks such as the COVID-19 pandemic. Furthermore, while cluster and multivariate methods have been applied, there is limited work that integrates a comprehensive set of macroeconomic indicators in a multivariate framework for the most recent year (2024), which would allow for a more nuanced understanding of latent economic patterns. This gap motivates the present study to provide an updated and methodologically rigorous analysis of macroeconomic heterogeneity among EU member states.

Overall, the literature confirms that the European Union comprises a heterogeneous group of economies with varying growth rates, monetary policies, and fiscal strategies. The application of multivariate and cluster methods enables the systematic mapping of these differences, the identification of latent patterns, and provides empirically grounded guidance for formulating policies that take into account the specific characteristics of each member state.

3. Methodology

3.1. Choice of variables

For the study of macroeconomic heterogeneity among EU member states in 2024, five indicators were selected. Their definitions, units of measurement, and abbreviations are presented in Table 1.

Table 1 Selected Macroeconomic Indicators of EU Countries

Indicator	Definition	Unit of measurement	Abbreviation
Gross Domestic Product per Capita	Economic Development Indicator	PPS, Purchasing Power Standard, adjusted	GDP
Unemployment Rate	Share of Unemployed in the Labor Force	Percentage of the Working Population	Unemp
Harmonized Index of Consumer Prices	Measure of Inflationary Pressures	Index (2015=100)	HICP
Public Debt	Government Fiscal Indebtedness	Percentage of GDP	Debt
Budget Balance	Government Fiscal Sustainability	Percentage of GDP	Surplus

Source: Compiled by the author based on Eurostat (AMICO).

The variables were standardized to z-scores (by subtracting the mean and dividing by the standard deviation) to ensure equal weighting in multivariate analyses and to prevent indicators with larger absolute values from dominating. Each country represents an observational unit, and the standardized values enable the comparison of macroeconomic patterns across countries and the reliable application of statistical methods.

The selected macroeconomic indicators cover the fundamental dimensions of economic heterogeneity: the level of economic development (GDP per capita in PPS), labour market stability (unemployment rate), monetary conditions (inflation measured by HICP), and fiscal sustainability (public debt and budget balance). This selection addresses the key aspects of macroeconomic stability and convergence within the EU, which are also commonly used in similar empirical studies. Including these specific variables allows for a balanced representation of developmental, monetary, and fiscal differences among member states, while maintaining analytical clarity and interpretative transparency of the model.

3.2 Applied Multivariate Methods

A set of complementary multivariate methods was applied to study macroeconomic heterogeneity among European Union member states. Their combined use enables the systematic grouping of the observed countries, the verification of the stability of the resulting clusters, and the extraction of the underlying dimensions that explain differences among them. This approach provides deeper insights into patterns of economic similarity and diversity within the Union, with each method serving a specific research purpose.

Cluster analyses (hierarchical and K-means methods) were applied as an initial step in uncovering structural patterns. The hierarchical method provides a clear overview of the relationships among countries and is used to initially determine the possible number of clusters. Its advantage lies in visualizing the hierarchy of similarities, which aids in understanding the overall data structure. Subsequently, the K-means method is applied, further optimizing the allocation of countries into groups and stabilizing the resulting clusters. The determination of the optimal number of clusters was based on the elbow method, which allows identifying the point where additional clusters no longer significantly reduce within-group variance, ensuring a balance between parsimony and interpretative clarity (Milligan & Cooper,

1985). This combination leverages the interpretability of the hierarchical approach and the robustness of the K-means algorithm, resulting in a more reliable and analytically clear clustering solution.

Discriminant Analysis (DA) was used as a tool to validate the cluster classification. Its purpose is to determine the extent to which macroeconomic indicators contribute to distinguishing the formed groups. In this way, the reliability of the classification can be assessed, and the variables with the greatest discriminative potential can be identified. In the context of studying macroeconomic heterogeneity, DA provides additional confirmation that the resulting clusters are not the product of random patterns but reflect actual economic differences among the countries.

Principal Component Analysis (PCA) was introduced as a method for reducing the dimensionality of the data. Since multiple macroeconomic indicators are used in the analysis, PCA enables their consolidation into a smaller number of mutually independent components. This facilitates the interpretation of complex relationships while retaining the maximum possible proportion of the total variability in the data. In addition to simplifying the analytical framework, PCA allows for the identification of the dimensions that best explain macroeconomic differences among the member states.

Factor Analysis (FA) is used as the final method, aiming to uncover latent factors underlying the interrelationships among variables. Unlike PCA, which focuses on statistical variability, FA emphasizes conceptual interpretation and the identification of hidden dimensions that link the observed indicators. In this way, deeper patterns can be identified, such as groups of variables that jointly reflect fiscal sustainability, monetary conditions, or labor market dynamics.

The sequence of methods applied in this study follows a logic of progressive refinement: first, country groups are formed (cluster analyses), then their stability and interpretative value are assessed (discriminant analysis). Next, the main dimensions of variability are extracted (PCA), and finally, the latent factors that more deeply explain the structure of similarities and differences within the European Union are identified (FA). This approach ensures a comprehensive methodological framework that combines quantitative precision with interpretative depth.

The combination of hierarchical and non-hierarchical cluster analyses is based on recommendations from the specialized literature (Hair et al., 2019; Everitt et al., 2011), with Everitt (2011) emphasizing the importance of comparing different clustering approaches to ensure the stability and interpretative clarity of the results. This approach enables the systematic grouping of the observed countries, the assessment of the stability of the resulting clusters, and the extraction of the underlying dimensions that explain differences among them.

4. Empirical evidence

4.1. Data Sources and Descriptive Overview

The data used in the analysis were obtained from the Eurostat (AMICO) database and cover the 27 European Union member states for 2024. The analysis is based on the values of five

macroeconomic indicators presented in Table 1 (Section 3.1), which were selected due to their relevance for assessing economic development, labour market conditions, inflationary pressures, and the fiscal situation of EU member states.

Table 2 presents the data for each country in 2024. All subsequent statistical and multivariate analyses are conducted on these values, with the data standardized beforehand (mean = 0, std = 1) to ensure equal weighting of all variables and to prevent variables with larger absolute values from dominating.

