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TWO-SPEED ROMANIA: AN ANALYSIS OF REGIONAL COMPETITIVENESS PATTERNS

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Abstract:

This study examines the regional competitiveness of Romanian NUTS 2 regions from 2016 to 2022, employing the EU Regional Competitiveness Index (RCI) 2.0. The research identifies a polarized "two-speed" developmental model by benchmarking these regions against relevant EU peers and utilizing a K-means clustering algorithm. The findings indicate that although the capital, București-Ilfov, has reached "Efficiency" levels similar to those of Western European regions, it continues to show structural imbalances caused by weaknesses in institutions and infrastructure. The other seven development regions of Romania are situated within a low-competitiveness cluster, which shows considerable volatility and reduced resilience relative to their Central European peers. The findings reveal that the primary barrier to convergence is not market size, but major obstacles in fundamental areas such as education and physical connectivity. The study concludes that existing "one-size-fits-all" cohesion policies are inadequate, recommending a distinctive strategy that emphasizes absorptive capacity for underdeveloped regions and enhancements in quality of life for the capital region.

Key words: *Regional Competitiveness, K-means clustering, Smart Specialization, RCI 2.0, Regional polarization*

1. Introduction

Regional competitiveness is a key concern in European economic geography, serving as a critical barometer of the effectiveness of Cohesion Policy. The performance of Eastern European regions is under close examination within the framework of the European Union's objective of reducing territorial disparities. This study analyzes the developmental trajectories of Romania's eight NUTS 2 regions between 2016 and 2022, a timeframe characterized by economic integration and major external shocks.

Romania, despite ongoing economic growth, presents one of the most substantial level of regional disparities within the EU. The București-Ilfov capital region has quickly aligned with Western GDP per capita standards, whereas other regions face persistent structural stagnation. This study seeks to advance beyond basic output metrics by employing the Regional Competitiveness Index (RCI) 2.0 to analyze the multifaceted factors contributing to this divergence.

This study makes three main contributions to the regional competitiveness literature. First, it combines peer benchmarking with K-means clustering to aasses the position of Romanian regions within the broader European Union context. This dual approach offers a more nuanced understanding of regional positioning than traditional comparative assessments, showing both the regions' relative performance against their peers and specific development trajectories from 2016 to 2022. Second, the research distinguishes between "dynamic" competitiveness, grounded in innovation capacity and institutional quality, and "static" competitiveness driven by temporary cost advantages. Tis way, the recent growth of Romania is assessed as whether it represents sustainable convergence or reliance on transient factors of competitiveness. Third, we provide policy-relevant insights by identifying specific structural issues in education and infrastructure that impede regional convergence, therefore overcoming traditional aggregate assessments. These findings inform the ongoing debate on Smart Specialization strategies, demonstrating the need for differentiated policy approaches that reflect the mixed realities of Eastern EU regions instead of applying uniform cohesion frameworks that ignore development particularities.

The paper is structured as follows. The next section presents the most important research directions relevant to our topis as identified in existing research. Further, the Methodology section outlines the research design, data used and the analytical tools employed. The Results section shows the most important findings and the Discussion section contrasts them against existing literature. The last section concludes, outlines the most relevant policy implications, delineates the main limitations of the research and suggests several avenues for future explorations.

2. Literature review

Regional competitiveness is a complex term that lies at the convergence of economic geography and development strategy. Although a singular universal definition is absent, it is commonly perceived as a region's ability to foster sustainable economic growth, with the objective of enhancing both productivity and the quality of life for its

residents. Malecki (2004) goes further on the OECD (1997) definition, arguing that competitiveness includes not only output measurement in addition to the capacity to attract and retain particular resources, including human capital and investment, over time. A significant theoretical differentiation exists between static and dynamic competitiveness (Camagni, 2002). Static competitiveness depends on temporary cost disparities, such as inexpensive labor or land. In contrast, dynamic competitiveness emphasizes long-term qualities such as innovation, institutional quality, learning systems, and adaptation.

