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Stoycho Rusinov[1]

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USING DYNAMIC CONVERGENCE CLUBS, WEAK CONVERGENCE, AND MACHINE LEARNING TO ADDRESS ECONOMIC CONVERGENCE IN THE EU[2]

This study employs machine learning-based clustering to analyse economic growth patterns among several EU countries, using Germany as a benchmark. It introduces the concept of "weak convergence", demonstrating that while economies cluster and shift over time, they maintain a stable long-run equilibrium relationship. This finding is crucial, as it suggests that poorer countries are not necessarily accelerating toward wealthier ones but instead persist in a relatively large gap. Although the disparities between clusters appear to narrow – driven by the slowdown of richer economies and the gradual catch-up of poorer ones – this pattern does not necessarily indicate true convergence. Cointegration analysis reveals that these shifts primarily result from ongoing macroeconomic adjustments influenced by trade flows and external shocks, such as the 2007-08 financial crisis. While these shocks disrupted existing economic relationships, they also led to a reduction in between-cluster variance over time, creating a form of pseudo-sigma convergence. However, this convergence was largely driven by the relative decline of richer economies rather than a substantial acceleration of poorer ones.

Keywords: weak convergence; European Union; K-means clustering; Vector Error Correction Model; convergence clubs
JEL: C38; C32; F15; O47; R11

1. Introduction

The promise of economic convergence has long underpinned European integration. Yet, stark income disparities persist and the sharply diverging growth paths that emerged after the 2007(-08) financial crisis underscore the need to reveal these dynamics (Palier et al., 2018). While poorer EU countries have shown some growth, the gap with wealthier members remains substantial – and, in some cases, is widening.

This paper re-examines convergence through a new lens: *weak convergence*, defined later not by income equalisation but by the existence of long-run equilibrium relationships between different economies (aggregated on cluster level). Using machine learning –

[1] *Stoycho Robertov Rusinov, Sofia University "St. Kliment Ohridski", email: srrusinov@yahoo.com, ORCHID: 0009-0003-3099-2688.*
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specifically K-means clustering – we classify EU countries by their GDP per capita, relative to a baseline, and test the persistence of these groupings over time. Unlike traditional approaches, our method accounts for structural breaks (e.g., the 1990 and 2007 crises), avoids the assumption of uniform growth paths, and allows for dynamic shifts in cluster membership. We extend Baumol (1986) and Jones (1997) by using Germany as our steady-state proxy to classify, analyse and decompose the structural sources of club convergence. This is necessitated by the pending question of whether the clusters themselves "diverge" or maintain a stable long-run relationships.

The study proceeds in four steps: (1) identifying convergence clubs via clustering, (2) analysing short- and long-run GDP dynamics, (3) testing for equilibrium relationships, and (4) modelling how economic shocks propagate across clusters. Together, these reveal a deeper, more complex structure of European growth – and challenge the notion that convergence is inevitable.

2. Literature Review

While the convergence literature is vast, this review focuses on tracing the theoretical evolution toward dynamic and structural interpretations – culminating in the concept of the *weak convergence lens*. Each segment is selected for its relevance to that transition.

a. The beta and sigma convergence argument

The beta convergence story has a long history. Baumol (1986) demonstrated beta convergence among industrialised economies, showing a negative relationship between initial GDP per worker in 1870 and subsequent growth through 1979. In contrast, Pritchett (1997) highlighted the rarity of convergence among the world's poorest countries. These contrasting findings marked a turning point in the 1990s literature, spurring the development of econometric methods to estimate convergence more rigorously.

To address the need for empirical precision, sigma and beta convergence were formalised by Barro and Sala-i-Martín (1990), with further econometric detail in Barro and Sala-i-Martín (1992). Sigma convergence captures the declining dispersion of income over time ($\sigma^2{}_{\mathrm{t}} > \sigma^2_{t+\tau}$), while beta convergence relates initial GDP levels to subsequent growth rates. Furceri (2005) later connected the two concepts by suggesting that sigma convergence can be sufficient for beta convergence (under specific conditions) but is not necessary for beta convergence to hold.

To arrive at an econometric estimation, Barro and Sala-i-Martín (1992) log-linearised cross-sectional regressions grounded in the Solow (1956), Cass (1965), and Koopmans (1965) models. They argue that per capita output transitions exponentially from its initial state toward a steady state, with β reflecting the influence of preferences, population growth, and technological progress – elements initially formalised by Ramsey (1928). Econometrically, β is often approximated using the average annual growth rate in a simple cross-sectional regression:

$$\frac{1}{\tau}\ln\left(\frac{y_{i,t+\tau}}{y_{i,t}}\right) = \alpha - \underbrace{\left(1 - e^{\lambda t}\right)}_{\beta}\ln y_{i,t} \ + \varepsilon_i$$

This formulation, as noted by Mathur (2005), assumes smooth, equidistant growth over the time horizon. Economic shocks, nonlinear dynamics, or volatility breaks that assumption-making the estimate fragile and prone to bias. Such problems will be absorbed by the weak convergence framework, since it does not assume equal growth between years.

The issue deepens when analysts substitute GDP per capita with GDP per person employed (labour productivity) – especially in ageing economies. Once decomposed (assuming a Cobb-Douglas form of the production function):

$$\frac{\Delta LP}{LP} = \frac{\Delta A}{A} + \alpha\left(\frac{\Delta K}{K} - \frac{\Delta L}{L}\right)$$ [3]

Labour force shrinkage ($\frac{\Delta L}{L} < 0$) causes capital deepening, mechanically inflating labour productivity – even without true efficiency gains. Raleva and Zlatinov (2024) provide important insights into labour productivity convergence dynamics during the transition period in Central and Eastern Europe (CEE). They highlight strong correlations between growth and initial levels of the labour productivity (LP) indicator. Building on their findings, this paper suggests that additional structural factors may have influenced long-term productivity patterns, allowing the weak convergence framework to absorb the distortions caused by the assumption of uniform growth.

The diversity of empirical findings in beta convergence studies underscores the need for alternative analytical perspectives. For instance, Barro and Sala-i-Martín (1992) report significant convergence between 1960 and 1986 across 20 OECD countries, 98 global economies, and 48 U.S. states. Within the EU context, Mathur (2005) estimates absolute and conditional convergence speeds ranging from 0.26% to 1.82% per year. In contrast, Zlatinov and Atanasov (2021) report an absolute convergence speed of 1.49%, which falls to 1.25% under a conditional specification. Although the estimated speeds of convergence (λ) appear modest – typically between 0.5% and 2% annually – even these small rates imply substantial long-term effects (e.g., a 2% annual rate would close 60% of initial disparities over 30 years). The question of whether such strong convergence has materialised in the Union since the 1980s reinforces the need for a "weak convergence" perspective.

b. From a cross-section to time series: stochastic convergence and its extensions

Most early studies rely on cross-sectional regressions and assume uniform growth paths across countries[4]. Yet, economic realities – such as structural shifts and external shocks –

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[3] Taking averages $\frac{1}{\tau}\ln\frac{LP_{t+\tau}}{LP_t}\uparrow \approx \underbrace{\frac{1}{\tau}\ln\frac{TFP_{t+\tau}}{TFP_t}}_{\sim 0} + \underbrace{\frac{\alpha}{\tau}\left(\ln\frac{K_{t+\tau}}{K_t} - \ln\frac{L_{t+\tau}}{L_t}\downarrow\right)}_{\uparrow}$ it is visible that under a demographic collapse the indicator may be driven by decline in labor, not necessarily technological improvements.

