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Structural Heterogeneity of European Union Member States: A Multivariate Analysis and Structural Divergence Index (2015–2024)

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ABSTRACT
This paper analyses EU structural heterogeneity (2015–2024) using a decadal panel perspective to identify persistent macroeconomic profiles. The analysis covers six indicators: gross domestic product per capita, unemployment rate, harmonised index of consumer prices (HICP), fiscal balance, public debt, and accumulated balance of payments. Cluster analyses (hierarchical and K-means) applied to mean values for 2015–2024 yield a stable classification of EU economies into distinct structural groups. Principal component analysis (PCA) is then used to reduce dimensionality and identify the underlying economic dimensions shaping these clusters. A key contribution of the paper is the introduction of the Structural Divergence Index (SDI), which quantifies within-cluster heterogeneity by measuring Euclidean distances from cluster centroids across all variables. SDI results reveal notable internal variation, with some countries closely aligned and others persistent outliers. These findings indicate that EU macroeconomic heterogeneity appears not only between clusters but also through pronounced divergences within them. The proposed approach offers a new instrument for assessing cohesion in an integrated economic area and provides relevant implications for designing convergence policies, fiscal rules, and targeted structural reforms.

KEY WORDS: structural heterogeneity, European Union, macroeconomic indicators, cluster analysis, principal component analysis (PCA)

JEL CLASSIFICATION: C38, E60, F15, O52, O47

1. Introduction

Macroeconomic heterogeneity among European Union countries poses a challenge for implementing coherent economic and monetary policies. Differences in economic growth, inflation, unemployment, fiscal balance, and public debt levels affect the Union's stability and shape the distinct economic profiles of its member states. Understanding these differences enables better policy evaluation, risk forecasting, and the promotion of cohesion among the countries. This paper contributes in three ways. First, it extends previous single-year analyses through a decadal panel approach. Second, it introduces the Structural Divergence Index (SDI) as a novel, cluster-centric and country-specific measure of within-cluster heterogeneity that positions each economy relative to its own group's structural centroid rather than the EU

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average, thereby isolating outliers within otherwise cohesive clusters. Third, it combines clustering with PCA and factor analysis into a comprehensive framework for analysing macroeconomic divergence in the EU. The aim of this study is to examine macroeconomic heterogeneity among EU countries over the period 2015–2024. Building on our previous analysis of the year 2024 (Čehulić & Hrbić, 2025), this study shifts the focus toward long-term structural stability and introduces a novel metric for internal cluster dynamics. Particular attention is given to analysing the factors shaping economic strength, fiscal stability, and the labour market, with a focus on their impact on economic cohesion. The study's hypothesis is that EU countries can be classified into several clearly distinct clusters based on a combination of macroeconomic indicators, and that these groups reflect underlying structural and macroeconomic differences within the Union. The structure of the paper includes a review of relevant literature, a description of the research methodology, the results of the conducted analyses, including cluster, discriminant, PCA, and factor analyses, and a discussion of the findings and conclusions. Finally, the paper presents the implications of the results for economic policies and suggests areas for future research.

2. Literature overview

Structural heterogeneity among European Union (EU) member states is a complex phenomenon encompassing differences in gross domestic product (GDP), inflation, unemployment rate, fiscal balance, public debt, and current account balance. Examining these differences is crucial for understanding convergence processes, the effectiveness of monetary and fiscal policies, and the identification of vulnerable countries within the Union (Jolliffe & Cadima, 2016; Hair et al., 2019). Multivariate methods, including cluster analysis, PCA, and factor analysis, allow for systematic mapping of latent structures and the identification of patterns in the data that are not apparent through simple descriptive statistics (MacQueen, 1967; Ward, 1963). Such methods facilitate the grouping of countries according to economic characteristics, highlighting those that deviate from the average and may require targeted policy interventions. Empirical literature indicates that convergence within the EU is not uniform. The "two-speed" phenomenon highlighted by Alcidi et al. (2018), with Central and Eastern European countries growing faster than some Western members, reflects differences in adjustment capacity and structural predispositions, a pattern echoed by Borsi and Metiu (2015) and Forgó and Jevčák (2015). Bolea and Duarte (2018) further show that previously convergent patterns can reverse, underscoring the sensitivity of integration to external shocks.

Recent studies confirm that EU heterogeneity also spans regional differences and "convergence clubs", groups sharing similar long-term growth and fiscal paths (Dräger et al., 2023; Licchetta & Mattozzi, 2023; Glavaški et al., 2023). Spatial dynamics have been examined through spatial quantile analysis (Cartone et al., 2021), the CEE-8 relative to the EU-15 (Cieślik & Wciślik, 2020), and EU-wide convergence clubs (Cutrini & Mendez, 2023). Bartkowska and Riedl (2012) and Monfort et al. (2012) apply clustering to detect similar patterns, while Gligor and Ausloos (2008) highlight latent structures in macroeconomic indicators. Real and monetary convergence have also been analysed (Brada et al., 2005; Canova, 2004), showing that ECB monetary policy can act heterogeneously and even amplify divergence. Building on this, the Structural Divergence Index (SDI) quantifies within-cluster heterogeneity by measuring each country's distance from its cluster centroid across the six macroeconomic variables (Eurostat, 2024a–f), helping to identify members that deviate from their group's average profile. Combined with PCA and factor analysis, it offers deeper insight into how within-cluster differences contribute to overall divergence. Overall, the literature confirms that the EU is characterized by heterogeneous economies with varying growth rates, fiscal policies, and

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market pressures. The application of multivariate methods, cluster analyses, PCA/factor models, and the SDI allows for a systematic mapping of latent patterns, identification of vulnerable countries, and the design of policies that account for heterogeneity both between and within clusters. Recent studies emphasize the importance of spatial and temporal dimensions of convergence, showing that policies must be flexible and tailored to the specific characteristics of individual countries and regions, especially in the context of global and European economic shocks.

3. Methodology

3.1. Selection of Variables and Time Period

For the study of macroeconomic heterogeneity among EU member states over the period 2015-2024, six indicators were selected. Their definitions, measurement units, 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, adjusted for purchasing power parity	GDP
Unemployment Rate	Share of Unemployed in the Labor Force	Percentage of the working-age population	Unemp
Harmonized Index of Consumer Prices	Measure of Inflationary Pressures	Index (2015=100)	HICP
Budget Balance	Government Fiscal Sustainability	Percentage of GDP	Surplus
Public Debt	Government Fiscal Indebtedness	Percentage of GDP	Debt
Accumulated Balance of Payments	Net international transactions	Percentage of GDP	AccBall

Source: Eurostat (AMICO), own calculations.

The selected macroeconomic variables were standardized (z-scores) 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 allow for comparison of macroeconomic patterns across countries and reliable application of statistical methods. The core classification of EU member states is based on ten-year averages (2015–2024) and reflects long-term structural characteristics. Unlike single-year analyses that may be biased by transitory shocks, this decadal approach ensures that the identified clusters represent persistent economic regimes. Year-by-year cluster analysis is applied as an exploratory robustness check to assess the stability of cluster membership under short-term shocks.