This dynamic viewpoint corresponds with Amartya Sen's Development as Freedom (1999). Similar to Sen's emphasis on individual capabilities rather than GDP, Camagni (2002) applies this reasoning to the spatial context, proposing that competitiveness is attained through cohesiveness in society and the enhancement of collective capabilities. Camagni and Capello (2023) explain this through the concept of territorial capital, which covers both material and immaterial assets, such as infrastructure, human resources, and knowledge networks, to provide sustainable value-added rather than simply reducing costs.

Porter (1990) presents the "cluster" perspective of competitiveness, arguing that regions compete through specialized knowledge and economic agglomerations. Localized clusters enhance productivity using knowledge spillovers and supplier networks. Critics like Tödtling and Trippl (2005) argue that Porter's approach frequently ignores the importance of institutions, especially in economies that are in transition. Rodríguez-Pose (2013) highlights the value of institutions, which include legal systems and policy frameworks. Effective development occurs when regions employ these institutions to identify their own competitive advantage, or "smart specialization" which promotes resource concentration and efficient implementation.

Institutions, characterized by North (1990) as the "rules of the game," serve as a fundamental accelerator for regional competitiveness, especially under the EU's multi-level governance framework. North argues that institutions determine the contextual validity of economic models, influence individual decision-making through subjective mental frameworks instead of perfect rationality, and provide an inseparable connection between political structures and economic outcomes. Rodrik, Subramanian, and Trebbi (2002) argue that institutional quality, particularly the rule of law and enforcement of property rights, frequently exceeds geographic endowment as a factor influencing development. Ultimately, solid institutional capability provides the necessary conditions for successful investment, innovation, and effective policy implementation (Belascu, 2015).

Human capital is a fundamental driver of regional competitiveness, based on Becker's (1993) theory that accumulated knowledge and skills enhance productivity for individuals and generate social spillovers that benefit entire regions. Thus, variations in educational investment directly intensify regional economic disparity, leaving human capital an essential factor for convergence. The European Commission (2022) and the Regional Competitiveness Index 2.0 show that favorable educational outcomes and lifelong learning are directly correlated with improved regional efficiency, positioning human capital as an accelerator for growth and an essential sign of a region's resilience.

The relationship between infrastructure and competitiveness is complex, acting as a "two-way street" that can either reduce or increase regional disparities (Puga, 2002).

Enhanced connectivity provides remote regions with access to markets, yet, it may paradoxically enable enterprises in prosperous hubs to serve those regions without relocating production, suggesting that physical infrastructure alone is insufficient without complementary elements such as labor mobility. Noring et al. (2022) perceive infrastructure as a strategic, multidimensional instrument requiring institutional coordination. Consequently, regions that combine physical connectivity with social equality and long-term planning are ideally positioned for global competitiveness.

Innovation accelerates regional diversification and value chain expansion (Chen et al., 2024). Edquist's (2005) advanced the concept of "Systems of Innovation," which underlines the relationship between stakeholders and institutions. This approach supports the EU's Smart Specialization Strategies. Nevertheless, Caloffi and Mariani (2018) indicate that lagging regions with limited absorptive capacities require tailored policy combinations instead of generic solutions. Schot and Steinmuller (2018) argue for a transition to transformative innovation policies that address societal challenges, emphasizing a dual challenge for Central and Eastern European regions: improving local systems while simultaneously addressing global digital and sustainable transitions (Perez, 2010; Tonin et al., 2025).

The EU Cohesion Policy has evolved from income convergence to promoting innovation through Smart Specialization Strategies (S3) (McCann, Ortega, & Foray, 2015), however effectiveness is uneven. Marrocu et al. (2023) observe that lagging regions frequently opt for targets that are incompatible with their economic frameworks, a misalignment that constrains transformative potential. This issue is exacerbated by obstacles in the local entrepreneurial environment, which Szerb et al. (2020) describe as major impediments to converting policy into growth. Therefore, the World Bank (2018) supports a comprehensive agenda that goes beyond simple project financing to strengthen institutions and overall development conditions, seeing competitiveness as a sustained process of structural improvement.