[4] Most of those studies (especially in the EU) relied on extremely limited sample sizes (20-40 countries). The nature of the cross-sectional regressions allowed for bootstrapping, but it was rarely done.

complicate these trajectories. Bernard and Durlauf (1995) introduce stochastic convergence, defined in time-series terms rather than cross-sectional comparisons, positing that country differences diminish to zero over an infinite horizon. Prochniak and Witkowski (2016) extend this by adjusting the GDP time series to remove the influence of growth determinants, acknowledging that countries are not homogeneous. They propose "stochastic conditional convergence," wherein convergence depends on varying economic factors. The base assumption is that if there is a convergence between countries j and i, then the limit of the conditional expectation $\left(\lim_{t\to\infty} E\left[\ln y_{it} - \ln y_{jt} \middle| \Omega_t\right]\right)$ should approach zero as time progresses. The methodology allows testing for convergence to a group mean $\left(\ln y_{it} - \frac{1}{N}\sum_{j=1}^{N} \ln y_{jt}\right)$, by assessing whether each country converges toward the average GDP of the group. It also allows for analysis of "groups" or perhaps "clusters" of convergence. Even though the convergence assumption is tested, no further relationships between the countries are identified because the process is treated as a statistical property, and the underlying mechanism is abstracted. This limits the analysis to a binary outcome: convergence or no convergence. That is likely the reason why Prochniak and Witkowski (2016)'s results indicate that pairwise convergence occurs in only 8.2% of the total number of country pairs. A major advantage of the weak convergence framework is that it allows for a more nuanced and less abstract analysis of this process.

c. Clustering as a remedy for spatial heterogeneity

Despite progress in convergence theory, heterogeneity across countries and regions persists, and traditional models often fail to account for spatial differences. "Convergence clubs" were introduced to address these disparities, but were later criticised as "premature" (Postiglione et al., 2020) and used as a grounding reason for spatial regressions.

Monfort et al. (2013), for example, identified two convergence clubs in the EU – aligning with our pre-2007 findings – yet did not investigate steady states, treat clusters as dynamic, or examine combined GDP. This revealed pronounced per capita income divergences. Likewise, the European Central Bank (2015) notes limited sustainable real convergence in the Eurozone due to structural rigidities, weak productivity, and inadequate macroeconomic policies. Empirical work confirms that convergence clubs mirror socioeconomic asymmetries among EU members, undermining the idea of a uniformly integrated Europe (Lafuente et al., 2020). Cavallaro and Villani (2021) observe productivity-based clustering rather than a single growth path. Holobiuc (2020) reports an EU convergence speed of 2% (1995–2019), while newer members converge at nearly 3%, underscoring their divergence from older states. *Institutional and Socio-Economic Convergence in the European Union* (2014) similarly finds stronger conditional convergence among newer members – and in the EU overall – compared to more competitive economies, reinforcing that convergence is far from uniform across the Union.

The idea behind convergence clubs is that economies within a club converge toward a shared steady state, while divergence persists across clubs. In our analysis, convergence clubs serve a strategic function: they reduce cross-sectional complexity by aggregating countries into income-based clusters. This aggregation enables us to test for equilibrium relationships across groups rather than individuals, addressing whether income disparities persist at the club level. More critically, we examine whether these clubs themselves exhibit structural equilibrium.

d. Spatial growth regressions and the β coefficient

While clustering techniques improved our understanding of convergence, they still failed to fully capture regional dependencies and spillover effects. Spatial growth regressions emerged as an alternative, incorporating geographical relationships into traditional convergence models. They were originally proposed by Ertur and Koch (2007). This approach extends the findings of Mankiw et al. (1992) and Barro and Sala-i-Martín (1992), which assume a uniform speed of convergence across all countries. By augmenting the model spatially, it distinguishes between homogeneous and heterogeneous models, offering more nuanced insights into convergence dynamics.

In spatially augmented approaches, the primary enhancement to the standard Solow growth model is the inclusion of spatially dependent components that capture structural relationships between different regions or countries. A significant contribution of Postiglione et al. (2020) lies in their successful estimation of the convergence rate coefficient for EU NUTS 3 regions using a spatially augmented model. The estimated convergence rate for the period 1981–2014 ranges from 4.57% in the non-spatial model to 7.48% in conditional spatial models. Notably, when the same methodology is applied to 1,133 NUTS regions over the shorter period 1991–2014, the convergence speed declines dramatically, reaching a maximum of just 3%. This result suggests that a mere ten-year difference in the analysed timeframe can reduce the estimated convergence speed by 4 percentage points, underscoring the sensitivity of convergence estimates to both spatial scale and temporal coverage. However, while this methodology accounts for spatial heterogeneity, it has notable limitations. Specifically, it:

- Fails to uncover the underlying relationships between regions, as the high level of disaggregation prevents the drawing of meaningful macroeconomic conclusions. (What cohesive policy could realistically target 1,133 NUTS regions?)
- Overlooks potential spillover effects.
- Does not distinguish between short- and long-term interactions or trade dynamics.

Next, we will consider the concept of weak convergence and how it relates to the other theories of convergence.

3. Constructing the Weak Convergence Argument

Weak convergence, as used in this paper, refers to the presence of stable long-run equilibrium relationships between economies or clusters – such as cointegration of income levels relative to a baseline – even in the absence of absolute convergence in GDP per capita. This concept is distinguished from 'strong' convergence, which implies a measurable narrowing of income gaps (e.g., via β-convergence). The term 'weak' is used here in contrast to 'strong' convergence, but it does not correspond to the formal definition of weak convergence in mathematics or probability theory.

To formalise this concept, consider an “ideal” steady-state income level $Y^*(t)$ which evolves dynamically due to societal advancements. We define a country’s relative position to this benchmark as:

$y_i(t) = \frac{Y_i(t)}{Y^*(t)}$,

where this normalisation transforms real GDP per capita into a relative measure, providing a comparative baseline for assessing economic progress. If $Y_i(t)$ grows but $y_i(t)$ remains constant, the country’s relative position is unchanged, meaning it does not converge in the traditional sense-it will grow but be bounded.

Consider countries i and k, along with a benchmark economy j. If the relative GDP per capita of a linear combination between i and k forms a stationary long-run relationship with respect to j, then

$E[y_i(t)|y_k(t)] = f(y_i(t))$,

where $f(y_i(t))$ represents a bounded function ensuring that deviations remain finite. For weak convergence to hold, there must exist a stationary linear combination of the GDP per capita relative to this baseline such that:

$$y_i(t) - \beta y_j(t) \sim I(0), \tag{3.1}$$

where $I(0)$ denotes stationarity, implying that there are no deviations from the stable long-run equilibrium. This differs from absolute convergence, where GDP levels directly converge $Y_i(t) \rightarrow Y_j(t)$, and from stochastic conditional convergence, as weak convergence is treated as an equilibrium condition, where temporary deviations are systematically corrected in the long run. This process is best understood within the framework of **cointegration theory**. If two or more economies share a long-run equilibrium relationship in their **relative GDP per capita**, they are **cointegrated**, meaning that deviations from equilibrium are **temporary and self-correcting**.

Additionally, by combining weak convergence and clustering methods, the cross-sectional dimension collapses into those “economic clusters”. This reduces the dimensionality of the data and allows for the application of cointegration statistical tests. Several other problems are also resolved:

Problem	Solution
Enhancing Conditional Convergence Models	• Unlike standard beta convergence models, weak convergence **does not require absolute GDP convergence** but only the presence of a stable **equilibrium relationship**. • The VECM structure allows for **multiple "betas"**, which account for both **short-run fluctuations** and **long-run equilibrium forces**.
Incorporating Macroeconomic Crises	• By introducing **exogenous shocks (e.g., the 1990 and 2007 financial crises)**, the model assesses how major economic events **disrupt or reinforce** weak convergence patterns. • This follows the contributions of the **conditional convergence hypothesis**, extending it with a **dynamic perspective**.
Dynamic Clustering and Evolving Convergence Clubs	• Unlike conventional approaches that treat clusters as **static**, this study allows **clusters to expand, contract, or reconfigure** over time. • This reflects the reality of economic integration, where **convergence patterns shift due to trade, investment, and policy changes**.
Decomposing the Causes of Convergence	• The study critically evaluates whether the **reduction in variance between clusters** is driven by: a) **Richer countries are slowing down** (stagnation). b) **Poorer countries accelerating growth** (catch-up effect). • This distinction is essential for designing **effective policy interventions**

4. Methodology

In this section, we outline the steps taken to (1) identify growth clusters using K-means, (2) select optimal cluster counts with the gap statistic, (3) compute average relative GDP per capita within clusters, and (4) evaluate both short- and long-term weak convergence dynamics through cointegration and vector error correction models (VECM). Finally, we examine shock propagation using forecast error impulse responses (FEIR).