3.2. Analytical Framework

An integrated approach combining multiple quantitative methods was applied to analyse differences and similarities among European Union member states. The aim of this approach is to group countries systematically and verify cluster stability, and identify the underlying dimensions that explain macroeconomic differences among them. Each method within the study has a clearly defined function, ranging from the initial structuring of the data to quantifying heterogeneity within the formed clusters. The first step involves cluster analyses, including both hierarchical and non-hierarchical (K-means) clustering. Hierarchical clustering provides a

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visual overview of the relationships among countries and helps initially determine the number of clusters, while the K-means method optimizes the allocation of countries into groups, ensuring a more stable and interpretatively clear classification. Discriminant analysis (DA) is then used to validate the obtained clusters, assessing the contribution of individual macroeconomic indicators in differentiating between clusters and ensuring that the grouping reflects genuine structural differences among countries rather than random patterns.

To reduce data complexity and identify the key dimensions of variability, Principal Component Analysis (PCA) was applied. PCA condenses the six observed macroeconomic indicators into a smaller set of mutually independent components, facilitating interpretation while retaining the maximum possible share of total variance. For a deeper understanding of latent dimensions and hidden patterns among the variables, Factor Analysis (FA) was employed, allowing the identification of underlying factors associated with key economic processes, such as fiscal sustainability, monetary conditions, or market dynamics. As a central element of the analysis, the Structural Divergence Index (SDI) is introduced to quantify the degree of heterogeneity among countries within each cluster. Each country i is represented as a vector of k standardized macroeconomic indicators (k = 6), while the cluster centroid c is defined as the vector of mean standardized values for all countries belonging to that cluster. The SDI is formally expressed as the Euclidean distance between the country's vector and its corresponding cluster centroid:

$$SDI_i = \sqrt{\sum_{j=1}^{k}\left(x_{ij} - \overline{x}_{cj}\right)^2} \quad (1)$$

Here j denotes the macroeconomic variable (j = 1…,6), x_{ij} is the standardized (z-score) value of variable j for country i, and $\bar{x}_{cj}$ is the centroid value of cluster c for the same variable. Because all variables are standardized, the SDI expresses each country's distance from the average structural profile of its cluster on a common scale: higher values indicate greater divergence, lower values closer alignment. Euclidean distance is preferred over the Mahalanobis distance for its direct interpretability with K-means centroids, giving a transparent measure of within-cluster heterogeneity.

The SDI is deliberately distinguished from other divergence measures. Unlike the Mahalanobis distance, which reweights dimensions by the inverse covariance matrix and becomes unstable in small samples (27 countries), it applies an unweighted Euclidean distance on standardized variables, preserving each dimension's interpretable contribution. Unlike entropy- or inequality-based indices (e.g., Theil or Gini), which summarise dispersion without a reference point, the SDI is cluster-centric: it measures each country's distance from its own group's centroid. It therefore isolates specific structural outliers within otherwise cohesive groups and tracks them over time, which pooled within-cluster variance analyses cannot do. The methods follow a logic of progressive elaboration: cluster analyses form groups of countries; discriminant analysis assesses their stability and interpretative value; PCA extracts the main dimensions of variability; factor analysis identifies latent factors; and the SDI quantifies structural divergence within clusters. Together they provide a comprehensive framework combining quantitative rigour with interpretative depth.

4. Empirical Data

4.1. Sources

The data used in this study are sourced from the Eurostat (AMICO) database and cover all European Union member states for the period 2015–2024. The analysis is based on six

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macroeconomic indicators presented in Table 1 (Section 3.1), selected to capture key dimensions of economic structure, including fiscal sustainability, inflationary trends, labour market conditions, and overall economic development. Table 2 presents the average values of these indicators per country over the period; these averages underpin all subsequent analyses. The data were standardized (mean = 0, SD = 1) so that all variables carry equal weight and larger-scale indicators do not dominate. This prepared dataset forms the basis for the cluster analyses, PCA, factor analysis, and the SDI, ensuring the results are comparable and statistically robust.

Table 2 Macroeconomic variables for EU countries in the period 2015-2024

	Country	GDP	Unemp	HICP	Surplus	Debt	AccBall
1	Belgium	117.6	6.4	112.1	-3.5	104.2	0.2
2	Bulgaria	56.9	6.1	111.7	-1.2	24.0	0.3
3	Czechia	91.6	2.9	117.5	-1.7	37.7	0.1
4	Denmark	128.7	5.5	106.4	2.2	38.9	8.6
5	Germany	121.7	3.5	110.1	-0.9	65.0	7.0
6	Estonia	81.4	6.2	119.0	-1.5	14.8	-0.6
7	Ireland	202.7	6.1	105.6	-0.1	56.6	2.9
8	Greece	66.7	17.4	105.5	-2.3	181.8	-4.5
9	Spain	89.7	15.5	107.9	-4.6	105.5	2.0
10	France	102.3	8.5	108.1	-4.7	105.3	-0.5
11	Croatia	67.8	8.8	109.0	-1.7	73.5	0.9
12	Italy	97.0	9.7	107.2	-4.8	137.9	1.7
13	Cyprus	91.9	8.7	104.3	0.1	93.8	-6.1
14	Latvia	67.1	7.8	115.8	-2.4	42.2	-1.0
15	Lithuania	82.9	7.2	118.6	-1.0	39.3	0.8
16	Luxembourg	257.5	5.8	109.3	0.9	23.1	6.7
17	Hungary	73.4	4.3	121.5	-4.3	73.1	-0.3
18	Malta	105.3	4.1	108.3	-2.3	47.8	8.9
19	Netherlands	131.5	5.0	111.0	-0.4	52.1	7.7
20	Austria	123.3	5.6	112.2	-2.7	79.8	1.7
21	Poland	74.7	4.1	115.3	-3.1	51.2	-0.5
22	Portugal	77.2	8.1	107.2	-1.7	118.7	0.4
23	Romania	68.7	6.0	115.8	-5.1	42.7	-5.2
24	Slovenia	86.8	5.4	109.2	-2.2	73.8	4.8
25	Slovakia	72.9	7.2	113.7	-3.1	54.4	-2.9
26	Finland	108.0	7.9	107.0	-2.2	71.7	-0.8
27	Sweden	118.8	7.6	110.9	-0.2	38.1	4.2

Source: Eurostat, Amico database, 2024.

4.2. Descriptive statistics

Descriptive statistics were performed on the dataset, covering measures of central tendency, dispersion, and distribution shape characteristics. Measures of central tendency include the mean, median, and quartiles, while dispersion is assessed through the standard deviation, minimum, and maximum values. The shape of the distribution is evaluated using skewness and kurtosis coefficients. Positive kurtosis values indicate a higher concentration of data around the mean with pronounced extremes, whereas negative values suggest a more uniform data distribution.