Table 2 Macroeconomic Variables for EU Countries in 2024

	Country	GDP	Unemp	HICP	Debt	Surplus
1	Belgium	117	5.7	131.5	24.1	-4.5
2	Bulgaria	66	4.2	137.6	43.6	-3
3	Czechia	91	2.6	151.9	31.1	-2.2
4	Denmark	128	6.2	119.1	62.5	4.5
5	Germany	115	3.4	129	23.6	-2.8
6	Estonia	79	7.6	155.1	40.9	-1.5
7	Ireland	211	4.3	119.4	154	4.3
8	Greece	70	10.1	119.3	102	1.3
9	Spain	92	11.4	123.3	113	-3.2
10	France	99	7.4	123.3	57.6	-5.8
11	Croatia	77	5	132	135	-2.4
12	Italy	98	6.5	122.3	65	-3.4
13	Cyprus	95	4.9	117.1	46.8	4.3
14	Latvia	71	6.9	145.3	38.2	-1.8
15	Lithuania	87	7.1	150.8	26.3	-1.3
16	Luxembourg	241	6.4	124.8	73.5	1
17	Hungary	77	4.5	166.6	47.4	-4.9
18	Malta	109	3.1	122.9	43.3	-3.7
19	Netherlands	135	3.7	131.9	81.8	-0.9
20	Austria	115	5.2	134.2	55.3	-4.7
21	Poland	79	2.9	148.7	94.9	-6.6
22	Portugal	82	6.5	122.2	54.8	0.7
23	Romania	79	5.4	149.9	67	-9.3
24	Slovenia	91	3.7	127.9	59.3	-0.9
25	Slovakia	75	5.3	143.2	82.1	-5.3
26	Finland	103	8.4	119.8	33.5	-4.4
27	Sweden	114	8.4	129	-1.5	-1.5

Source: Eurostat, AMICO (2024).

4.2. Descriptive statistics and correlation analysis

For the dataset, descriptive statistics were calculated, including measures of central tendency, dispersion, and distribution shape. Measures of central tendency include the mean, median, and quartiles. Measures of dispersion encompass the standard deviation, minimum, and maximum. The shape of the distribution is represented by skewness and kurtosis, with positive kurtosis values indicating a more pronounced concentration of data around the center of the distribution with heavier tails, and negative values suggesting a more uniform distribution.

Table 3 Descriptive Statistics of Macroeconomic Variables

Variable	N	Mean	Std. Dev.	Min.	Lower Quartile	Median	Upper Quartile	Max.	Skewness	Kurtosis
GDP	27	103.56	39.97435	66	79	92	115	241	2.37	6.09
Unemp	27	5.81	2.173428	2.6	4.2	5.4	7.1	11.4	0.73	0.42
HICP	27	133.26	13.50343	117.09	122.3	129	145.32	166.56	0.82	-0.29
Debt	27	61.29	35.20929	-1.5	38.2	55.3	81.8	153.6	0.92	0.95
Surplus	27	-2.15	3.324081	-9.3	-4.5	-2.4	-0.9	4.5	0.37	0.26

Source: Compiled by the author based on Eurostat (AMICO)

The analysis of the statistical indicators points to the following:

- The variability of GDP among countries is high, with a few countries exhibiting exceptionally high values, reflected in positive skewness and pronounced kurtosis of the distribution.
- The unemployment rate ranges within moderate limits, with the highest values observed in Spain and Greece.
- HICP exhibits slight positive skewness, while the fiscal indicators (Debt and Surplus) reflect the heterogeneity of fiscal exposure and sustainability among the member states.

To assess the relationships between variables, a Pearson correlation matrix was calculated (Table 4).

Table 4 Pearson Correlation Matrix

Pearson Correlation Coefficients, N = 27 Prob > r under H0: Rho=0					
	GDP	Unemp	HICP	Debt	Surplus
GDP	100,000	-0.09341	-0.39934	0.23445	0.43198
		0.6431	0.0391	0.2392	0.0244
Unemp	-0.09341	100,000	-0.27076	0.03833	0.0889
	0.6431		0.1719	0.8495	0.6592
HICP	-0.39934	-0.27076	100,000	-0.23101	-0.49355
	0.0391	0.1719		0.2463	0.0089
Debt	0.23445	0.03833	-0.23101	100,000	0.18186
	0.2392	0.8495	0.2463		0.364
Surplus	0.43198	0.0889	-0.49355	0.18186	100,000
	0.0244	0.6592	0.0089	0.364	

Source: Compiled by the author based on Eurostat (AMICO),

GDP per capita shows a statistically significant positive correlation with the budget balance ($r = 0.43$; $p < 0.05$), suggesting that more developed countries generally maintain a more favorable fiscal position. The correlation between GDP and public debt is weak and statistically insignificant.

Inflation (HICP) is negatively correlated with GDP and the budget balance, with the relationship with the balance being significant ($r = -0.49$; $p < 0.01$), indicating that countries experiencing higher inflationary pressures in 2024 tend to have weaker fiscal equilibrium.

The unemployment rate does not show statistically significant correlations with the other variables, suggesting that, during the observed period, the labor market functions relatively independently of other macroeconomic indicators.

The analysis of interrelationships reveals the following:

- GDP shows a statistically significant positive correlation with the budget balance, while its correlation with public debt is weak and insignificant. HICP is negatively correlated with both GDP and the budget balance, reflecting the differing fiscal and monetary conditions in 2024.
- The unemployment rate is not strongly correlated with the other observed variables, suggesting that in 2024 there was no significant relationship between the labor market and other economic indicators.

The results of the descriptive and correlation analyses provide the foundation for further multivariate analyses, including cluster analyses, PCA, and factor analysis, and facilitate the interpretation of the relationships among macroeconomic variables in 2024.

The observed descriptive and correlation patterns indicate pronounced differences among the member states and confirm the justification for applying multivariate methods for the systematic grouping and identification of latent dimensions of macroeconomic heterogeneity. In conclusion, the descriptive statistics and correlation analysis confirm that there are pronounced differences among EU member states in terms of the level of development, inflationary pressures, and fiscal sustainability, while the labour market appears to be less correlated with other indicators. These findings suggest the existence of potentially distinct groups of countries, thereby justifying the application of multivariate clustering methods. The following chapter conducts a cluster analysis aimed at identifying structural patterns and differentiating macroeconomic profiles within the European Union.

5. Results and discussion

This chapter presents the results of the analysis of macroeconomic indicators for EU member states in 2024. The analysis was conducted using the methods described in Chapter 3: hierarchical and non-hierarchical K-means cluster analysis, discriminant analysis, principal component analysis (PCA), and factor analysis (FA). The main objective was to identify groups of countries with similar economic profiles and latent patterns of variability in macroeconomic indicators.