Existing research on regional competitiveness in Central and Eastern Europe relies to a large extent on aggregate national comparisons and assumes similar development patterns within countries, overlooking significant intra-country heterogeneity. Furthermore, the literature lacks granular identification of specific structural issues that restrain regional development and rarely combines peer benchmarking with clustering methodologies with the aim of revealing particular competitiveness profiles. This gap is particularly critical for informing policy interventions, as current cohesion strategies at EU level assume uniform development paths despite fundamentally different regional realities across the EU and specifically at its Eastern periphery.

3. Methodology

Our methodology is based on two main parts. First, we benchmark Romanian NUTS 2 regions against their main EU peers between 2016 and 2022 with the purpose of showing their progress and relative vulnerabilities. Second, we apply a clustering algorithm whereby Romanian regions are benchmarked against the other EU NUTS 2 regions. We employ a K-means based algorithm enhanced with unsupervised machine-learning features, whose objective resides in detecting the most homogeneous possible groups

(clusters) of EU regions – this means identifying groups of regions that are highly similar within the groups but highly different from them. For this purpose, we work with the three main categories of RCI – Basic, Efficiency and Innovation -, that contain indicators at regional and country level. This is an important limitation of RCI pillars, as also highlighted in Huggins (2013) and Maza and Hierro (2024). However, when interpreting the results we will be careful to distinguish between the sub-pillars of RCI that are fully region-based and the ones that contain indicators from both regional and country level, as well as only country-based indicators. Another limitation refers to the number of regions included in the analysis. There are 234 regions covered by RCI 2.0, but territorial reorganization that took place in some EU countries (Croatia, France, Ireland, Latvia, and Poland) between 2016 and 2022 led to data not being available for several regions in 2016. As a result, only 224 regions are included in the analysis that belong to 24 out of the 27 EU member states (Latvian, Irish and Croatian regions were excluded).

For each main sub-pillar of RCI we include all regions and years 2016 and 2022 to study the relative positions over time of Romanian regions compared to their peers and the other EU regions. Dissecting the RCI into its main competitiveness components allows us to discover the specific strengths and vulnerabilities of Romanian regions and the progress (or not) made by each of them compared to direct peers and EU regions.

The K-means clustering algorithm was first proposed by Hartigan (1975) but it is enriched with the method of expected maximization (EM) of Lloyd (1982). Three main advantages distinguish the EM clustering algorithm from basic K-means. The technique employs probability distributions to assess how likely each observation (region, in our case) belongs to different clusters, thus maximizing the overall likelihood to determine final assignments. Additionally, it may include different types of data, such as categorical and continuous variables. Perhaps most notably, the method autonomously determines the appropriate number of clusters using cross-validation procedures, in contrast with K-means clustering where researchers must specify the cluster count before running the algorithm.

Euclidean distance (ED) was used to form the clusters, which is a measure of the straight-line distance between two points in space – for n points (or variables), ED is calculated as below:

$$ED(x, y) = (\sum_i^n (x_i - y_i)^2)^{1/2} \qquad (1)$$

where ED and xi and yi are the coordinates of vectors x and y – in this analysis they are the RCI indicators included in the clustering algorithm.

Points that are closer together (so they have a smaller distance) are considered more similar and are more likely to be included in the same cluster. The K-means algorithm typically assigns each observation to the cluster whose centroid (or centre point) has the minimum ED to that observation. It is important to mention that Euclidean distance assumes all variables are measured on comparable scales, therefore data standardization if the typical procedure before running the algorithm. In our case, however, RCI indicators are already calculated against the EU average (that takes the value of 100), so standardization is not necessary.

The Ward amalgamation methos was implemented in Tibco Statistica to form the clusters. Beginning with a configuration where each observation forms its own cluster, the algorithm sequentially merges clusters by selecting combinations that return the least growth in within-cluster sum of squares at each step (Murtagh and Legendre, 2014). This strategy effectively minimizes intra-cluster variation, shows superior performance when handling outliers and noisy observations relative to other clustering techniques, and pairs well with ED calculations.