a. Clustering with K-means

Conceptually, each country is plotted on a two-dimensional map: one axis represents its relative GDP per capita at the beginning of a period (t), and the other at the end (t +τ). Countries that lie close together in this space form clusters, reflecting shared economic progress. This approach aligns in part with the traditional beta convergence hypothesis, which compares initial GDP levels to subsequent outcomes. Formally, each country i is represented by the vector $\boldsymbol{x}_i = (RGDPPC_t^i, RGDPPC_{t+\tau}^i)$, which captures its GDP per capita relative to a baseline at two points in time. The algorithm partitions the n observations into k clusters, $S_1, \dots, S_k$, by minimising the within-cluster sum of squared deviations:

$$WCSS_k = \sum_{i=1}^{k} \sum_{x \in S_i} ||\boldsymbol{x} - \mu_i||^2 \tag{4.1}$$

where the centroid μ_i of cluster S_i is given by:

$$\mu_i = \frac{1}{|S_i|}\sum_{x \in S_i} \boldsymbol{x} \tag{4.2}$$

K-means then proceeds iteratively by updating centroids until assignments stabilise. $WCSS_k$ scores are then plotted for various k values. For robustness, we also apply the Gap Statistic:

$$GAP(k) = \frac{1}{B}\sum_{b=1}^{B}(\ln WCSS_k^{(b)} - \ln WCSS_k) \tag{4.3}$$

which compares the observed $WCSS_k$ with that from B bootstrapped reference datasets. A larger gap indicates more distinct clustering. Finally, we compute the average GDP per capita, relative to a baseline, of each cluster as the unweighted mean of its members' values:

$$ARGDPPC_{kit} = \frac{1}{|C_k|}\sum_{i=1}^{|C_k|} RGDPPC_{kit} \tag{4.4}$$

This approach was preferred due to its relatively straightforward and computationally efficient nature, combined with its ease of interpretability.

b. Cointegration and weak convergence

To examine weak convergence between two clusters, we apply the Engle–Granger two-step procedure over two periods (1980–2007 and 1980–2018). We estimate the long-run relationship:

$$y_i(t) = \beta_0 + \beta_1 y_j(t) + u_i(t),$$

where $u_i(t)$ represents deviations from equilibrium. If clusters approach each other in relative terms $(y_i(t) \rightarrow y_j(t))$, this systematic relationship breaks down, and relative GDP per capita should approach unity uniformly[5]. After testing for stationarity in $u_i(t)$, we construct the following short-run relationship:

$$\Delta y_i(t) = \alpha + \beta' \cdot u_i(t-1) + \rho \cdot \Delta y_i(t-1) + \sum_i \gamma_i \cdot \Delta y_j(t-i) + \varepsilon_t$$

where the coefficient β' measures how quickly the clusters return to equilibrium in the short run, while ρ and γ are short-run adjustment parameters.

[5] The relationship will be adequate as long as the reference country does not significantly deviate from the other industrialized economies. The clustering algorithm ensures that Germany is grouped with other industrialized economies, suggesting it follows a stable growth trajectory along its peers.

To test for "weak convergence" among multiple clusters, we apply Vector Error Correction Models (VECM) based on Johansen's cointegration test. This test assesses whether a linear combination of non-stationary series is stationary (Villacampa Portuguez, 2024; Adebanjo & Shakiru, 2022). Cointegration is critical for VECM estimation, as it identifies stable long-run relationships (Moroke, 2014) and allows for the distinction between long-run equilibrium forces and short-term deviations (Vishwakarma, 2021).

We estimate a VECM on the average relative GDP per capita (*ARGDPPC*) of each cluster. The model is formally defined as:

$$\Delta\mathbf{ARGDPPC}_{\mathrm{t}} = c + \Pi \cdot \mathbf{ARGDPPC}_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta\mathbf{ARGDPPC}_{t-i} + \boldsymbol{\phi}\boldsymbol{D}_{2007} + \varepsilon_t \quad (4.5)$$

Where:

- $\Pi \cdot \boldsymbol{ARGDPPC}_{t-1}$ represents the **long-term equilibrium structure**, ensuring that clusters return to equilibrium after deviations. A significant **error correction term (**α) would confirm that deviations from equilibrium are only **temporary** and that economies **adjust back** to a long-run stable relationship.
- $\sum_{i=1}^{p-1} \Gamma_i \Delta\boldsymbol{ARGDPPC}_{t-i}$ captures **short-term adjustments**, showing how economic clusters react to shocks.
- ε_t is the residual, assumed normally distributed, and homoscedastic.

This model can be implemented in **R**, which enables easy switching between VECM and VAR models depending on the number of cointegrating relationships. However, given the relatively limited number of observations compared to the number of estimated parameters, the following cointegration and VECM analyses are conducted in an exploratory framework, seeking indicative patterns rather than precise effect estimates.

We analyse shock propagation across clusters using Forecast Error Impulse Responses (FEIR), which track how disturbances in GDP per capita relative to a baseline spread over time, without imposing strong causality assumptions. The FEIR at horizon h is given by:

$$\Psi_h = \sum_{i=0}^{h} \Phi_i \Sigma, \quad (4.6)$$

where:

- Ψ_h is the **FEIR matrix** at a given time horizon h**.**
- Φ_i represents the **coefficients** from the moving average representation of the **VAR model**.
- Σ is the **variance-covariance matrix**, which captures how variables fluctuate together.

5. Data

The primary source used is the Madison 2020 database. We define Relative GDP per capita as a country's GDP per capita divided by Germany's GDP per capita:

$$RGDPPC_{jt} = \frac{GDP\ per\ capita_{jt}}{GDP\ per\ capita_{Germany,t}}, \tag{5.1}$$

Germany serves as the baseline due to its steady-state proximity and stable long-run growth, analogous to Jones (1997) using the U.S. for global comparisons. This choice ensures methodological robustness, though future studies could refine this approach by approximating steady-state conditions through macroeconomic modelling – beyond the scope of this paper due to space constraints.

Furthermore, Luxembourg and Ireland are considered outliers and were omitted from the analysis. Prior testing indicated that their inclusion could significantly bias the K-means clustering algorithm. To ensure meaningful long-run comparisons, we include only countries established before 1980, preventing distortions caused by major crises. While future research could reconstruct pre-independence growth trajectories, this requires sophisticated historical approximations beyond the present scope. Approximating country-specific steady states and introducing more robust machine learning algorithms is also a possible direction.