5.1. Hierarchical cluster analysis

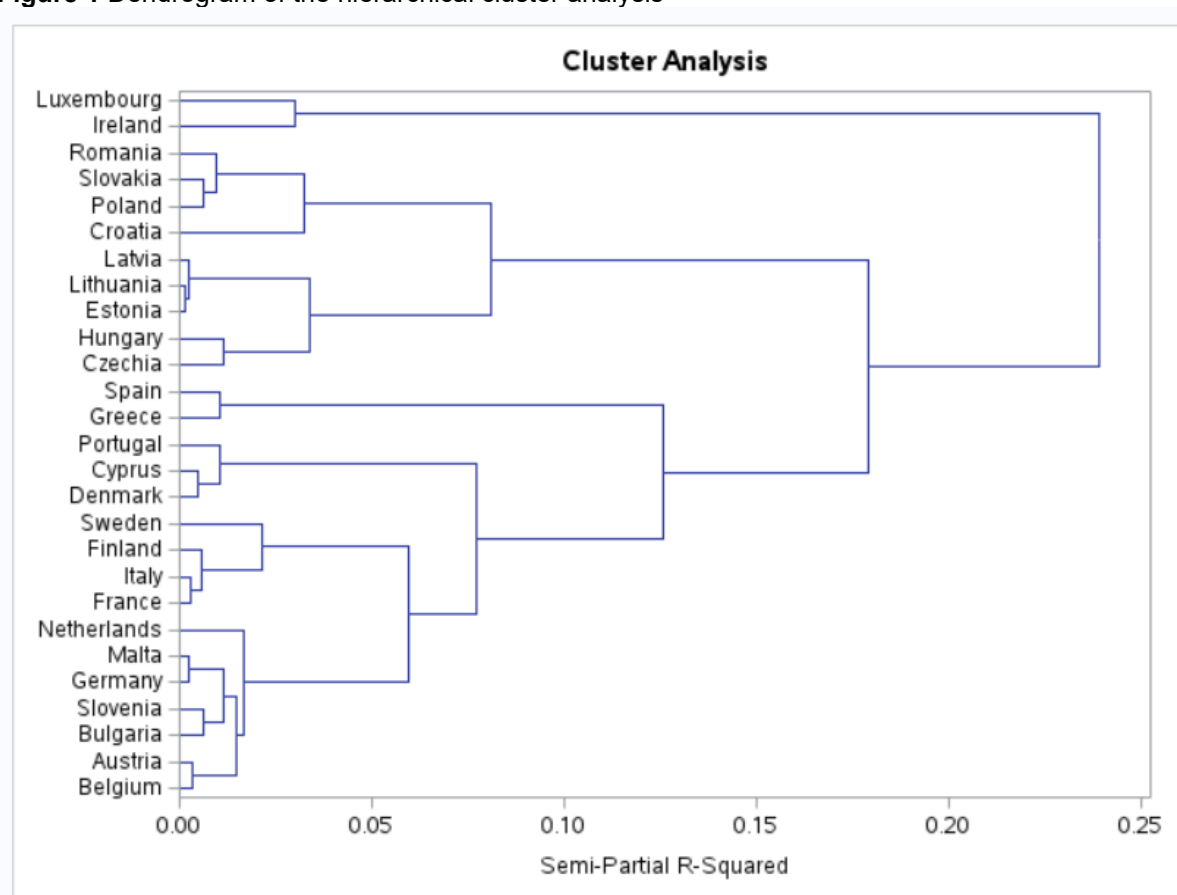
Hierarchical cluster analysis was conducted to group EU member states based on the similarity of their macroeconomic indicators. The dendrogram (Figure 1) illustrates how individual countries merge into progressively larger clusters. It shows the initial merging of countries with the most similar economic profiles, for example:

- Estonia and Lithuania
- Germany and Malta
- France and Italy
- Belgium and Austria.

As the merging progresses, larger groups are formed, encompassing countries with similar economic characteristics. For example, the Estonia-Lithuania group merges with Latvia, while the Belgium-Austria group joins the Netherlands. A similar structure is observed for other regional groups of countries.

In addition to the visual interpretation of the dendrogram, the partial R-squared value was calculated for each cluster merger. This measure indicates the contribution of each merger to the total variance and helps confirm the selection of the optimal number of clusters. Based on the partial R-squared values and the visual “break” in the dendrogram, four clusters were selected as the optimal solution.

Figure 1 Dendrogram of the hierarchical cluster analysis



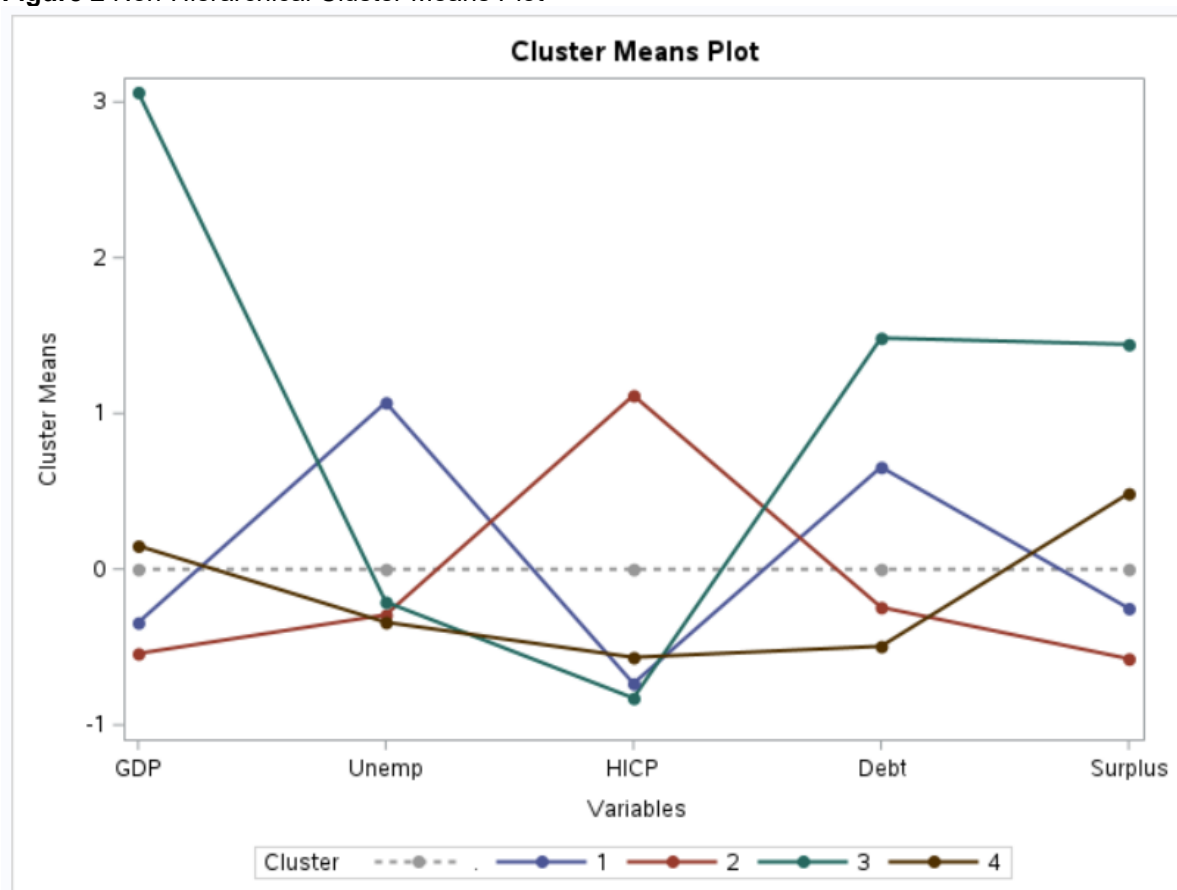
Source: Compiled by the author based on Eurostat (AMICO).