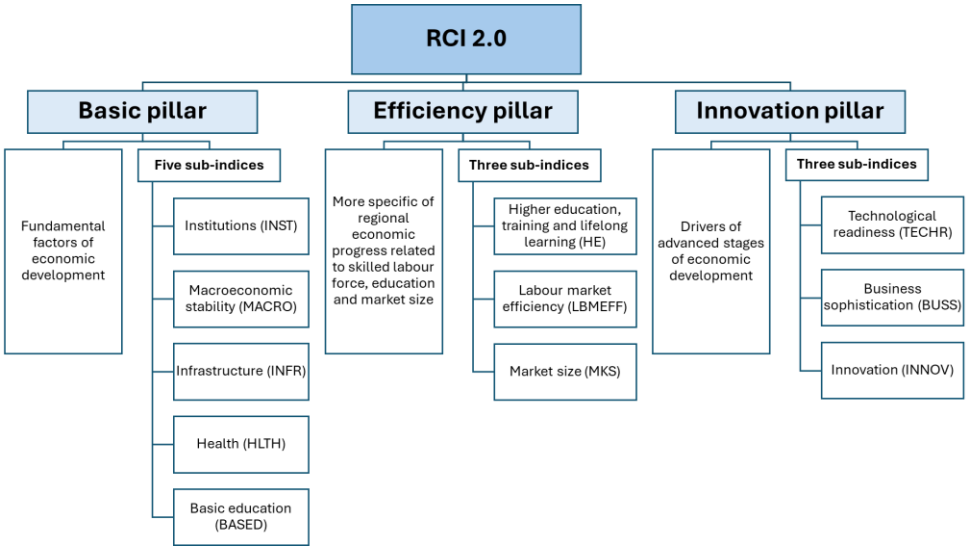
Our analysis forms the clusters using the indicators (or sub-pillars) of the three main RCI pillars (see below in RCI data sub-section), for each RCI pillar separately and for two moments – 2016 and 2022. Afterwards we study the position of Romanian regions in the clusters and that of their peers and identify their relative progress over time. To test the statistical significance of the indicators for clusters' formation we employed ANOVA methodology.

For the benchmarking analysis, peer regions were selected based on their recurrence across the three RCI editions, prioritizing the top five most frequent regions as the most relevant ones. To streamline the analysis and minimize redundancy, Romanian regions with structural similarities and shared peer profiles were grouped into pairs: Nord-Vest & Centru, Nord-Est & Sud-Est, and Sud-Muntenia & Sud-Vest Oltenia.

This analysis draws on Eurostat data and the EU Regional Competitiveness Index (RCI) spanning 2016, 2019, and 2022 from the European Commission's regional competitiveness portal (European Commission, 2023). The RCI evaluates competitiveness factors across EU NUTS-2 regions, measuring their capacity to attract businesses and provide quality living conditions for residents (Dijkstra et al., 2011). While the index debuted in 2010 with triennial updates, methodological revisions made temporal comparisons difficult. However, the 2022 release introduced RCI 2.0, which, besides methodological updates it recalculated the 2016 and 2019 indicators using the new framework (see, in this respect, Dijkstra et al., 2023), enabling consistent cross-temporal analysis across all three recent editions.

Figure 1 shows the main pillars of RCI 2.0, which encompass 11 sub-pillars that are constructed using 68 indicators at regional and country level. The three main pillars are: (1) The Basic pillar, which captures the essential developmental factors for an economy incorporated in five sub-indices: Institutions (INST), Macroeconomic stability (MACRO), Infrastructure (INFR), Health (HLTH), and Basic education (BASED); (2) The Efficiency pillar, which includes the more specific factors that drive regional development grouped in three sub-indices: Higher education, training and lifelong learning (HE), Labour market efficiency (LBMEF), and Market size (MKS); (3) The Innovation pillar, which includes the drivers of more advanced economic development through three sub-indices: Technological readiness (TECHR), Business sophistication (BUSS), and Innovation (INNOV). All sub-indices and pillars are calculated using the EU average as a benchmark (which takes the value of 100), therefore all values above 100 indicate a better performance than the EU and those below 100 signalling a worse performance than of the EU.