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Table 3 Descriptive statistics of macroeconomic variables for EU Countries (2015-2024)

Variable	N	Mean	Std. Dev.	Min.	Lower Quartile	Median	Upper Quartile	Max.	Skewness	Kurtosis
GDP	27	102.37	43.200	56.9	73.4	91.6	118.8	257.5	2.29	6.29
Unemp	27	7.09	3.213	2.9	5.43	6.16	8.05	17.43	1.90	4.49
HICP	27	111.12	4.624	104.26	107.23	110.06	115.31	121.52	0.64	-0.48
Surplus	27	-2.02	1.818	-5.12	-3.13	-2.19	-0.85	2.19	0.15	-0.16
Debt	27	68.40	38.361	14.83	39.3	56.61	93.78	181.82	1.17	1.59
AccBall	27	1.35	3.9778	-6.05	-0.62	0.44	4.17	8.88	0.30	-0.27

Source: Eurostat (AMICO), own calculations.

The descriptive statistics analysis of the observed macroeconomic indicators reveals significant variability among the EU member states:

- The indicators display substantial cross-country variability. GDP per capita shows the widest dispersion (mean = 102.37; SD = 43.20; range 56.9–257.5), with high-income outliers such as Luxembourg and Ireland. Unemployment (mean = 7.09%; SD = 3.21) peaks in Spain and Greece, while HICP is comparatively balanced (skewness 0.64). Fiscal indicators reveal the greatest heterogeneity: public debt ranges widely across member states, and the budget balance and accumulated balance of payments differ markedly in fiscal exposure and sustainability.

This analysis confirms the presence of significant heterogeneity in EU economic indicators, particularly in variables measuring economic output and fiscal exposure, while inflation and accumulated balance of payments indicators are relatively balanced. To assess the interrelationships among variables, the 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	Surplus	Debt	
GDP	100,000	-0.221	-0.320	0.490	-0.218	0.539
		0.268	0.104	0.010	0.275	0.004
Unemp	-0.221	100,000	-0.436	-0.246	0.699	-0.387
	0.268		0.023	0.217	<.0001	0.046
HICP	-0.320	-0.436	100,000	-0.265	-0.499	-0.200
	0.104	0.023		0.181	0.008	0.316
Surplus	0.490	-0.246	-0.265	100,000	-0.418	0.460
	0.010	0.217	0.181		0.030	0.016
Debt	-0.218	0.699	-0.499	-0.418	100,000	-0.316
	0.275	<.0001	0.008	0.030		0.108
AccBall	0.539	-0.387	-0.200	0.460	-0.316	100,000
	0.004	0.046	0.316	0.016	0.108	

Source: Eurostat (AMICO), own calculations.

The analysis of interrelationships among macroeconomic variables reveals several interesting patterns among EU member states:

- GDP correlates positively with the budget surplus (0.49) and the accumulated balance of payments (0.54), while unemployment is strongly associated with public debt (0.70) and negatively with HICP (−0.44). Fiscal indicators are mutually heterogeneous: the surplus correlates negatively with debt (−0.42) and positively with the accumulated balance of payments, which in turn moves with GDP (0.54) and the budget surplus (0.46).

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These findings provide a solid basis for the further application of multivariate methods, including cluster analysis, PCA, and factor analysis, enabling a more detailed interpretation of the relationships among macroeconomic indicators over the observed period. Given the existing heterogeneity, particularly in GDP, unemployment rates, and fiscal indicators, the application of the Structural Divergence Index (SDI) allows for additional analysis of within-cluster differences and the identification of countries that are statistical outliers within their groups.

5. Results and Discussion

This chapter presents the results of the analysis of macroeconomic indicators for EU member states over the period 2015–2024. The methods described in Chapter 3 were applied: hierarchical and K-means cluster analysis, discriminant analysis, PCA, and factor analysis. The main focus of the analysis is on identifying groups of countries with similar economic profiles and quantifying the heterogeneity within these groups using the Structural Divergence Index (SDI). The SDI allows for distinguishing countries that are close to the cluster centroid from those at the periphery, providing a basis for further interpretation of differences and similarities among EU member states.

5.1. Country Clustering

This part of the analysis groups EU member states by their macroeconomic profiles and identifies those deviating from their group's average. Hierarchical clustering first determines the number of clusters; K-means then allocates countries into stable groups; and discriminant analysis evaluates the distinctness of the groups and flags borderline cases. In addition to the average classification for the entire period, year-by-year cluster dynamics (2015–2024) are examined to assess the stability of group membership over time. This forms the basis for quantifying within-cluster heterogeneity using the Structural Divergence Index (SDI), which is addressed in the following subsections.

5.1.1. Hierarchical Cluster Analysis

Hierarchical cluster analysis was applied to identify the initial grouping structure among EU member states from the similarity of their macroeconomic indicators. Countries with the most similar profiles first form small groups, which progressively merge into broader clusters, revealing the underlying structure of economic similarities and increasing heterogeneity at higher levels. Semipartial R^2 values were computed for each merge to gauge its contribution to total variance and help determine the optimal number of clusters. Based on the pronounced “breaks” in the dendrogram and the semipartial R^2 analysis, a three-cluster solution was identified as optimal and used as the basis for the subsequent K-means and SDI analysis.

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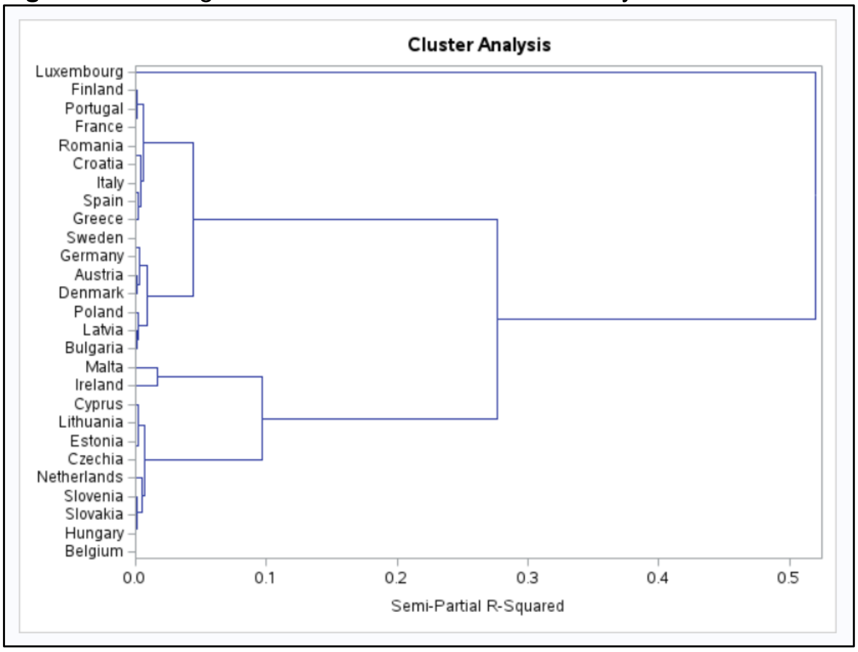
Figure 1 Dendrogram of the hierarchical cluster analysis



Source: Eurostat (AMICO), own calculations.

Using Ward's minimum variance method, the cluster history reveals a pronounced increase in semipartial R^2 when moving from three to two clusters ($\Delta R^2 = 0.276$), indicating a clear loss of homogeneity and supporting the three-cluster solution. This result is corroborated by the non-hierarchical FASTCLUS procedure, which yields an overall R^2 of 0.532 and a pseudo-F statistic of 13.65, providing additional support for the three-cluster structure.