5.2. Non-Hierarchical (K-Means) cluster analysis

To further explore the structure of similarities among EU member states, a non-hierarchical K-means cluster analysis was conducted. The analysis was performed for four clusters, in accordance with the decision from the hierarchical clustering.

Figure 2 shows the cluster centroids for each of the four identified clusters. The graph clearly illustrates the differences in the central values of the clusters, allowing for a visual identification of groups of countries with similar economic profiles.

Figure 2 Non-Hierarchical Cluster Means Plot



Source: Compiled by the author based on Eurostat (AMICO).

Based on the results of the non-hierarchical K-means cluster analysis (Figure 2), four clearly defined clusters of EU member states were identified. Each cluster groups countries with similar macroeconomic profiles, considering GDP, unemployment rate, inflation, budget surplus/deficit, and public debt. To facilitate interpretation, the clusters are further described in terms of geographic location and economic performance:

- Cluster 1, Southern Europe, includes countries with moderate to medium GDP, high unemployment, low inflation, and average fiscal outcomes and debt. These countries face challenges in employment and fiscal stability.
- Cluster 2, Central and Eastern Europe, is characterized by low GDP, low unemployment, high inflation, and low debt. These are transition economies exhibiting moderate economic performance and relative fiscal stability.
- Cluster 3, Leaders, consists of Ireland and Luxembourg, with high GDP, low unemployment and inflation, and high budget surplus and debt. These countries are stable, developed economies with strong performance.

- Cluster 4, the Northwestern European Core, includes countries with medium GDP, low unemployment and inflation, low budget surplus, and average debt. This cluster comprises countries with fiscal surpluses and high economic stability.

Table 5 provides a more detailed overview of the members of each cluster, their macroeconomic characteristics, and the suggested types according to economic profile. This allows for comparison and further interpretation of the results shown in the cluster means plot (Figure 2).

Table 5 Summary of Cluster Members, Macroeconomic Profiles, and Performance in the Non-Hierarchical K-Means Analysis

Cluster	Members	GDP / Unemp / HICP / Surplus / Debt	Profile	Performance
Southern Europe (1)	Croatia, Finland, France, Greece, Italy, Spain	Middle / High / Middle / Middle / Middle	Countries Facing Employment Challenges	Middle
Central and Eastern Europe (2)	Austria, Bulgaria, Czechia, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia	Low / Low / High / Middle / Low	Transition Economies	Middle
Liders (3)	Ireland, Luxemburg	High / Low / Low / High / High	Stable Developed Countries	High
North-western European core (4)	Belgium, Cyprus, Denmark, Germany, Malta, Netherlands, Portugal, Slovenia, Sweden	Middle / Low / Low / Low / Middle	Countries with Fiscal Surplus	High

Source: Compiled by the author based on Eurostat (AMICO).

The analysis reveals clear heterogeneity among EU countries. Cluster 3 represents the economically strongest members with high GDP and a surplus, while Cluster 2 includes countries facing higher inflationary pressures and a relatively weaker economic position. Clusters 1 and 4 encompass countries of medium strength, with Cluster 1 characterized by somewhat higher unemployment and Cluster 4 by a slight positive surplus and lower debt. The overall within-cluster R-squared is 0.715, indicating that the clusters explain the variability in the data well. The pseudo F statistic = 9.28 confirms the significance of the grouping, while the Cubic Clustering Criterion = 1.526 indicates the stability of the selected number of clusters. To assess the clarity of separation among the formed clusters and to identify the variables that contribute most to differentiating the groups of countries, a discriminant analysis was conducted.

5.3. Discriminant analysis

Discriminant analysis was used to assess the ability of macroeconomic variables to differentiate between the clusters identified in the non-hierarchical K-means cluster analysis. The analysis was conducted using a linear discriminant function on five variables: GDP, unemployment rate, inflation (HICP), public debt, and budget surplus.

The total sample comprises 27 countries distributed across four clusters, with the individual clusters having the following number of members:

- Cluster 1: 6 Countries
- Cluster 2: 10 Countries
- Cluster 3: 2 Countries
- Cluster 4: 9 Countries

The pooled covariance matrix is non-singular, with a matrix rank of 5, allowing for a stable estimation of the linear discriminant functions. The generalized squared distances between clusters show the greatest differentiation between Clusters 2 and 3 (142.98), while Clusters 1 and 4 are relatively close (11.26). The linear discriminant functions for each cluster revealed significant coefficients for all variables, confirming the relevance of the selected macroeconomic indicators in distinguishing among clusters. The classification results are presented in two stages:

1. Resubstitution (Calibration), using the same dataset:
 - A total of 96.3% of countries were correctly classified.
 - The largest misclassification occurred in Cluster 2, where one member was assigned to Cluster 4.
2. Cross-Validation - using the “leave-one-out” method:
 - A total of 93.3% of countries were correctly classified.
 - Misclassified countries are shown in Table 6.

Table 6 Misclassified Countries in the Cross-Validation of the Discriminant Analysis

Country	Actual cluster	Predicted cluster	Probability predicted
Austria	2	4	0.88799
Croatia	1	2	0.49448

Source: Compiled by the author based on Eurostat (AMICO)

The results indicate that the linear discriminant function effectively differentiates the clusters. Most countries were correctly classified, with misclassifications occurring primarily in clusters that are geographically and economically similar, which is consistent with the previous findings from the cluster analysis.

The identified clusters broadly align with established macroeconomic and policy groupings within the European Union. Cluster 1 (Southern Europe) corresponds largely to the Mediterranean economies that share structural challenges in fiscal sustainability and labour market flexibility, a grouping often discussed in the literature on fiscal coordination and the Eurozone’s periphery (De Grauwe & Foresti, 2016). Cluster 2 (Central and Eastern Europe) coincides with the post-transition economies of the newer EU members, characterized by robust growth but higher inflationary pressures, consistent with the findings of Alcidi et al. (2018). Cluster 3 (Leaders) includes the small, highly developed Eurozone economies, Luxembourg and Ireland, whose fiscal positions and productivity levels distinguish them from all other groups. Cluster 4 (North-Western Core) overlaps with the “core Eurozone” countries, exhibiting macroeconomic stability and moderate fiscal surpluses. These alignments suggest that the empirical clustering mirrors the well-documented division between the Eurozone core and periphery and between older and newer EU member states, supporting the relevance of these groupings in interpreting macroeconomic heterogeneity across the Union.

The observed heterogeneity among these clusters arises from a combination of structural and policy-driven factors. Structural determinants include long-term economic development levels, labor market rigidities, demographic trends, and historical convergence patterns. Policy-driven factors reflect differences in fiscal policies, monetary policy implementation, and institutional frameworks that shape countries' responses to economic shocks. For example, Southern European countries (Cluster 1) face structural challenges in employment and fiscal flexibility, compounded by policy constraints, whereas Central and Eastern European countries (Cluster 2) exhibit high growth potential moderated by inflationary pressures resulting from transitional policy frameworks. This integrated perspective highlights how structural and policy factors jointly shape the macroeconomic profiles of EU member states and provides a nuanced understanding of heterogeneity, supporting the interpretation of the clusters and informing the design of tailored economic policies.