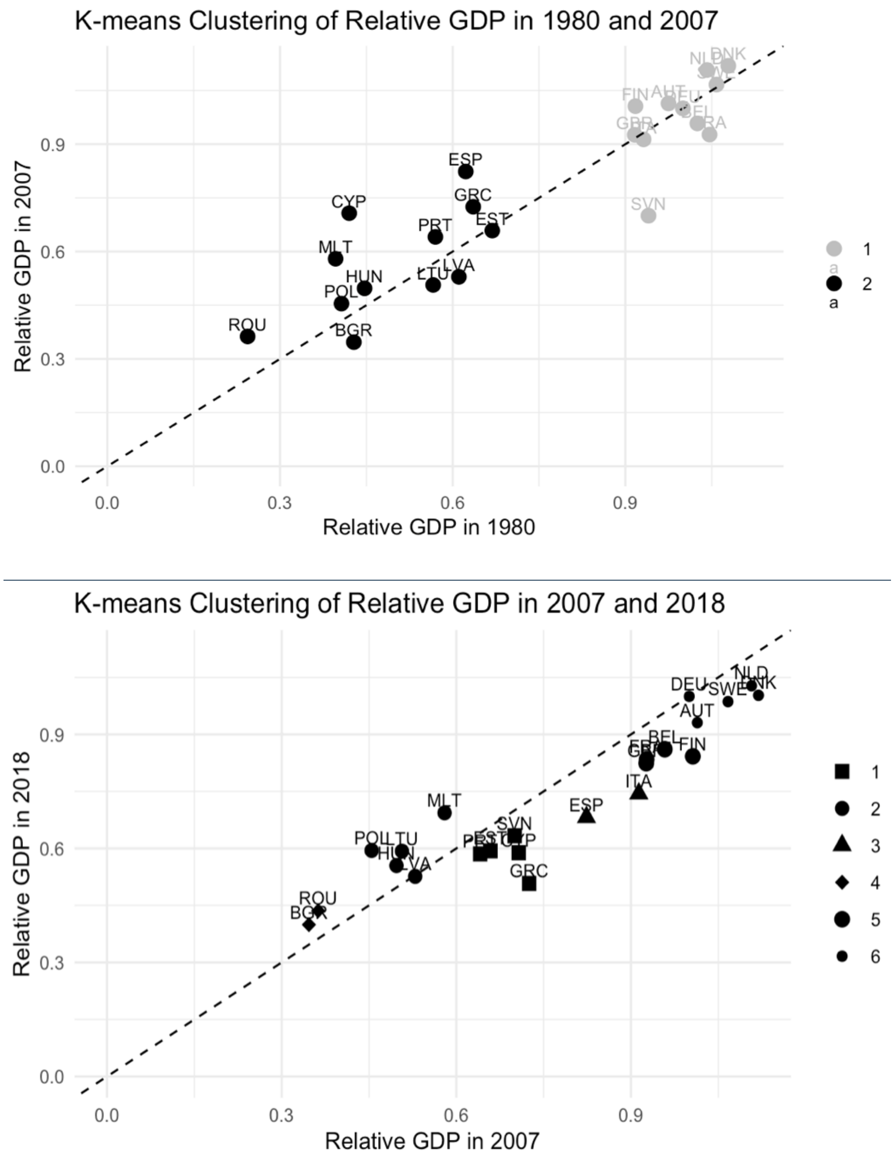
6. K-Means Clustering Results

The K-means clustering results (Figure 1) use the default Hartigan and Wong (1979) algorithm, revealing distinct growth patterns. The dotted line in Figure 1 divides countries into two regions: those above the line have higher relative GDP per capita (RGDPPC) compared to their baseline, and those below have lower RGDPPC than their initial values. The derived convergence clubs *reflect socioeconomic asymmetries among EU members (as mentioned in the literature review)*.

Before the 2007 financial crisis (first graph in Figure 1), the within-cluster sum of squares (Figure A.1, upper left corner) and the GAP statistic (Figure A.1, upper right corner) both indicate that $k = 2$ is optimal. Two clusters emerge visually: a grey cluster (Cluster 1) with generally higher growth (though it includes some negative outliers), and a black cluster (Cluster 2) with minimal or negative growth (e.g., Slovenia). The black cluster shows greater variance in RGDPPC, reflecting diverse economic performance, while the grey cluster is more homogeneous and remains close to its baseline growth path. This suggests that richer countries are growing slowly, while the poorer countries exhibit a heterogeneous growth path – some improving substantially, others not.

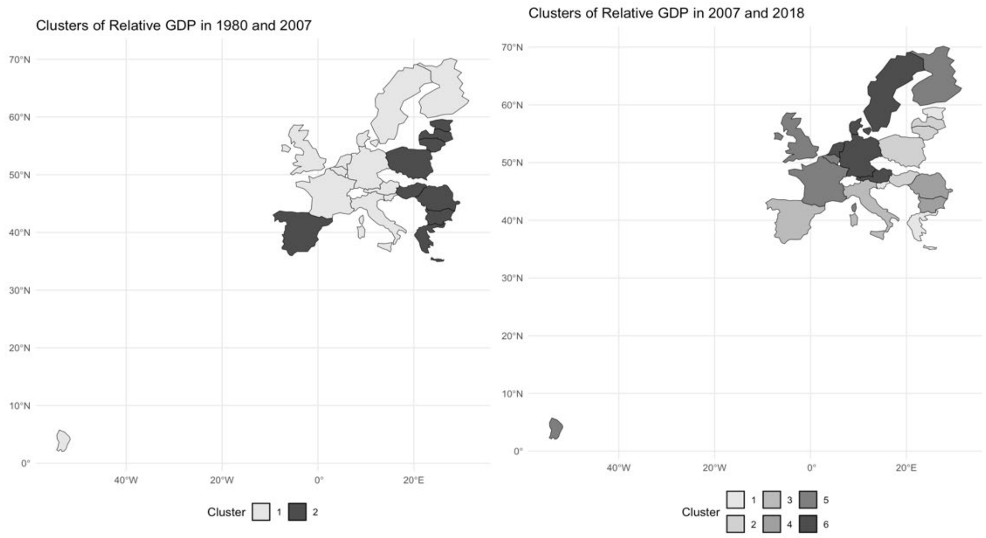
Under the standard convergence hypothesis (with Germany approximating the steady state), countries near equilibrium (RGDPPC ≈ 1) generally grow more slowly, while those further from it grow faster. However, post-2007 results (second graph in Figure 1) challenge this idea. The within-cluster sum of squares again points to two main clusters (Figures A.1, lower left corner), but the GAP Statistic (Figure A.2, lower right corner) highlights up to six possible centroids, indicating more fragmented growth patterns and increased heterogeneity – or divergence – after the crisis.

Figure 1. K-means clustering for the periods 1980–2007 and 2007–2018



Source: Own processing.

Figure 2. Geospatial mapping of identified clusters for the periods 1980–2007 and 2007–2018



Source: Own processing

Figure 2 visualises the clustering dynamics across Europe: the left panel represents the pre-2007 period, while the right panel illustrates post-2007 shifts. Table 1 tracks transitions in cluster membership, with unassigned countries shown as isolated cases. These findings reinforce a non-random, spatially driven clustering pattern, aligning with literature linking trade, knowledge diffusion, and geographic proximity to synchronised growth. Before the 2007 financial crisis, the first two clusters exhibited a distinct geospatial structure, with the grey cluster (Cluster 1) forming the economic core and the black cluster (Cluster 2) surrounding it (Figure 2, left). This spatial arrangement underscores the role of trade networks, technological spillovers, and capital mobility in driving regional economic synchronisation.

Post-2007, this geospatial arrangement eroded (Figure 2, right), leading to fragmentation and a blurred distinction between "rich" and "poor" economies. The once-clear cluster centroids converged, signalling a decay in equilibrium dynamics. This structural shift suggests a disruption in the underlying forces that previously sustained economic convergence – potentially driven by financial instability, policy divergences, and asymmetric crisis transmission. In Table 1, we present the final cluster specifications. We generally identified four major clusters that retained their previous relationships. However, since the cluster constructed from Slovenia, Italy, and Spain contains countries that did not maintain their previous positions, we didn't include it in the VECM model estimation. The Bulgarian and Romanian cluster is too small for meaningful comparison and was also removed. Next, we explore these considering the *weak convergence* hypothesis.

Table 1. Cluster movements and reconfigurations

Country	1980–2007	2007–2018	Country	1980–2007	2007–2018
BEL	1	5	AUT	1	6
FIN	1	5	DEU	1	6
FRA	1	5	DNK	1	6
GBR	1	5	NLD	1	6
CYP	2	1	SWE	1	6
EST	2	1	HUN	2	2
GRC	2	1	LTU	2	2
PRT	2	1	LVA	2	2
BGR	2	4	MLT	2	2
ROU	2	4	POL	2	2
SVN	1	1			
ITA	1	3			
ESP	2	3			

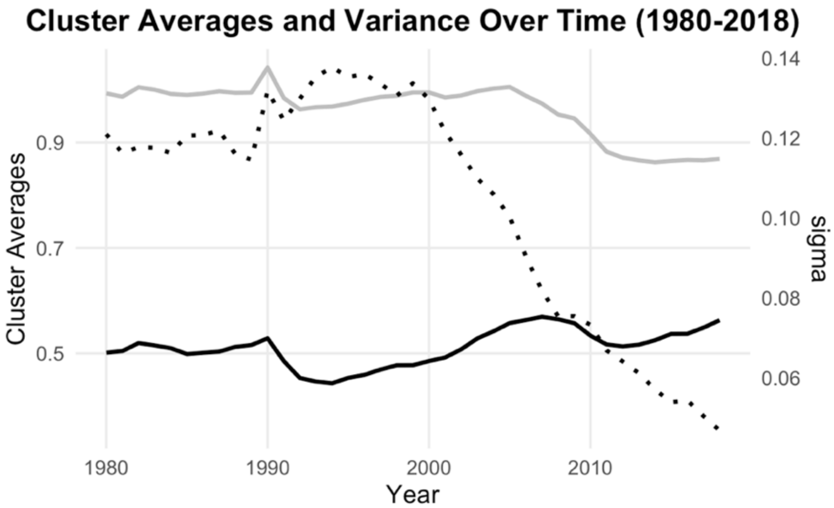
Source: Own processing

7. Between Cluster Error Correction Mechanisms

a. The traditional two-cluster case

Previously, we identified two pre-2007 clusters. Figure 3 maps their average relative GDP per capita (ARGDPPC), illustrating how they evolved over 39 years.