Figure 1. RCI 2.0 pillars and sub-pillars



Source: Authors' representation based on Dijkstra et al. (2023)

Table 1 presents the variables used in the analysis, using the information available at RCI 2.0.

Table 1. RCI Pillars included in the analysis

Variable (sub-pillar)	Notation	Included indicators
Basic Pillar		
Institutions	INST	Corruption; Quality and accountability; Impartiality; Individuals using Internet to interact with public authorities
Macroeconomic	MACRO	Macroeconomic indicators at country level: General government deficit/surplus; National savings; Government bond yields; Government debt; Net international investment position NIIP
Infrastructure	INFR	Road transport performance; Rail transport performance; Accessibility to passenger flights
Health Pillar	HLTH	Road fatalities; Healthy life expectancy; Infant mortality; Cancer death rate; Heart disease death rate; Suicide death rate
Basic education Pillar	BASED	Education data - country level: Share of low-achieving 15-year-olds in reading, maths and science
Efficiency Pillar		
Higher education and long life learning	HE	Higher educational attainment; Lifelong learning; Early school leavers; University accessibility; Lower-secondary completion
Labour Market Efficiency	LBMEF	Employment rate (excl. agriculture); LT Unemployment; Unemployment; Labour productivity; Gender balance unemployment; Gender balance employment; NEET; Labour market slack; Tenporary employment
Market Size	MKS	Disposable income per capita; Potential market expressed in GDP and population
Innovation Pillar		
Technological readiness	TECHR	Households with broadband access; Individuals buying over Internet; Access to high-speed broadband; Individuals with

		above-basic digital skills (NUTS2) PLUS Enterprises having received orders online; Enterprises with fixed broadband access (Country)
Business sophistication	BUSS	Employment in K-N sectors; GVA in K-N sectors; Innovative SMEs collaborating; Marketing or organisational innovators
Innovation	INNOV	Total patent applications; Core creative class employment; Knowledge workers; Scientific publications; R&D expenditure; HR in science and technology; Employment in HT-KIS; Trademark applications; Design applications; Sales of new-to-market and new-to-firms innovation

Source: Authors' work based on RCI 2.0

4. Results/findings

Benchmarking Romanian regions against peers

Bucuresti-Ilfov (RO32)

București-Ilfov (RO32) aligns with the trend of EU capital regions exceeding national averages. In the 2016 RCI it was positioned at 161st with a score of 53.4. Peer regions comprised Oberpfalz, Lombardia, Madrid, Praha, and various German regions such as Köln and Düsseldorf. The Basic dimension showed its lowest score at 53.4, characterized by an abrupt difference between high Macroeconomic Stability at 97.9 and a significantly low score in Basic Education at 11.4. In comparison to peers, Institutions (27.3), Infrastructure (45), and Health (78.5) have been identified as weaknesses. Efficiency (110.6) exceeded EU averages, due to solid scores in Higher Education, Labor Market, and Market Size. Innovation (84.1) was below the EU average; although the Innovation pillar was strong (109.1), Technological Readiness (61.1) was lacking.

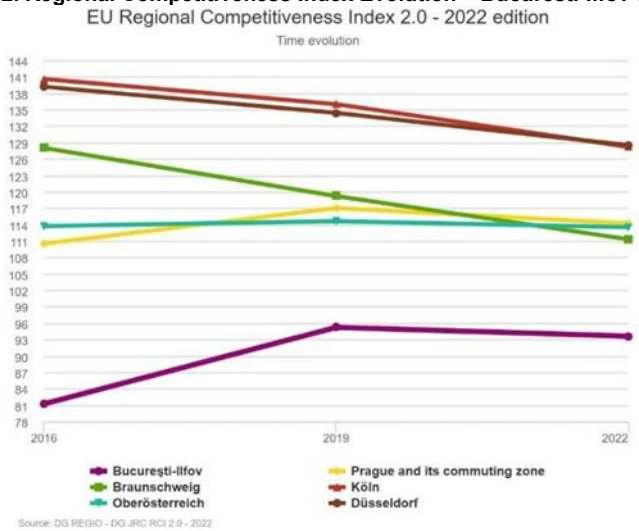
In 2019, noteworthy regions included Braunschweig, Köln, Praha, and Oberösterreich. The Basic score remained stable at 53.4, while Macroeconomic Stability decreased to 77.8; however, other indicators showed improvement. Efficiency increased to 120.6, while Market Size expanded to 146.7. Innovation displayed no change (84.1); advancements in Readiness were counterbalanced by reductions in Business Sophistication.