The identification of distinct macroeconomic clusters has important policy implications. Countries in different clusters are likely to experience divergent effects of ECB monetary policy, as the transmission of interest rate changes may vary depending on structural characteristics, labor market flexibility, and fiscal space. For instance, Cluster 1 (Southern Europe) may face slower transmission due to higher unemployment and structural rigidities, while Cluster 3 (Leaders) could respond more efficiently to monetary adjustments given their stable fiscal and economic environment. Similarly, fiscal coordination within the EU could benefit from recognizing these groupings, as countries with similar profiles may require differentiated fiscal rules or support mechanisms to maintain stability. Understanding the heterogeneity captured by the clusters can help policymakers tailor interventions more effectively, mitigate asymmetric shocks, and enhance cohesion and resilience across the Union.

Discriminant analysis confirms the reliability of the identified clusters and the relevance of the macroeconomic variables in distinguishing economic profiles among EU countries, providing additional validation of the cluster grouping results. These findings serve as a foundation for further interpretation of latent economic patterns and preparation for the principal component analysis (PCA).

5.4. Principal Component Analysis (PCA)

To identify latent patterns and reduce the dimensionality of the data, a principal component analysis (PCA) was conducted on the same five macroeconomic variables: GDP, unemployment rate, inflation (HICP), public debt, and budget surplus. The aim was to reduce the complexity of variability among countries to a smaller number of independent components. Table 7 presents the eigenvalues and the proportion of explained variance. The first three principal components account for a total of 80.4% of the variance, indicating a satisfactory representation of the information contained in the original variables.

Table 7 Eigenvalues and Proportion of Explained Variance

Eigenvalues of the Correlation Matrix				
	Eigenvalue	Difference	Proportion	Cumulative
1	2.04676667	0.94327920	0.40940000	0.40940000
2	1.10348747	0.23541853	0.22070000	0.63010000
3	0.86806893	0.34090268	0.17360000	0.80370000
4	0.52716626	0.07265558	0.10540000	0.90910000

5	0.45451067		0.09090000	1.00000000
---	------------	--	------------	------------

Source: Compiled by the author based on Eurostat (AMICO).

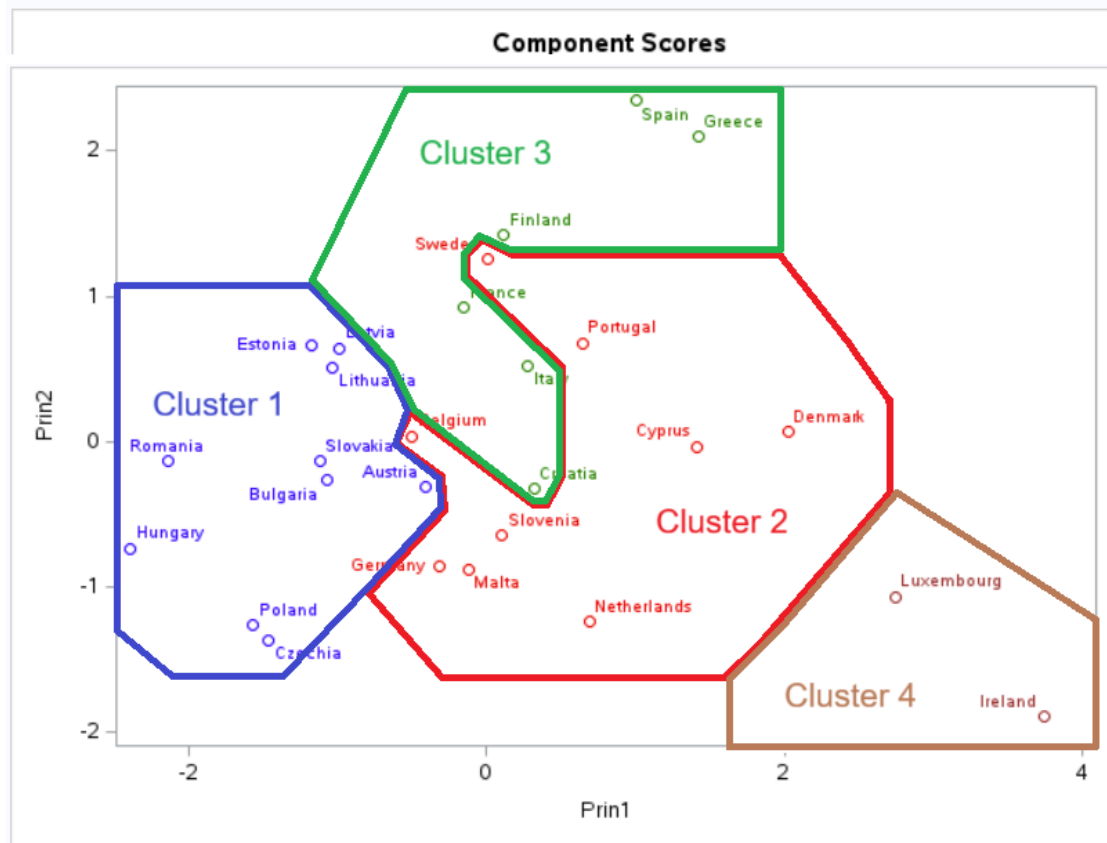
The first component (40.9%) is primarily associated with budget surplus and GDP (positively), while it correlates negatively with inflation. The second component (22.1%) is strongly determined by the unemployment rate, and the third component (17.4%) is mainly associated with public debt (Table 8).

Table 8 Eigenvectors by Component

Variable	Eigenvectors				
	Prin1	Prin2	Prin3	Prin4	Prin5
GDP	0.499921	-0.397725	-0.164832	0.680614	0.318573
Unemp	0.159323	0.875687	0.088692	0.239420	0.377623
HICP	-0.562377	-0.231910	0.127947	-0.057126	0.781227
Debt	0.336325	-0.138431	0.922360	-0.123698	0.040907
Surplus	0.543427	-0.045175	-0.312803	-0.678880	0.379371