Figure 3. Dynamics of the two clusters: the light gray line represents Cluster 1, and the black line represents Cluster 2; the dotted line indicates the variance over time



Source: Own processing.

Both clusters show contrasting ARGDPPC trends. Over the entire period, the first cluster remained near a fixed mean, then declined sharply (by 13 %). Meanwhile, the second cluster slightly improved (by 12%), narrowing the gap from below, until the 2007 crisis triggered stagnation in Cluster 1 and a brief downturn in Cluster 2. After a quick recovery, in 2018 the second cluster ended slightly above its 1980 baseline – approaching the first cluster from below as it was declining. This pattern reflects poorer catching up, while richer countries experienced a relative decline.

Table 2. Error correction model for the two-cluster case

	First stage model		Second stage model	
Span:	**1980–2007**	**1980–2018**	**1980–2007**	**1980–2018**
ARGDPPC for second cluster	0.238***	-0.418*		
ECT_1			-0.308	0.012
ΔCluster 1_{t-1}			-0.073	-0.1
ΔCluster 2_t			0.759***	0.944***
Constant	0.871***	1.175***	-0.002	-0.005**
Observations	**28**	**39**	**26**	**37**
Adjusted R2	**0.26**	**0.053**	**0.522**	**0.539**
F-Statistic	**10.63****	**3.16***	**10.091*****	**15.034*****
ADF on residuals	**-3.66*****	**-1.69***	**2.44****	**3.17*****
Durbin-Watson	**0.02**	**<2.2e-16*****	**0.07**	**0.04**
Breusch-Pagan	**0.1**	**0.006*****	**0.83**	**0.52**

Notes: Statistical significance indicators: p-value<0.10, p-valu**e<0.05, p-value***<0.01. The standard OLS estimation is used.*

In Table 2, we apply the Engle and Granger (1987) method outlined in the methodology. For the period 1980–2007, the narrative is one of measured stability. The residuals in this era are stationary, affirming the presence of a stable equilibrium among the clusters and thereby indicating "weak convergence" dynamics. Although the initial regression modestly explains 26% of the variation in the data, the second-stage model dramatically enhances this explanatory power to an adjusted R^2 of 54%. This leap is driven primarily by robust short-run dynamics. Interestingly, Cluster 1 appears almost inert in its short-run adjustments – with its lagged changes (ΔCluster$_1$(t-1)) hovering near zero – suggesting that it remains largely unresponsive to immediate past fluctuations. However, even in this relatively stable period, the error correction component does not achieve statistical significance, and there is a subtle hint of autocorrelation as flagged by the Durbin–Watson statistic. This implies the need to diversify the clusters, because their current fragmentation does not yield a meaningful error correction mechanism.

The story takes a different turn when we extend the analysis through 2018. As seen from Table 2, with the post-2007 data in play, the ADF test loses some of its conviction – achieving only marginal significance at the 10% level (compared to the pre-2007 period results, which were significant at 5%, bordering on 1% significance) – and hints at the re-emergence of a unit root. The long-run relationship, once being -0.3, weakens markedly – the *possible* weak convergence is lost; the ECT coefficient slips to a mere 0.012. Moreover, while the first-stage model previously enjoyed an acceptable fit, its R^2 plunges by nearly 80%, a clear sign that the equilibrium has been disrupted.

Adding to this narrative, the variance between clusters – depicted as a dotted line in Figure 3, – begins to decline sharply – a signal of sigma convergence, implying that the 2007 crisis altered the relationship between clusters.

In essence, the pre-2007 era was characterised by a stable relationship among clusters – a kind of equilibrium where, despite modest adjustments, the overall balance was maintained. However, the financial crisis appears to have upended this balance. The stability evaporated, weak convergence faded, and the shrinking variance indicates that if any convergence did occur, it did so at the expense of richer clusters losing their relative advantages. This disruption can either happen because of major economic reforms[6] or an exogenous macroeconomic shock.

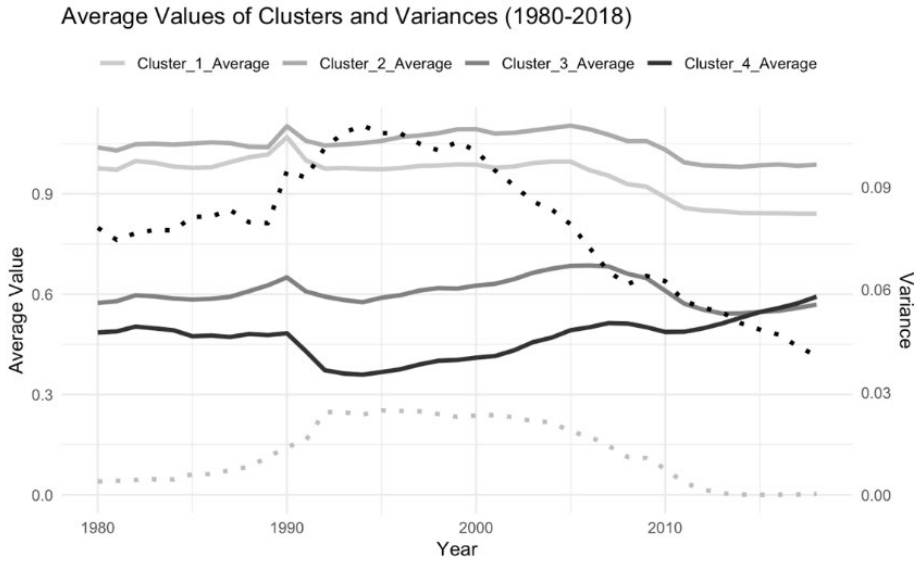
To delve even deeper into this transformation, we subsequently fragment the clusters post-2007, setting the stage for a more nuanced investigation of their behaviours. We diverge from the traditional 2-cluster case by testing multiple long-run relationships characterised by the interactions of multiple cluster configurations.

8. Post-2007 Cluster Fragmentation

Figure 4 encapsulates our refined K-means analysis, revealing striking variance dynamics. The dark dotted line shows overall variance, while the light dotted line isolates variance for Clusters 3 and 4. Instead of a systematic decline, variance exhibits episodic sigma convergence from the early 2000s, driven by two key clusters. Notably, Cluster 2 – having split from a stable Cluster 1 (which hovers near unity) – embarks on a steady descent. After the 2007 crisis, Clusters 1, 2, and 3 declined at different rates, but the poorest cluster rose persistently, overtaking Cluster 3 and eliminating their variance gap for the first time in 30 years. This visual evidence indicates that at most three cointegrating relationships should emerge in Johansen tests – Clusters 1 and 3 share similar long-run dynamics (aside from Cluster 2's decline), while Clusters 2 and 4 deviate from equilibrium. The more fundamental question pertains to what will happen with the error correction mechanism once we correct for exogenous shocks. Will a long-run error correction mechanism emerge?

[6] Consider, for example, the Japanese case outlined in Wells (2002), where a set of controversial policies caused a rapid growth during the period 1950–1960. Or the even the more controversial "shock therapy" in Poland and Czechoslovakia (outlined in Kennedy & Sandler (1999)), both of which caused a substantial economic changes following periods of stagnating growth.

Figure 4. Dynamics of the four clusters. The dotted lines show the variance in time



Source: Own processing

a. Analysis with only one structural shock

To assess weak convergence via cointegration, we first test stationarity using the ADF and KPSS methods. A series that is non-stationary in levels but stationary in first differences is classified as $I(1)$ (Moroke, 2014; Shah et al., 2021). As mentioned earlier, in such cases, a VECM is suitable for capturing both short-term dynamics and long-term equilibria (Anindyntha & Fuddin, 2023). We perform these tests (at levels and first differences) for each of the four cluster formations. Table 3 summarises the results.