5.1.2. Non-hierarchical (K-means) Cluster Analysis

To validate the results of the hierarchical clustering and to allocate countries into statistically stable groups, a non-hierarchical K-means clustering analysis was applied. The analysis was conducted for three clusters, which was identified as the optimal solution based on the hierarchical approach. Alternative solutions (k = 2, k = 4, k = 5) were examined, but the three-cluster structure provided the clearest and most consistent separation of macroeconomic profiles, while higher-order solutions resulted in less stable groupings. Figure 2 presents the mean values of the variables for each of the three clusters. This visualization highlights the structural differences among the groups and enables a clear interpretation of the dominant macroeconomic characteristics within each cluster:

- Cluster 1, referred to as Convergence Economies, is characterized by lower GDP per capita, elevated inflation, and relatively favourable levels of public debt. These countries are in the process of economic convergence toward the EU average.
- Cluster 2, referred to as Fiscal-Labour Challenge Economies, comprises countries with moderate to mid-range GDP levels, higher unemployment, and more pronounced fiscal challenges, including substantial public-debt burdens. These economies are more vulnerable to macroeconomic instabilities.
- Cluster 3, referred to as High-Performing Developed Economies, includes countries with high GDP per capita, low unemployment, and stable public finances. This cluster represents the most economically developed segment of the European Union.

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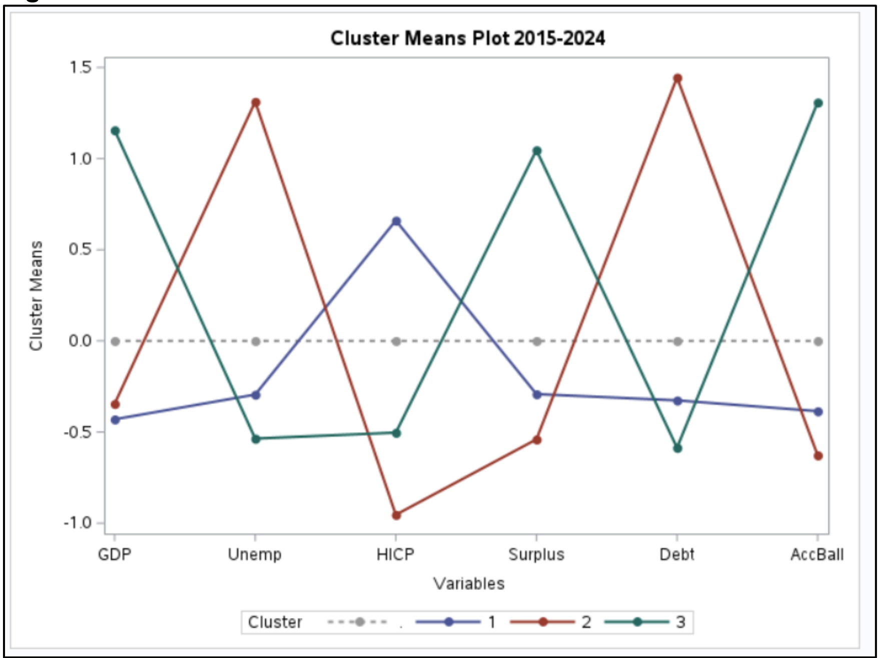
In this way, a clearer picture of the heterogeneity of macroeconomic profiles among EU member states is obtained.

Figure 2 Non-Hierarchical Cluster Means Plot



Source: Eurostat (AMICO), own calculations.

Table 5 provides an overview of the members of each cluster and their average macroeconomic characteristics, enabling a deeper interpretation of the results presented in the cluster-centroid 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 / AccBall	Profile	Performance
Convergence Economies (1)	Belgium, Bulgaria, Czechia, Estonia, Croatia, Latvia, Lithuania, Hungary, Austria, Poland, Romania, Slovenia, Slovakia, Finland	Low / Middle / High / Middle / Middle / Middle	Transition countries	Middle
Fiscal-Labour Challenge Economies (2)	Greece, Spain, France, Italy, Cyprus, Portugal	Low / High / Low / Middle / High / Low	Employment-challenged	Low
High-Performing Developed Economies (3)	Denmark, Germany, Ireland, Luxembourg, Malta, Netherlands, Sweden	High / Low / Middle / High / Low / High	Stable developed	High

Source: Eurostat (AMICO), own calculations.

The analysis reveals clear heterogeneity among EU countries. Cluster 3 includes high-performing developed economies with high GDP, low unemployment, and moderate inflation. Cluster 2 consists of economies facing pronounced labour-market and fiscal pressures, with lower GDP, higher unemployment, and lower inflation. Cluster 1 includes convergence economies characterized by lower GDP, moderate unemployment, and relatively higher inflation. The total within-cluster R-squared is 0.532, indicating that the formed clusters explain a substantial portion of the data variability. The pseudo-F statistic of 13.65 confirms the

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statistical significance of the clustering, while the Cubic Clustering Criterion (CCC) of 6.66 suggests stability of the chosen number of clusters. To further verify the distinctness of the clusters and identify the variables that contribute most to differentiating the groups of countries, discriminant analysis was conducted.

5.1.3. Discriminant Analysis

Discriminant analysis assessed how well the six macroeconomic variables (GDP, unemployment, inflation (HICP), budget surplus, public debt, and AccBall) differentiate the clusters from the K-means analysis, using a linear discriminant function. The 27 countries split into Cluster 1 (14), Cluster 2 (6) and Cluster 3 (7); the pooled covariance matrix was non-singular (rank 6), allowing stable estimation. The greatest separation is between Clusters 2 and 3 (generalized squared distance 28.84), while Clusters 1 and 2 are closer (11.52). The coefficients of the linear discriminant functions for each cluster were statistically significant, indicating that all selected indicators contribute to distinguishing among the groups. Classification results show high accuracy: in resubstitution, 100 % of countries were correctly classified, while in cross-validation ("leave-one-out"), the overall correct classification rate was 87.0 %. However, resubstitution accuracy may overestimate model performance, and therefore cross-validation results provide a more reliable estimate. A small number of misclassifications occurred in Clusters 1 and 2 (Table 6).

Table 6 Misclassified countries in the cross-validation of the discriminant analysis

Country	Actual cluster	Predicted cluster	Probability predicted
Belgium	1	2	0.617
Cyprus	2	1	0.986
Finland	1	2	0.650
Slovenia	1	3	0.714

Source: Eurostat (AMICO), own calculations.

The results indicate that the linear discriminant function provides a meaningful, though not perfect, separation of the clusters. Most countries are correctly classified, but a few misclassifications occur where structural profiles partially overlap. Because the analysis uses the same variables that defined the clusters, it should be read as an internal consistency check rather than independent validation; the misclassified cases mark countries with borderline or transitional profiles.

5.1.4. Results for Individual Years (2015-2024)

For additional insight into cluster dynamics, an annual K-means analysis was conducted with three predefined clusters for each year in the period 2015–2024. The results are presented in Table 7.