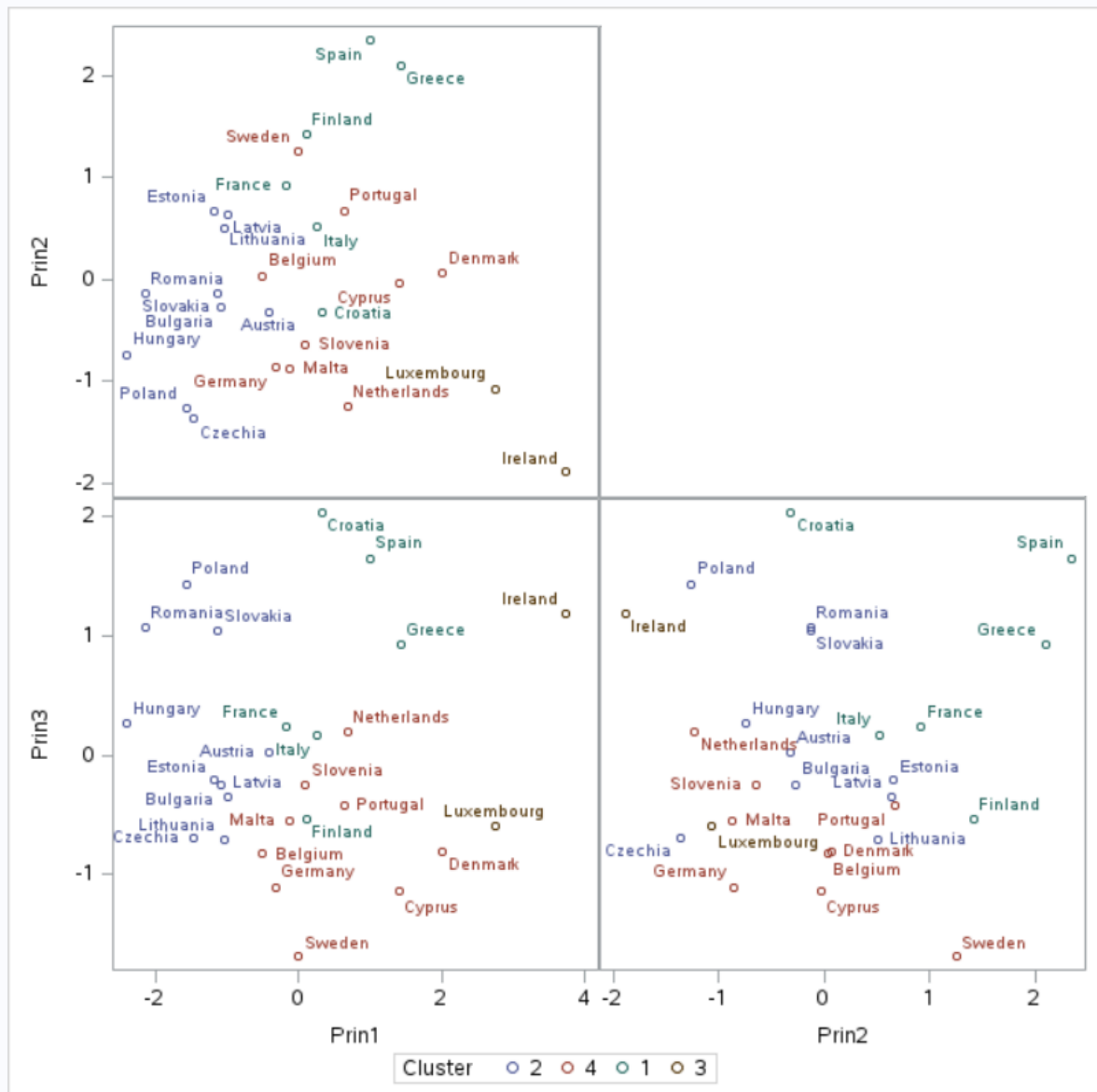
Source: Compiled by the author based on Eurostat (AMICO)

The graphical representation of countries according to the first and second principal components (Figure 3) shows the separation of clusters identified in the previous analyses. Although the cores of the groups are clearly distinguishable, the arrangement is not entirely orderly. Some countries are positioned at the edges of their clusters, creating “tentacle-like” extensions from the cluster centres. This structure suggests that the clusters are not perfectly circular but irregularly shaped. The first two components explain 63.0% of the total variance, while the remaining 37.0% contained in higher components accounts for partial overlaps and the irregular shape of the clusters.

Figure 3 Plot of Component 2 versus Component 1 Results

Source: Compiled by the author based on Eurostat (AMICO).

A projection in the three-dimensional space defined by the first three components was also analyzed (Figure 4), providing a clearer insight into the separation of countries and confirming the existence of four groups that largely correspond to the results of the cluster analysis.

Figure 4 Plot of the Relationships Among Components 1, 2, and 3

Source: Compiled by the author based on Eurostat (AMICO).

The PCA results confirm that the complexity of the macroeconomic indicators can be reduced to three dimensions with intuitive interpretation:

- Component 1: “Economic Strength and Fiscal Balance” (GDP, budget surplus, negative correlation with inflation)
- Component 2: “Labor Market” (primarily unemployment)
- Component 3: “Public Debt and Fiscal Sustainability”

These three components form the core for further analyses of latent structures, including factor analysis, which further simplifies interpretation and highlights subsets of variables that jointly define the economic profiles of EU countries.

5.5. Factor Analysis of Macroeconomic Variables

To further examine and simplify the latent structure among macroeconomic variables, a factor analysis using the principal factor method was conducted. Factor analysis enables the extraction of latent dimensions that explain the shared variance among variables, complementing the PCA findings. Unlike PCA, whose primary goal is dimensionality reduction while retaining total variance, factor analysis emphasizes explaining the common variance among variables.

The overall Kaiser Measure of Sampling Adequacy (MSA) was 0.6427, indicating satisfactory suitability of the data for factor analysis. Table 9 presents the Kaiser MSA results for each variable, the initial estimates of communalities based on squared multiple correlations (SMC), and the final communality estimates (FCS) after factor extraction.

- The MSA indicates how suitable each variable is for factor analysis; values above 0.6 are considered to reflect good adequacy.
- The SMC represents the portion of a variable's variance that can be explained by the other variables before factor extraction.
- The FCS shows the common variance of a variable explained by the factor model after factor extraction.

Table 9 Kaiser Measure of Sampling Adequacy and Variable Communality Estimates

Variable	MSA	SMC	FCS
GDP	0.650	0.285	0.399
Unemp	0.390	0.122	0.205
HICP	0.633	0.364	0.493
Surplus	0.800	0.079	0.111
Debt	0.693	0.310	0.410

Source: Compiled by the author based on Eurostat (AMICO).

Based on the eigenvalue criterion (eigenvalues > 1) and the scree plot (Figure 5), two factors were retained. The eigenvalues of the reduced correlation matrix are presented in Table 10.