Table 3. ADF and KPSS tests for stationarity at levels and in first differences

	At levels			First differences		
Cluster	**ADF Test**	**KPSS Test**	**Conclusion**	**ADF Test**	**KPSS Test**	**Conclusion**
1	-1.10	0.75***	**Not Stationary?**	-3.43***	0.24	**Stationary**
2	-0.66	0.35*	**Not Stationary**	-4.26***	0.26	**Stationary**
3	-0.13	0.16	**Not Stationary**	-2.39**	0.14	**Stationary**
4	0.74	0.40*	**Not Stationary**	-2.55**	0.34	**Stationary**

Notes: Statistical significance indicators: $p-value^{*} < 0.10, p-value^{**} < 0.05, p-value^{***} < 0.01$

Table 3 shows the ADF and KPSS tests at levels and first differences, confirming that all four clusters are $I(1)$. Furthermore, based on AIC, SC, FPE, and HQ (Table A.1), two lags provide the best fit.

With two lags and one structural shock in 2007, the Johansen test identifies three cointegrated relationships at the 5% level (Table A.2), though the result is not significant at the 1% level, leaving open the possibility that a cointegration rank of two may still be sufficient. This was an expected result because some clusters notably broke the equilibrium. The final VECM specification includes only two error correction terms, a choice made to preserve degrees of freedom and avoid model overparameterization. The VECM results appear in Table 4, with adequacy tests in Table A.3.

Table 4. The results from the performed VECM with one structural shock

Equation	ΔCluster 1	ΔCluster 2	ΔCluster 3	ΔCluster 4
Long-run				
ECT_1	-0.2′	-0.015	-0.17*	-0.23*
ECT_2	0.04	-0.67′	0.12	0.43
Intercept	0.29	0.68**	0.17	-0.03
Lag 1				
ΔCluster 1	-0.02	-0.89*	0.05	-0.3
ΔCluster 2	-0.91**	0.23	-0.6**	0.7*
ΔCluster 3	0.79*	-0.57′	0.87**	0.51
ΔCluster 4	-0.2	-0.1	0.012	0.41′
Lag 2				
ΔCluster 1	0.39	0.35	0.17	0.11
ΔCluster 2	-1.11′	-1.00*	-0.39	-0.55
ΔCluster 3	0.60	0.59′	0.27	0.26
ΔCluster 4	-0.15	0.27	0.16	0.21
Exogenous				
2007 dummy	-0.02**	-0.03***	0.02**	-0.11

*Notes: Statistical significance indicators: ′p-value < 0.10; *p-value <0.05; **p-value < 0.01, ***p-value < 0.001. The ML estimator is used.*

Table 4 reveals a clear divide in long-run adjustment across clusters. Clusters 3 and 4 maintain equilibrium through a strong, significant error correction mechanism, whereas Cluster 2 shows only marginally significant results. This was expected, given Cluster 2's divergence from Cluster 1 beginning in 1990, suggesting an omitted structural shock at that time. The 2007 financial crisis further deepened the split: Clusters 1 and 2 (wealthier economies) experienced growth declines, while Cluster 3 (poorer nations) showed a temporary growth boost. In the short run, Cluster 3's growth is significantly negatively related to Cluster 2's, implying that growth in richer clusters only weakly transmits to weaker ones.

Impulse-response analysis (Figure A.2) underscores these relationships. Cluster 2 reacts sharply to shocks from Cluster 1 but quickly stabilises. Interestingly, Cluster 3 is the only configuration that reacts positively to shocks propagating from all four clusters, with shocks from Cluster 2 lasting longer compared to the other two. This may imply that if the equilibrium is disturbed, this cluster shows positive readjustments towards higher relative growth rates, showcasing that macroeconomic deviations in the Union may substantially change the equilibrium relationships and cause unexpected relative growth in poorer nations.

b. Adding the 1990 crisis as a secondary structural shock

We consider the crisis of 1990 as a second structural shock. By specification $\boldsymbol{D_{1990}} := \begin{cases} 1, & if\ t \in (1990{,}1993) \\ 0, & if\ t \notin (1990{,}1993) \end{cases}$, where we generally allow 3 years of recovery. The optimal lag in the VECM remains two (confirmed by all listed criteria), and the Johansen cointegration test indicates at most three cointegrating relationships (again, using only two ECT components for comparability and degrees of freedom preservation). However, there are changes in both the short- and long-term dynamics of the model, while the changes in AIC and BIC are negligible.

Table 5. The results from the performed VECM with 2 structural shocks

Equation	ΔCluster 1	ΔCluster 2	ΔCluster 3	ΔCluster 4
Long-run				
ECT_1	0.1	0.04	0.03	-0.16′
ECT_2	-0.57**	-0.66***	-0.45**	-0.59***
Intercept	0.55*	0.64***	0.45**	0.62***
Lag 1				
ΔCluster 1	-0.33	-1.05**	-0.19	0.06
ΔCluster 2	0.51	0.32	0.36	0.17
ΔCluster 3	0.72*	0.64*	0.79**	0.44
ΔCluster 4	-0.15	0.05	0.023	0.02
Lag 2				
ΔCluster 1	-0.04	0.3	-0.2	-0.38
ΔCluster 2	-0.74′	-1.15**	0.014	0.09
ΔCluster 3	0.57	0.67*	0.18	0.02
ΔCluster 4	0.35	0.27	0.32′	0.41′
Exogenous				
2007 dummy	-0.022*	-0.03**	-0.02**	-0.02**
1990 dummy	-0.016	-0.07	-0.012	-0.03*

*Notes: Statistical significance indicators: 'p-value < 0.10; *p-value <0.05; **p-value < 0.01, ***p-value < 0.001. The ML estimator is used.*

Table 5 shows that the revised estimation enhances the short-term dynamics: all clusters now exhibit significant error correction terms, confirming the existence of long-run equilibrium relationships. Larger absolute coefficients indicate a significant negative short-term interaction between the two wealthier clusters. While the 1990 crisis dummy remains mostly insignificant (except for Cluster 4), the 2007 dummy is now uniformly significant and negative. This is consistent with the demographic collapses, macroeconomic shocks, and widespread economic instability during that period. The weak convergence framework absorbs these distortions.

Although short-term deviations are positive, long-run corrections remain negative, indicating that the system gradually restores equilibrium after shocks. In relative terms, structural changes are eventually reversed. These results support the possibility of weak convergence under normal conditions, although the 1990 and 2007 crises significantly disrupted the dynamics. The findings underscore that major macroeconomic collapses in the Union alter long-run equilibrium relationships and lead to cluster restructuring. Once corrections occur, the clusters re-establish robust long-run links, as reflected in the shift in p-values. Overall, any reduction in income disparities does not appear to stem from a natural process of faster growth among poorer nations; rather, short-term fluctuations are typically corrected over time.

Figure A.3 refines the impulse-response analysis for this model. Incorporating the 1990 dummy narrows confidence intervals and increases the significance of certain impulses – Cluster 1 now reacts more strongly to shocks from Cluster 2, and Cluster 3 shows a more pronounced response to shocks from all clusters – highlighting greater interdependence and the impact of the crisis variable on both short- and long-run behaviour.