Table 7 Results of clustering by individual years (2015-2024)

	Country	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
1	Belgium	1	1	1	1	1	1	1	1	2	2
2	Bulgaria	1	1	1	1	1	1	1	1	1	1
3	Czechia	1	1	1	1	1	1	1	1	1	1
4	Denmark	3	3	3	3	1	3	3	3	3	3
5	Germany	3	3	3	3	1	3	3	3	3	1
6	Estonia	1	1	1	1	1	1	1	1	1	1
7	Ireland	3	3	3	3	3	3	3	3	3	3

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8	Greece	2	2	2	2	2	2	2	2	2	2
9	Spain	2	2	2	1	2	2	2	2	2	2
10	France	1	1	2	1	1	1	2	2	2	2
11	Croatia	1	1	1	1	1	1	1	2	1	1
12	Italy	1	2	2	1	2	2	2	2	2	2
13	Cyprus	1	1	1	1	3	1	2	2	2	2
14	Latvia	1	1	1	1	1	1	1	1	1	1
15	Lithuania	1	1	1	1	1	1	1	1	1	1
16	Luxembourg	3	3	3	3	1	3	3	3	3	3
17	Hungary	1	1	1	1	1	1	1	1	1	1
18	Malta	3	1	3	3	1	1	3	1	1	1
19	Netherlands	3	3	3	3	1	3	3	3	3	3
20	Austria	1	1	1	1	1	1	1	1	1	1
21	Poland	1	1	1	1	1	1	1	1	1	1
22	Portugal	2	2	2	1	1	1	2	2	2	2
23	Romania	1	1	1	1	1	1	1	1	1	1
24	Slovenia	1	1	1	3	1	1	1	1	1	1
25	Slovakia	1	1	1	1	1	1	1	1	1	1
26	Finland	1	1	1	1	1	1	1	2	2	2
27	Sweden	1	3	1	1	1	3	3	3	3	1

Source: Eurostat (AMICO), own calculations.

To ensure comparability of cluster labels across years, each year's three K-means clusters were matched to the baseline ten-year (2015–2024) structure by minimum Euclidean distance between centroids across the six variables. This keeps “Cluster 1–3” structurally comparable over time, so observed changes in assignment reflect genuine shifts in macroeconomic profiles rather than arbitrary year-to-year numbering. Although a three-part typology can be identified based on the ten-year average, (1) Convergence Economies, (2) Fiscal-Labour Challenge Economies, and (3) High-Performing Developed Economies, the results for individual years reveal notable fluctuations in cluster membership. For example, Belgium and Finland are assigned to the Fiscal-Labour Challenge Economies cluster in several years, indicating temporary fiscal or structural vulnerability relative to the High-Performing Developed Economies cluster. In 2019, Germany and Denmark are assigned to the Convergence Economies cluster, suggesting short-term alignment of macroeconomic indicators in a period of heightened economic uncertainty. Particular attention is drawn to 2018 and 2019, when one of the clusters included a very small number of countries. This may indicate increased homogeneity among the remaining member states or temporary shocks such as fiscal disturbances, pandemics, or geopolitical disruptions.

These findings indicate that, although a basic three-part structure of the EU exists, the membership of individual countries is not entirely stable. Therefore, additional quantification of the distance from cluster centroids using the SDI index is important, as it enables a more precise identification of countries with marginal values and temporary deviations. To make the temporal stability of cluster membership explicit, Table 8 classifies member states according to their cluster volatility over the 2015–2024 window, measured by the number of year-on-year changes in cluster assignment. Twelve countries remained structurally stable and never changed cluster; nine displayed moderate volatility (one or two transitions); and six exhibited high volatility (three or more transitions).

Table 8 Classification of EU member states by cluster volatility (2015–2024)

Stability profile	No. of countries	Transitions	Member states

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Structurally stable	12	0	Austria, Bulgaria, Czechia, Estonia, Greece, Hungary, Ireland, Latvia, Lithuania, Poland, Romania, Slovakia
Moderately volatile	9	1–2	Belgium, Croatia, Denmark, Finland, Luxembourg, Netherlands, Portugal, Slovenia, Spain
Highly volatile	6	3–5	Cyprus (3), France (3), Germany (3), Italy (3), Sweden (4), Malta (5)

Source: Eurostat (AMICO), own calculations.

Table 9 summarises the aggregate year-on-year transitions between clusters over the period. Two patterns stand out. First, the Convergence Economies cluster (Cluster 1) functions as the central and most stable group as well as the transit route between the two extremes: direct transitions between the Fiscal-Labour Challenge Economies (Cluster 2) and the High-Performing Developed Economies (Cluster 3) essentially never occur (zero transitions in either direction), so countries shifting between these profiles pass through Cluster 1. Second, the most volatile economies (Malta, Sweden and Cyprus) and the 2019 realignment, when Denmark, Germany, Luxembourg and the Netherlands temporarily moved into Cluster 1, illustrate the sensitivity of otherwise stable economies to common shocks. These results confirm that structural stability is concentrated in a core of Central and Eastern European convergence economies, whereas several high-income and Southern European economies are more responsive to external disturbances such as the COVID-19 pandemic and the 2022 energy crisis.

Table 9 Transition matrix of year-on-year cluster movements (2015–2024, count of transitions)

From \ To	Cluster 1	Cluster 2	Cluster 3
Cluster 1	130	10	10
Cluster 2	5	36	0
Cluster 3	12	0	40

Source: Eurostat (AMICO), own calculations.

5.2. Analysis of Latent Dimensions

5.2.1. Principal component analysis (PCA)

To identify latent patterns among countries and reduce the dimensionality of the dataset, Principal Component Analysis (PCA) was conducted on the six macroeconomic variables listed in Table 1. The aim was to simplify the multidimensional structure and identify the key components that explain the largest share of variability among EU member states.

Table 10 Eigenvalues and proportion of explained variance

Eigenvalues of the Correlation Matrix				
	Eigenvalue	Difference	Proportion	Cumulative
1	2.605	0.747	0.434	0.434
2	1.858	1.255	0.310	0.744
3	0.603	0.158	0.101	0.844
4	0.445	0.142	0.074	0.919
5	0.303	0.118	0.051	0.969
6	0.185		0.031	1.000

Source: Eurostat (AMICO), own calculations.

The first three principal components explain 84.4 % of the total variance. The first component accounts for 43.4 %, the second for 30.97 %, and the third for 10.05 %, indicating that a substantial share of the information contained in the original variables is captured by these dimensions.