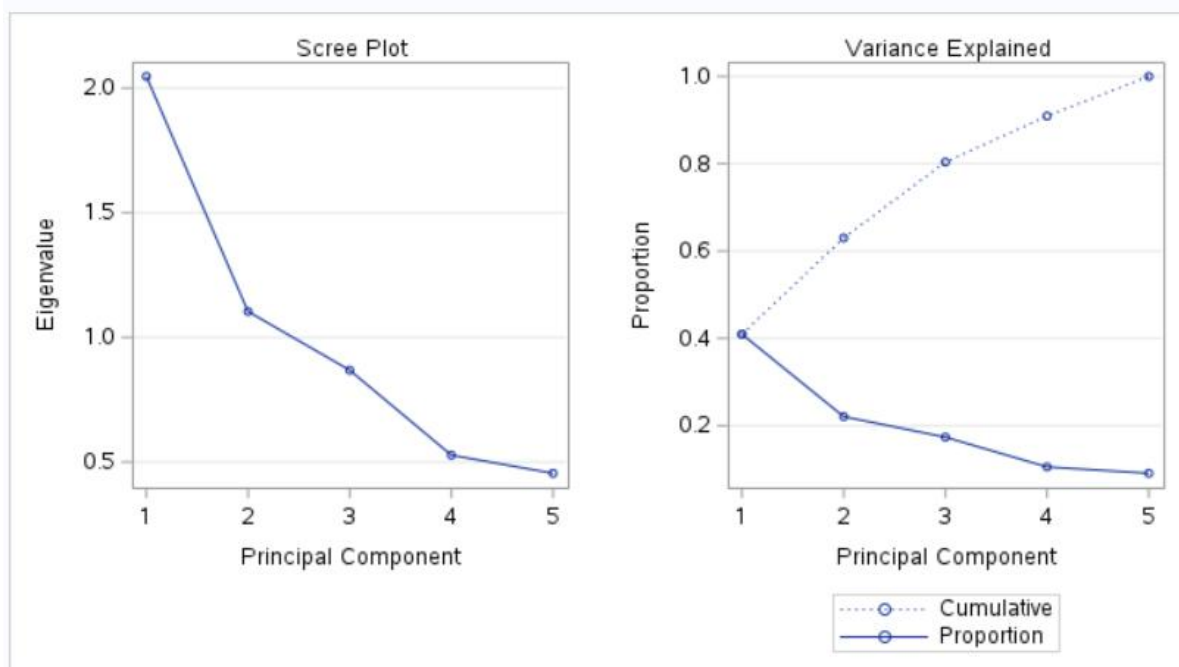
Table 10 Eigenvalues of the Reduced Correlation Matrix

Eigenvalues of the Reduced Correlation Matrix: Total = 1.15941709 Average = 0.23188342				
1	1.342	1.067	1.158	1.158
2	0.275	0.296	0.238	1.395
3	-0.020	0.163	-0.017	1.378
4	-0.183	0.072	-0.158	1.220
5	-0.255		-0.220	1.000

Source: Compiled by the author based on Eurostat (AMICO).

Based on the eigenvalues presented in Table 10, it was decided to retain two factors, which explain a significant percentage of the variance, while the remaining variance remains unexplained, as further confirmed by the scree plot in Figure 5.

Figure 5 Scree Plot of Factor Eigenvalues



Source: Compiled by the author based on Eurostat (AMICO).

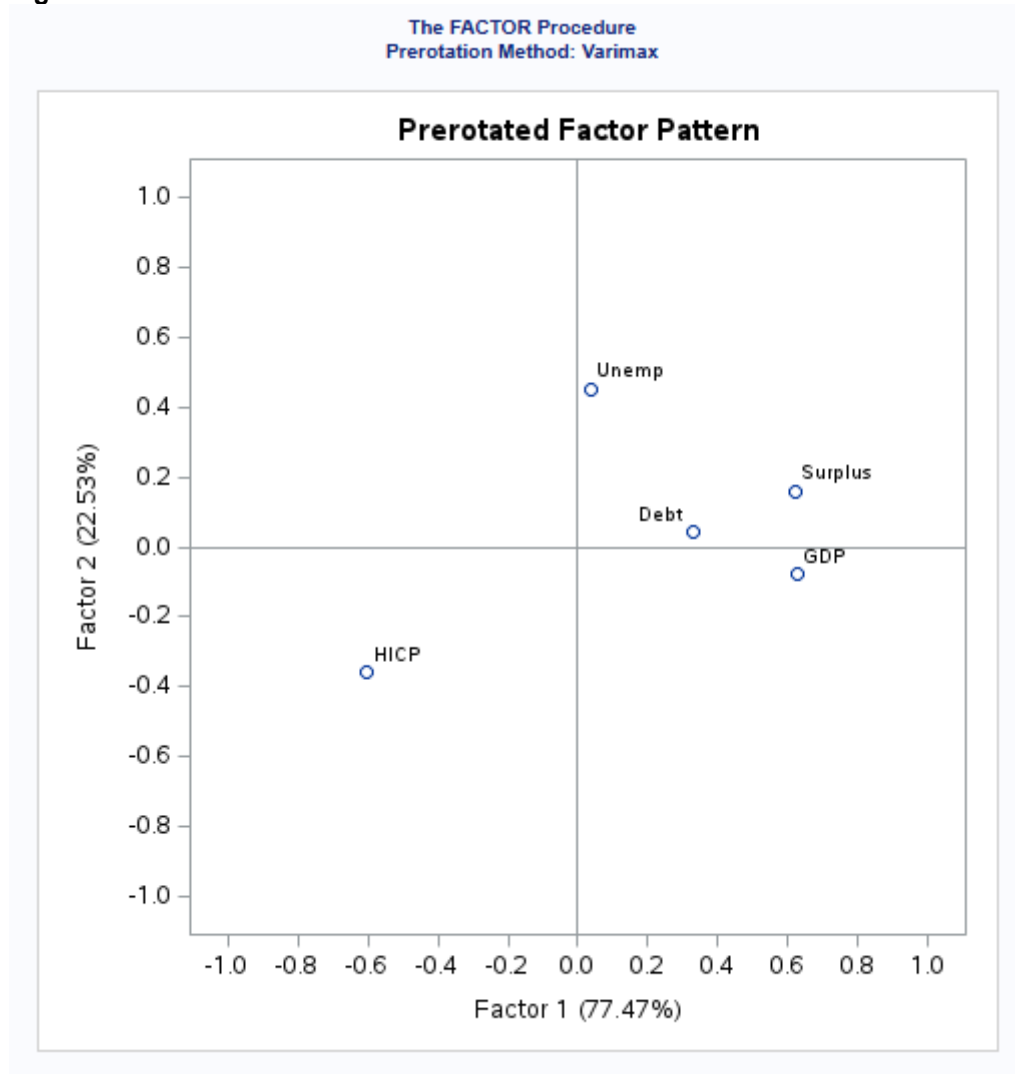
Applying Varimax rotation yielded clear loading patterns (Table 11).

Table 11 Rotated factor patterns (Varimax)

Rotated Factor Pattern		
	Factor 1	Factor 2
GDP	0.627	-0.078
Surplus	0.621	0.155
Debt	0.330	0.045
HICP	-0.604	-0.358
Unemp	0.035	0.451

Source: Compiled by the author based on Eurostat (AMICO).

For visual interpretation, Figure 6 shows the Varimax rotation of the factor loadings.

Figure 6 Varimax rotation of Factor Pattern

Source: Compiled by the author based on Eurostat (AMICO).

Factor analysis identified two main dimensions that shape the economic profile of EU countries.

- The fiscal-economic factor, with strong positive loadings for GDP and budget surplus and a negative loading for inflation, reflects the combined fiscal and economic potential of the countries.
- The second factor, predominantly driven by the unemployment rate, with a secondary contribution from inflation, can be understood as an index of market and monetary pressures.