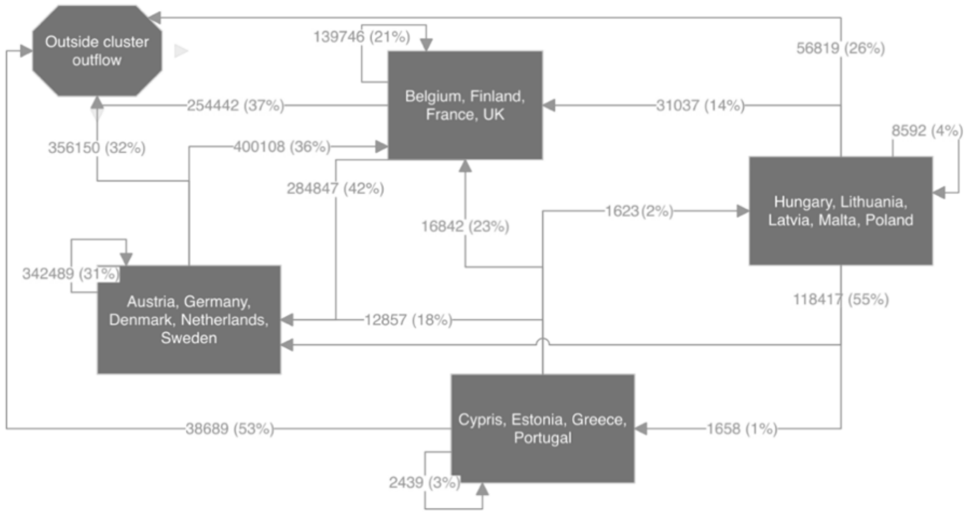
9. Between-, Within- and Outside-Clusters Trade Flows

A very notable concern, posed by Postiglione et al. (2020), was that cluster selection is "random". In this section, we address this by illustrating that the countries, part of the said clusters, participate in economically meaningful trade relationships (Figure 5). Following the gravity model of trade, which links trade intensity to size and proximity, commercial flows were used to measure interconnectedness. The strong geographic pattern observed across clusters (Figure 2) confirms the structural cohesion implied by these trade linkages. Notably, only Cyprus, Estonia, Greece, and Portugal exhibit significant outflows beyond the cluster model, with approximately 53% of their exports to the top five trade partners directed outside the whole configuration. In contrast, the Austrian and Belgian clusters demonstrate the highest levels of intra-cluster independence. Specifically, 31% and 21% of their trades with top partners occur within the cluster, while 36% and 42% are exchanged between these two clusters. Exports to partners outside the cluster model account for only 32% and 37% of their total top-five trade flows, respectively. The Hungarian cluster stands out for its strong connectivity with the Austrian cluster, sharing 55% of its top exports with it. Despite this, the Hungarian cluster exhibits relatively low external outflows, with only about 26% of its top exports leaving the overall configuration.

These findings align with the dynamics observed in Figure 4. Wealthier clusters, such as Cluster 1 and Cluster 2, tend to be closely linked in terms of relative income and trade activity. In contrast, poorer clusters are more fragmented, with the Hungarian cluster serving as a notable intermediary because it maintains robust trade relationships with both wealthier clusters (14% and 55%, respectively) while displaying weaker internal connectivity with the Cypris cluster, for example. This pattern of export flows suggests that trade does not necessarily lead to wealthier nations disproportionately benefiting. Instead, poorer countries also gain significant exposure to affluent importers, which may foster economic growth and maintain the long-run equilibrium.

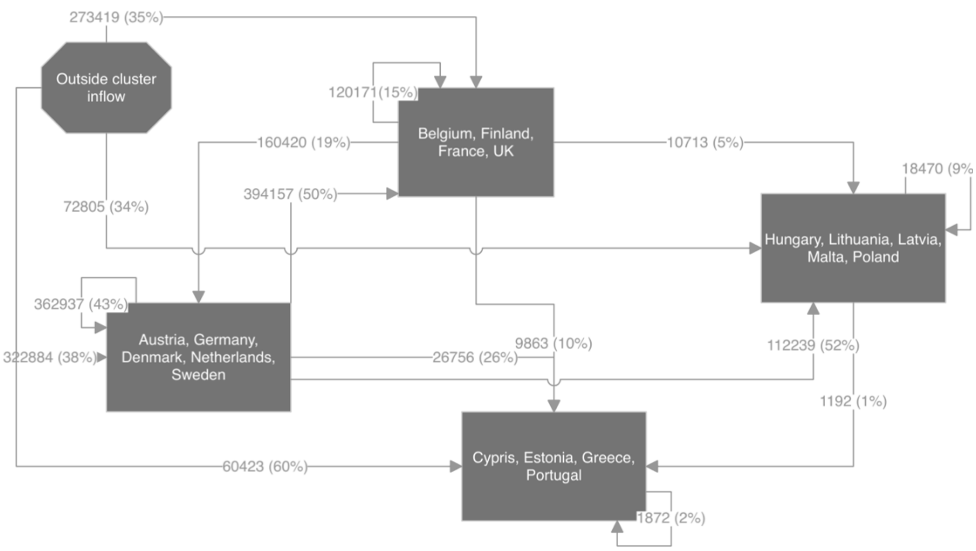
Figure 6 presents the flow diagram of trade inflows within, between, and outside the identified clusters. The results are similar to those presented in Figure 6, although the cluster configuration appears to be more dependent on outside-cluster inflows of goods, and there is a slight increase in within-cluster import rates for the Austrian and the Hungarian cluster, as well as a slight reduction in the intra-import rates for the Hungarian cluster.

Figure 5. Trade outflows (exports) at the cluster level for 2018 to each country's top five trade partners



Source: World Integrated Trade Solutions

Figure 6. Trade inflows (imports) at the cluster level for 2018 for each country's top five trade partners



Source: World Integrated Trade Solutions

The conclusion from this section is that the cluster configurations are unlikely to be "random"; they maintain robust trade relationships with one another and are bound by logical interconnectedness.

10. Conclusion

This paper reinterprets the process of economic convergence within the European Union through the concept of weak convergence, revealing that the reduction in income disparities is neither automatic nor necessarily the result of accelerated growth in poorer nations. Instead, the clustering and cointegration analyses demonstrate that much of the observed convergence is attributable to the relative decline of wealthier economies rather than to the meaningful catch-up of lagging countries. More importantly, the paper demonstrates that economic clusters are possibly bounded by complex long-run relationships, not just statistical noise.

The application of machine learning-based clustering, followed by a dynamic long-run analysis using vector error correction models, shows that stable long-run relationships between economic clusters exist, but true income equalisation remains elusive. These relationships were significantly disrupted by major external shocks – specifically the 1990 and 2007 crises – leading to a temporary narrowing of income gaps rather than sustained convergence driven by organic growth.

The findings challenge traditional interpretations of convergence that rely purely on beta- or sigma- frameworks. They suggest that observed reductions in variance between countries are often driven by macroeconomic shocks and structural stagnation in wealthier clusters, not by robust, sustainable growth in poorer ones. Without these shocks, long-term equilibrium relationships persist, maintaining the relative positions of countries over decades.

Finally, convergence within the EU should not be interpreted simply as an outcome of integrated policies or market mechanisms. Rather, it appears to be conditional, fragile, and heavily dependent on external disruptions. This insight has critical implications for policy: it highlights the need for proactive structural reforms, targeted investment in lagging regions, and a reconsideration of assumptions underpinning cohesion policy and convergence funding. This study thus offers a necessary recalibration of the convergence debate by framing it within a dynamic, equilibrium-centred perspective. It invites future research to incorporate weak convergence as a lens for understanding persistent inequalities across integrated economies.

Notation

RGDPPC – *GDP per capita relative to a baseline (Germany) (Fixed 2011 prices)*

ARGDPPC – *GDP per capita relative to a baseline (Germany), averaged at the cluster level. (Fixed 2011 prices)*

WCSS – *Within-Cluster Sum of Squares*

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Conflict of Interests

None

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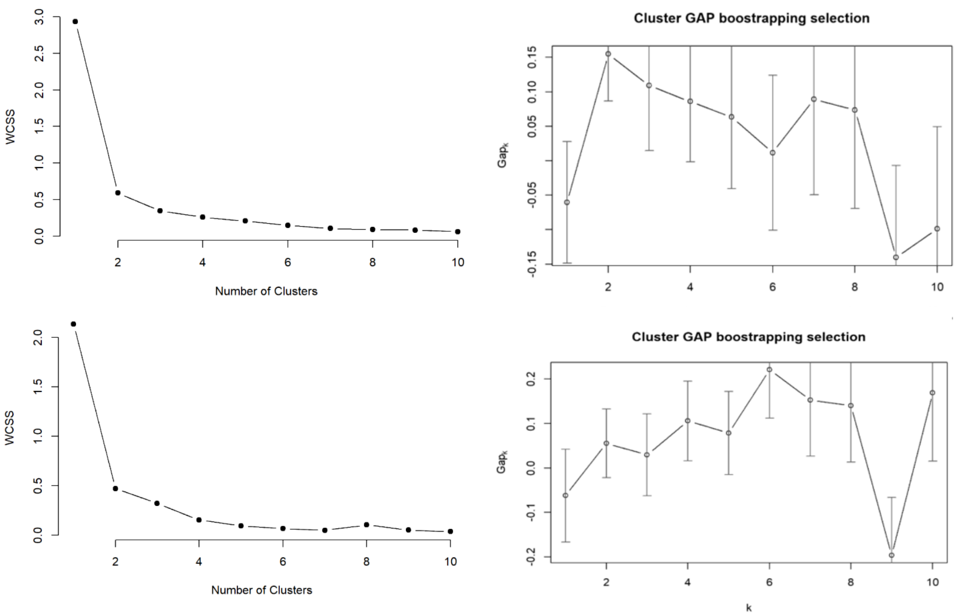
Appendix