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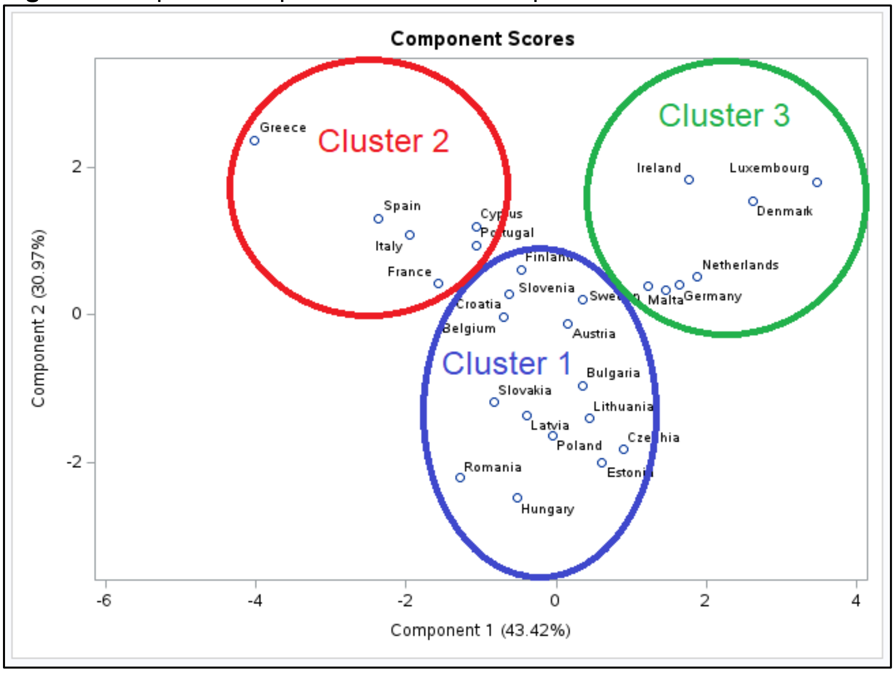
Table 11 Eigenvectors by Component

Eigenvectors						
Variable	Prin1	Prin2	Prin3	Prin4	Prin5	Prin6
GDP	0.4015	0.376	0.235	0.793	0.089	0.071
Unemp	-0.457	0.359	-0.251	0.066	0.754	-0.164
HICP	0.063	-0.678	0.046	0.176	0.476	0.526
Surplus	0.437	0.273	-0.726	-0.173	-0.000	0.421
Debt	-0.477	0.368	0.281	-0.057	-0.209	0.715
AccBall	0.456	0.244	0.524	-0.550	0.392	0.044

Source: Eurostat (AMICO), own calculations.

The principal components are interpreted from the eigenvector loadings. The first loads positively on GDP, budget surplus and the accumulated balance of payments and negatively on public debt and unemployment, reflecting economic performance and fiscal position. The second is driven by unemployment and HICP, capturing labour-market and inflationary pressures. The third, dominated by public debt and the accumulated balance of payments, represents financial sustainability and external balances. The projection of countries onto the first two principal components illustrates their relative positioning by economic structure, with high-income economies separating clearly from convergence economies along the first component.

Figure 3 Graph of Component 2 versus Component 1 results



Source: Eurostat (AMICO), own calculations.

The PCA results indicate that the complexity of macroeconomic indicators can be summarized into three components with interpretable economic meaning. The first component reflects economic performance and fiscal position, the second captures labour-market and inflationary pressures, and the third represents financial sustainability and external balances. These components provide a basis for further exploration of latent structures through factor analysis.

5.2.2. Factor analysis

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To further examine the latent structure among macroeconomic variables, factor analysis was conducted using the principal factor method. Factor analysis extracts latent dimensions that explain the shared variance among variables, complementing the PCA findings. Unlike PCA, which focuses on total variance, factor analysis emphasizes common variance. The overall Kaiser Measure of Sampling Adequacy (MSA) was 0.648, indicating moderate suitability of the data for factor analysis. Table 12 presents the Kaiser MSA values for each variable, the initial estimates of communalities based on Squared Multiple Correlations (SMC), and the final communalities after factor extraction (Final Community Estimates, FCS).

- The MSA indicates the suitability of each variable for factor analysis; values above 0.6 are considered acceptable.
- The SMC represents the proportion of a variable's variance that can be explained by the other variables before factor extraction.
- The FCS indicates the proportion of a variable's variance explained by the factor model after factor extraction.

Table 12 Kaiser's Measure of Sampling Adequacy and Variable Communalities

Variable	MSA	SMC	FCS
GDP	0.780	0.410	0.487
Unemp	0.738	0.562	0.620
HICP	0.497	0.610	0.697
Surplus	0.609	0.504	0.514
Debt	0.589	0.688	0.758
AccBall	0.759	0.433	0.489

Source: Eurostat (AMICO), own calculations.

Based on the eigenvalue criterion (eigenvalue > 1) and the scree plot (Figure 4), two factors were retained. The sum of final communalities is 3.564, indicating that the two factors explain approximately 59.4 % of the total variance, while the remaining variance reflects unique or variable-specific components. The eigenvalues of the reduced correlation matrix are presented in Table 13.

Table 13 Eigenvalues of the reduced correlation matrix

Eigenvalues of the Reduced Correlation Matrix: Total = 3.207 Average = 0.535				
1	2.143	0.722	0.668	0.668
2	1.421	1.311	0.443	1.111
3	0.110	0.223	0.034	1.146
4	-0.114	0.046	-0.035	1.110
5	-0.160	0.034	-0.050	1.060
6	-0.194		-0.060	1

Source: Eurostat (AMICO), own calculations.

Varimax rotation was applied to facilitate interpretation of the factor structure and identify the variables that contribute most to each factor.

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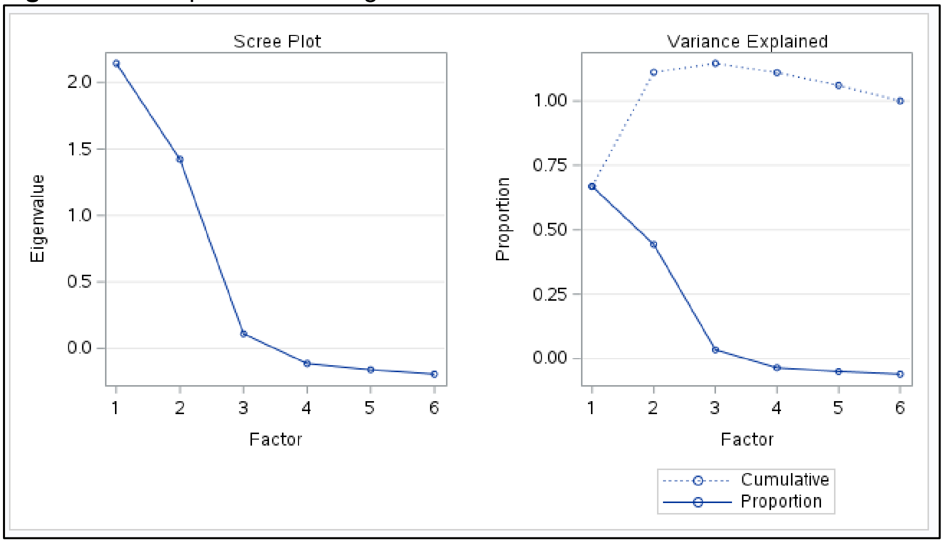
Figure 4 Scree plot of factor eigenvalues



Source: Eurostat (AMICO), own calculations.

Applying Varimax rotation yielded clear loading patterns (Table 14).