This two-dimensional structure enables a concise comparison of countries based on their economic and fiscal profiles, while preserving the key features of macroeconomic data. The results of the factor analysis confirm the findings of PCA, but in a more compact and interpretatively simpler form, which further facilitates the analysis of the latent structures of macroeconomic variables.

In conclusion, the results of the factor analysis suggest that the macroeconomic profiles of EU countries can be summarized into two basic latent dimensions, fiscal-economic potential and market-monetary pressures. This confirms the heterogeneity within the Union, while also revealing recurring patterns across different groups of countries. These findings provide the foundation for the final interpretation and discussion of the implications of the results in the context of economic convergence and divergence within the EU.

6. Conclusion

The research confirmed the existence of pronounced macroeconomic heterogeneity among EU countries in 2024. The hypothesis of the existence of several clearly separated groups of countries was empirically validated, with the results of cluster, discriminant, PCA, and factor analysis showing that EU countries can be grouped according to a combination of economic growth, inflation, unemployment, fiscal balance, and public debt levels. The obtained clusters and latent dimensions clearly reflect geographical and developmental differences within the Union. The conducted analysis contributes to a better understanding of economic patterns and provides a systematic framework for interpreting the heterogeneity among member states. The findings are also practically relevant, as they can serve policymakers in formulating targeted economic and fiscal measures that take into account the specificities of individual country groups. In this way, the research results can be used to foster cohesion and strengthen the resilience of the European economy. However, the analysis was based on data for a single year and a limited set of variables, which reduces the possibility of capturing long-term trends and the complexity of the macroeconomic environment. Future research should extend the time horizon, include additional indicators (e.g., trade, demographic, and structural), and apply advanced methodological approaches to better understand the processes of convergence and divergence within the EU. Future research could extend this study by applying dynamic panel methods or time-series clustering, incorporating additional indicators such as trade, demographic, and structural variables, and examining temporal evolution of heterogeneity. Continuous monitoring of heterogeneity and analysis of its implications for economic policies remains a crucial prerequisite for making effective decisions aimed at balanced development, fiscal stability, and sustainable economic cohesion within the European Union.

Literature

- Alcidi, C., Núñez Ferrer, J., Di Salvo, M., Musmeci, R., & Pilati, M. (2018). *Income convergence in the EU: A tale of two speeds*. Centre for European Policy Studies.
- Bilas, V. (2005). Teorija optimalnog valutnog područja; Euro i europska monetarna unija. *Zbornik Ekonomskog fakulteta u Zagrebu*, 3, 39-53.
- Borsi, M., & Metiu, N. (2015). The evolution of economic convergence in the European Union. *Empirical Economics*, 48(2), 657–681. <https://doi.org/10.1007/s00181-014-0801-2>
- Corrado, L., Martin, R., & Weeks, M. (2004). *Identifying and interpreting convergence clusters across Europe*. Centre for Economic Policy Research.
- De Grauwe, P., & Foresti, P. (2016). Fiscal rules, financial stability and optimal currency areas. *Economics Letters*, 145, 278–281. <https://doi.org/10.1016/j.econlet.2016.07.010>

- Dräger, L., Kolaitis, T., & Sibbertsen, P. (2023). Measuring macroeconomic convergence and divergence within EMU using long memory. *Empirical Economics*, 65, 2333–2356. <https://doi.org/10.1007/s00181-023-02426-6>
- Eurostat. (2024a). Unemployment by sex and age – annual data [une_rt_a]. Available at: https://ec.europa.eu/eurostat/databrowser/view/une_rt_a/default/table (3.11.2025).
- Eurostat. (2024b). Harmonized index of consumer prices – annual data [prc_hicp_aind]. Available at: https://ec.europa.eu/eurostat/databrowser/view/prc_hicp_aind/default/table (3.11.2025).
- Eurostat. (2024c). *General government deficit/surplus [tec00127]*. Available at: <https://ec.europa.eu/eurostat/databrowser/view/tec00127/default/table> (3.11.2025).
- Eurostat. (2024d). *General government gross debt – annual data [teina225]*. Available at: <https://ec.europa.eu/eurostat/databrowser/view/teina225/default/table> (3.11.2025).
- Eurostat. (2024e). *GDP per capita in PPS [tec00114]*. Available at: <https://ec.europa.eu/eurostat/databrowser/view/tec00114/default/table> (3.11.2025).
- Everitt, B. S., Landau, S., Leese, M., & Stahl, D. (2011). *Cluster Analysis* (5th ed.). Wiley.
- Forgó, B., & Jevčák, A. (2015). Economic convergence of Central and Eastern European EU member states over the last decade (2004–2014). *European Economy - Discussion Papers 001*. Directorate General Economic and Financial Affairs, European Commission.
- Glavaški, O., Beker Pucar, E., Beljić, M., & Pejčić, J. (2023). Fiscal adjustment heterogeneity in inflationary conditions in the Eurozone: A non-stationary heterogeneous panel approach. *Journal of Risk and Financial Management*, 17(11), 493. <https://www.mdpi.com/1911-8074/17/11/493>
- Gligor, M., & Ausloos, M. (2006). *Convergence and cluster structures in EU area according to fluctuations in macroeconomic indices*. arXiv preprint physics/0606203.
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.
- Jolliffe, I., & Cadima, J. (2016). Principal component analysis: A review and recent developments. *Philosophical Transactions of the Royal Society A*, 374(2065), 20150202. <https://doi.org/10.1098/rsta.2015.0202>
- Licchetta, M., & Mattozzi, G. (2023). Convergence in GDP per capita in the Euro Area and the EU at the time of COVID-19. *Intereconomics*, 58(1), 43–51.
- Lungu, A. (2024). Analysis of Economic Convergence in the European Union. *Proceedings of the International Conference on Business Excellence*, 18(1), 405–423. <https://doi.org/10.2478/picbe-2024-0035>
- MacQueen, J. (1967). Some methods for classification and analysis of multivariate observations. *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability*, 1, 281–297.
- Milligan, G.W., Cooper, M.C. An examination of procedures for determining the number of clusters in a data set. *Psychometrika*, 50, 159–179 (1985). <https://doi.org/10.1007/BF02294245>
- Monfort, P., Cuestas, J. C., & Ordóñez, J. (2012). Real convergence in Europe: A cluster analysis. *European Central Bank Working Paper No. 1411*.
- McKinnon, R. I. (1963). Optimum currency areas. *American Economic Review*, 53(4), 717–725.

- Mundell, R. A. (1961). A theory of optimum currency areas. *American Economic Review*, 51(4), 657–665.
- Onuferová, M., Čabinová, V., & Matijová, T. (2020). Categorization of the EU Member States in the context of selected multicriteria international indices using cluster analysis. *Review of Economic Perspectives*, 20(3), 394-401. <https://doi.org/10.2478/revecp-2020-0018>
- Ward, J. H. (1963). Hierarchical grouping to optimize an objective function. *Journal of the American Statistical Association*, 58(301), 236–244. <https://doi.org/10.1080/01621459.1963.10500845>