Figure A.1. Within-cluster sum of squares results for 10 rounds of K-means clustering procedures assuming a maximum of 10 centroidc and GAP statistics results



Source: Own processing

Table A.1. Optimal lag selection

Criterion	Lag 1	Lag 2	Lag 3	Lag 4
AIC	-36.49	-38.31	-38.14	-38.26
HQ	-36.13	-37.7	-37.28	-37.15
SC	-35.43	-36.53	-35.66	-35.06
FPE	1.43E-16	2.45E-17	3.28E-17	3.74E-17

Source: Own processing

Table A.2. Johansen cointegration tests and eigenvalues

Eigenvalue	**0.62**	**0.54**	**0.42**	**0.1**
Rank	**Trace Statistic**	**10%**	**5%**	**1%**
r ≤ 3	4.1	7.52	9.24	12.97
r ≤ 2	24.27	17.85	19.96	24.6
r ≤ 1	53.2	32	34.91	41.07
r = 0	89.06	49.65	53.12	60.16

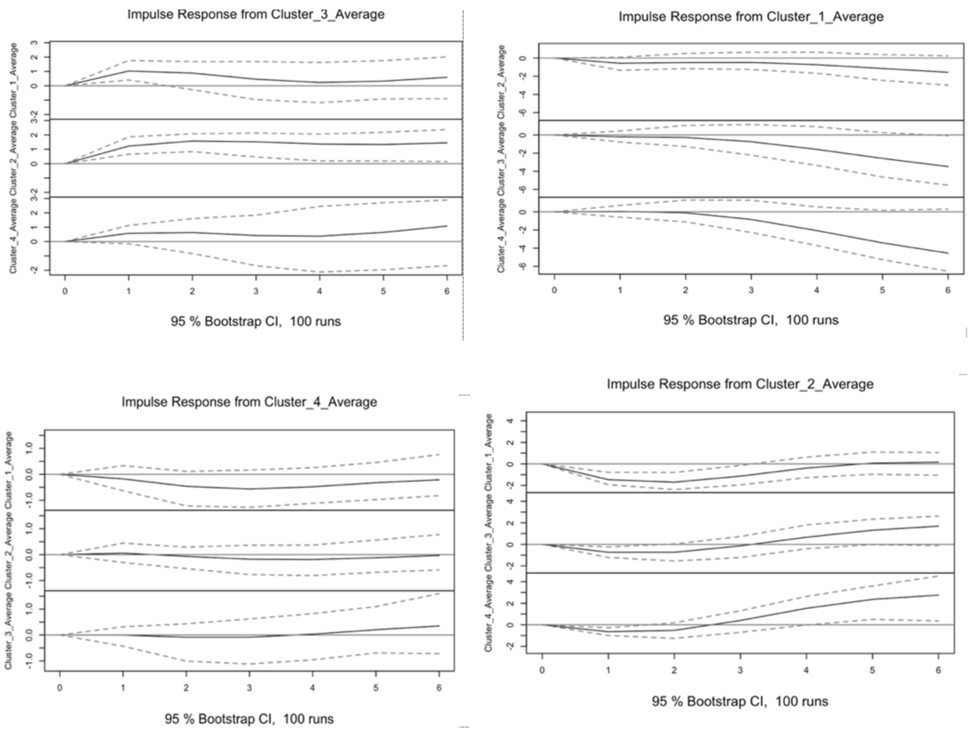
Source: Own processing

Table A.3. Adequacy tests performed on the transformed VECM model

Test	Statistic	DF	p-val	Comment
Portmanteau Test (adjusted)	196.71	228	0.18	The adjusted for small samples Portmanteau Test shows no significant autocorrelation in the residuals with a p-value of 0.18
JB Test (Multivariate)	1.31	8	0.96	JB Test and the individual tests for skewness and kurtosis indicate that the residuals do not significantly deviate from normality
Skewness (Multivariate)	0.7	4	0.95	
Kurtosis (Multivariate)	0.61	4	0.96	

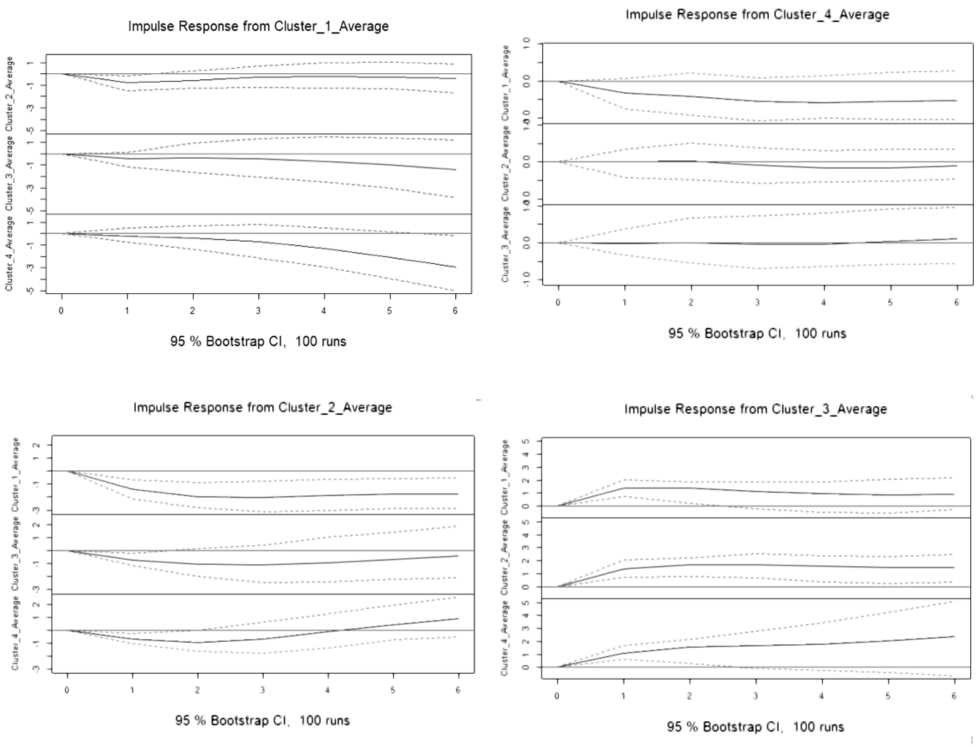
Source: Own processing

Figure A.2. Impulse-response analysis on all of the clusters



Source: Own processing

Figure A.3. Impulse-response analysis on all of the clusters



Source: Own processing

R-packages used

R package	Official citation
Vars	Pfaff B (2008). "VAR, SVAR and SVEC Models: Implementation Within R Package vars." Journal of Statistical Software, 27(4). https://www.jstatsoft.org/v27/i04/
tsDyn	Stigler M (2019). "Nonlinear time series in R: Threshold cointegration with tsDyn." In Vinod HD, Rao C (eds.), Handbook of Statistics, Volume 41, volume 42, 229-264. Elsevier. doi:10.1016/bs.host.2019.01.008.
Cluster	Maechler M, Rousseeuw P, Struyf A, Hubert M, Hornik K (2024). cluster: Cluster Analysis Basics and Extensions. R package version 2.1.8 – For new features, see the 'NEWS' and the 'Changelog' file in the package source), https://CRAN.R-project.org/package=cluster.
Ggplot2	Wickham H (2016). ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag New York. ISBN 978-3-319-24277-4, https://ggplot2.tidyverse.org.
urca	Pfaff B (2008). Analysis of Integrated and Cointegrated Time Series with R, Second edition. Springer, New York. ISBN 0-387-27960-1, https://www.pfaffikus.de.
dynlm	Zeileis A (2019). dynlm: Dynamic Linear Regression. R package version 0.3-6, https://CRAN.R-project.org/package=dynlm.