Table 14 Rotated Factor Patterns (Varimax)

Rotated Factor Pattern		
	Factor 1	Factor 2
Surplus	0.705	-0.130
GDP	0.697	-0.012
AccBall	0.678	-0.168
Debt	-0.308	0.814
Unemp	-0.280	0.736
HICP	-0.438	-0.710

Source: Eurostat (AMICO), own calculations.

For visual interpretation, Figure 5 shows the Varimax-rotated factor loadings.

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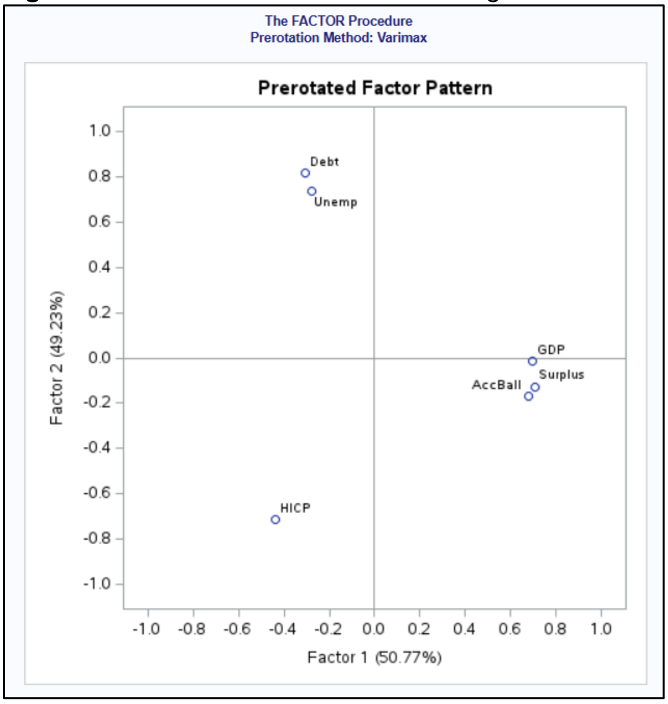
Figure 5 Varimax rotation of factor loadings



Source: Eurostat (AMICO), own calculations.

The factor analysis identified two latent dimensions. The first factor ("fiscal-economic potential") loads positively on GDP, budget surplus, and the accumulated balance of payments, while inflation loads negatively. The second factor ("labour-market and monetary pressures") is primarily determined by unemployment, with additional contributions from inflation and public debt. However, interpretation should be approached with caution, as the overall MSA value is moderate and certain variables, most notably HICP, exhibit lower individual MSA scores. This suggests that the factor structure is informative but not fully robust across all variables. HICP was retained despite its lower individual MSA (0.497) on both empirical and theoretical grounds. A sensitivity checks re-estimating the PCA without HICP leaves the variance explained by the first two components virtually unchanged (74.5% versus 74.5%), confirming that HICP does not distort the dominant structure; its removal only weakens the second dimension (from about 31% to 22%), since HICP is one of its two defining variables. Moreover, HICP has the highest final communality of all variables (0.697), so it is well represented once factors are extracted, and it captures the monetary and inflation dimension essential to the EU's macroeconomic structure. Its low MSA reflects weak partial correlations with the fiscal and real indicators rather than a lack of shared variance. The two-factor solution provides a useful but approximate summary of the underlying relationships, complementing the PCA findings without replacing them. PCA emphasizes total variance and is useful for dimensionality reduction, whereas factor analysis provides insight into the shared variance among indicators. Together, the two approaches offer a more comprehensive framework for understanding latent economic structures.

5.3. SDI, Measure of Structural Divergence

The Structural Divergence Index (SDI) is used to quantify the heterogeneity of countries within clusters identified in the previous cluster and PCA analyses. SDI measures the distance of each country from the centroid of its own cluster across all six macroeconomic variables listed

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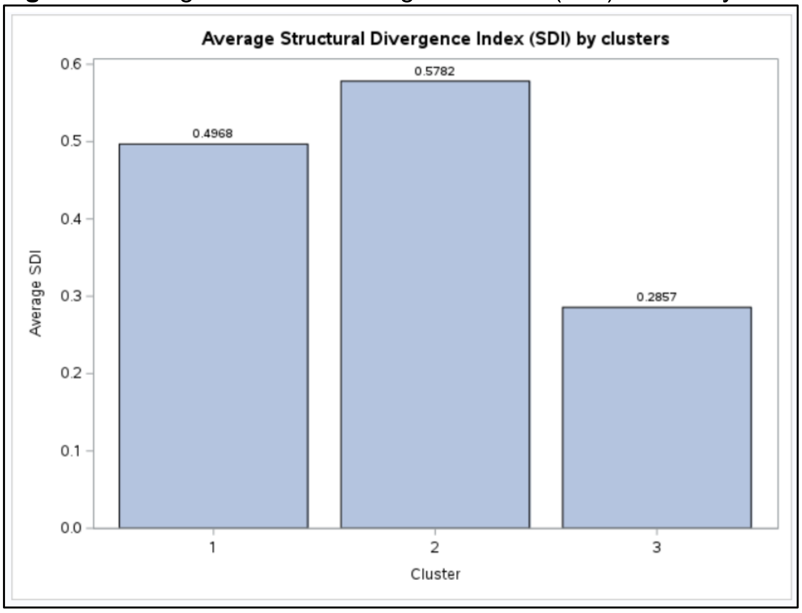
in Table 1. The application of the SDI allows for distinguishing countries that align with the average structural profile of their cluster from those that deviate and consistently emerge as structural outliers. This provides an additional dimension for understanding within-cluster heterogeneity, complementing the descriptive and multivariate cluster analyses.

5.3.1. Structural Divergence Index by Clusters and Countries

The SDI analysis by clusters reveals varying levels of within-group homogeneity. Figure 6 presents the average SDI values for each cluster.

- Cluster 1 exhibits relatively low average divergence, indicating a high degree of structural cohesion. Most countries are positioned close to the cluster centroid, while a few show more pronounced deviations.
- Cluster 2 shows greater dispersion of SDI values, indicating an asymmetric distribution and the presence of several structurally divergent countries.
- Cluster 3 also displays heterogeneity, including at least one country that deviates notably from the cluster mean.

Figure 6 Average Structural Divergence Index (SDI) values by cluster



Source: Eurostat (AMICO), own calculations.

5.3.2. Interpretation of Within-Cluster Heterogeneity

To provide a more detailed view of divergence within clusters, a box-plot representation was used. Figure 7 shows the SDI distribution by cluster, highlighting the following elements:

- The lower and upper whiskers indicate the boundaries of normal dispersion within the cluster, defined as 1.5 times the interquartile range above the 75th percentile and below the 25th percentile.
- Black dots represent extreme outliers, countries that deviate substantially from the typical structure of the cluster.

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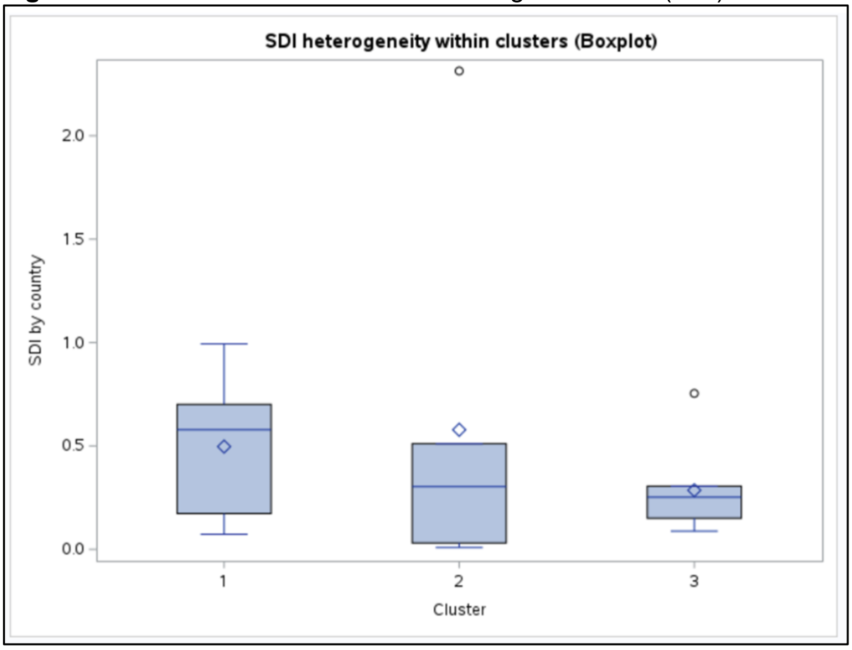
- The blue square represents the average SDI value within the cluster. Its deviation from the median indicates asymmetry and the presence of heterogeneous subgroups within the cluster.

For illustration, the following patterns can be observed:

- In Cluster 1, the mean lies within the interquartile range, and the whiskers extend on both sides, indicating a relatively symmetrical and homogeneous distribution.
- In Clusters 2 and 3, the mean is shifted upward or downward, and the whiskers do not extend symmetrically, indicating asymmetry and the presence of extreme values. Black dots denote countries with substantial deviations, while the blue square facilitates comparison of central tendencies across clusters.

These findings indicate that macroeconomic heterogeneity in the EU is present not only between clusters but also within them. The SDI therefore serves as a useful tool for identifying countries with atypical structural profiles, which may require closer monitoring in the context of cohesion policy and targeted structural reforms.

Figure 7 Distribution of the Structural Divergence Index (SDI) within clusters



Source: Eurostat (AMICO), own calculations.

5.4. Discussion

This chapter synthesizes the main findings from the cluster analysis, PCA, factor analysis, and SDI, and discusses their implications for EU cohesion and convergence policies.

5.4.1. Summary of Findings

The average indicators for 2015–2024 identified three structural profiles: Convergence Economies (Cluster 1: lower GDP, moderate unemployment, favourable public debt), Fiscal-Labour Challenge Economies (Cluster 2: lower or medium GDP, higher unemployment, pronounced fiscal pressures), and High-Performing Developed Economies (Cluster 3: high GDP, low unemployment, stable public finances). A detailed year-by-year analysis (Section 5.1.4) shows that cluster membership is not entirely stable, even after harmonisation of cluster labels across years. Several countries shift between clusters in certain years, reflecting

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temporary structural or fiscal pressures. In some years, one of the clusters contains only a small number of countries, suggesting temporary shocks or increased homogeneity among the remaining members. The Structural Divergence Index (SDI) adds an additional layer to the analysis by quantifying heterogeneity within clusters. Boxplots and scatter plots show that even within relatively stable clusters, some countries deviate substantially from the centroid. SDI therefore enables the identification of marginal values and outliers, providing deeper insight into intra-cluster heterogeneity. The combination of the average three-part cluster structure and the dynamics of country membership over the 2015–2024 period indicates that, although fundamental structural profiles exist, temporary fluctuations and intra-cluster heterogeneity are significant and should be considered in policy design. The identification of two latent dimensions, fiscal-economic potential and labour-market and monetary pressures, provides additional insight into the internal structure of the clusters and helps explain why certain countries deviate from cluster averages.

5.4.2. Implications for EU Cohesion and Convergence Policies

The findings point to several important implications for EU cohesion and convergence policies:

- Identification of vulnerable countries: Countries that occasionally deviate from their clusters may require targeted measures to support fiscal and structural stability.
- Intra-cluster heterogeneity: Divergences within clusters indicate that cohesion policies should not be uniform for all members. SDI can support more precise targeting of resources.
- Monitoring temporary shocks: Fluctuations in cluster membership highlight the sensitivity of some countries to crises, pandemics, or geopolitical disturbances. Policy frameworks should remain flexible to accommodate such temporary deviations.
- Promoting convergence: For countries in the Convergence Economies cluster and those with higher within-cluster heterogeneity, targeted structural reforms and support may be needed in areas such as labour markets, fiscal policy, and investment dynamics.
- Measurement tools: SDI complements traditional descriptive and multivariate analyses, enabling continuous monitoring of cohesion and divergence among EU member states.

These findings connect directly to current EU instruments. The 2024 reform of the Stability and Growth Pact (Regulation (EU) 2024/1263, in force since 30 April 2024) replaced uniform benchmarks with country-specific medium-term fiscal-structural plans built around a bespoke net-expenditure path derived from each member state's debt-sustainability analysis. This move towards differentiated adjustment paths mirrors the paper's central message: because within-cluster divergence is substantial, a single fiscal rule cannot fit all members. The SDI can serve as a complementary diagnostic, flagging countries whose structural profile deviates markedly from their cluster average. The same logic applies to investment resources. Next Generation EU and its Recovery and Resilience Facility (running to end-2026, allocated by member states' economic circumstances) and the 2021–2027 Cohesion Funds both aim to reduce structural disparities. The SDI offers a cluster-centric lens: rather than targeting resources by aggregate income alone, policymakers can use within-cluster distance to identify divergent economies within each group, for example, high-debt outliers among the Convergence Economies or high-unemployment members among the Fiscal-Labour Challenge Economies, and calibrate support accordingly.

6. Conclusion

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The aim of this study was to analyse the structural heterogeneity of EU member states over 2015–2024 using a multivariate approach. The initial hypothesis, that EU member states can be grouped into several clearly distinct macroeconomic clusters, is supported by the analysis. Cluster analysis identified three distinct structural profiles, while the yearly dynamics of cluster membership revealed temporary fluctuations and within-group heterogeneity. PCA and factor analysis identified two key latent dimensions, fiscal-economic potential and labour-market and monetary pressures, that structure EU economic profiles. The Structural Divergence Index (SDI) quantified deviations of individual countries from their cluster centroids, providing a measure of within-cluster heterogeneity. The results confirm that macroeconomic heterogeneity in the EU exists both between and within clusters, with implications for convergence and cohesion policies: the SDI can flag economies requiring tailored structural reforms and can be embedded in the reformed fiscal-governance and cohesion instruments as an operational monitoring tool. Its principal methodological contribution is a cluster-centric, country-specific measure that complements, rather than duplicates, Mahalanobis-type distances, entropy-based indices, and conventional within-cluster variance analyses. Limitations include the choice of indicators, the ten-year horizon, and the assumption of cluster stability; future research could extend the time span, add variables, or test alternative divergence measures.

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