Longitudinal analysis reveals that Praha and Braunschweig consistently serve as peers across the three editions, while Oberösterreich, Düsseldorf, and Köln are peers in the years 2016 and 2019. Bucuresti-Ilfov demonstrated the most significant growth, exceeding 12 percentage points, followed by Praha. In contrast, Western peers (Braunschweig, Düsseldorf, Köln) experienced a decline of over 10 percentage points, returning to the EU average, whereas Oberösterreich remained stable at approximately 113.5. This indicates that Eastern regions are advancing in development, whereas Western counterparts are experiencing a deceleration (Figure 2).

In relation to the Basic sub-index, only Praha showed advancement, increasing from 96.2 in 2016 to 104.2 in 2022. In contrast, German regions experienced a decrease of 15–18 percentage points, whereas Oberösterreich saw a minor decline of 1 pp. Bucuresti-Ilfov displays considerable lag. Although the leading region (Köln) experienced a decline of 3.4%, the disparity persists at 73.7%, reduced from 86 percentage points in 2016. This polarization is influenced by deficiencies in infrastructure, institutions, and basic

education (Figure 3). Basic Education, as a national metric, is severely evaluated at 12.3. Bucuresti-Ilfov faces challenges related to institutions and infrastructure. Similarly, Braunschweig and Oberösterreich have below-average infrastructure scores. The other German regions maintain a performance approximately 50% above the mean, despite a decline from their peak score of around 225 in 2016.

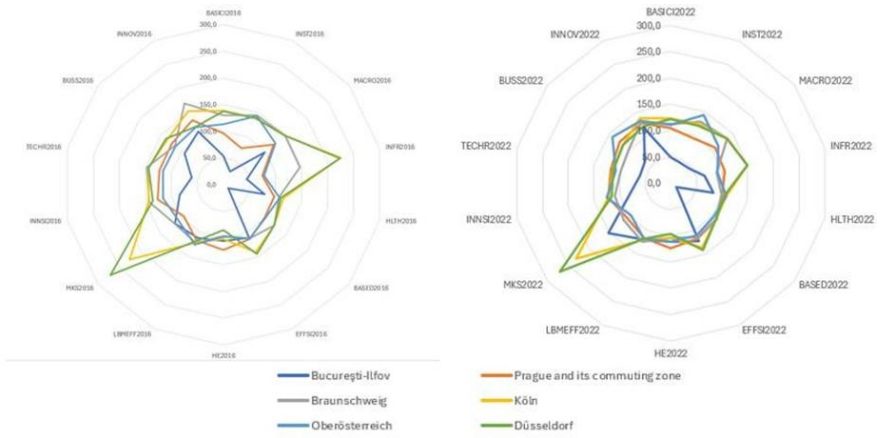
Figure 2. Regional Competitiveness Index Evolution – Bucuresti-Ilfov & peers



Source: (European Commission, 2022)

In the dimension of Efficiency, all peers exceed the EU average. Although Düsseldorf and Köln experienced declines, the remaining three regions showed improvement, with Bucuresti-Ilfov advancing from 6th place in 2016 to 3rd place in 2022. While Higher Education and Labor Market scores reflect parity within the group, Market Size is an important driver contributing to divergence, with Düsseldorf (270.2) and Köln (130.2 above average) leading. București-Ilfov consistently ranks in the third position, while other regions remain close to the EU average. Only Oberösterreich demonstrated improvement in the Innovation sub-index. German regions experienced major decreases, exceeding 20 percentage points, with Braunschweig showing a significant drop of 34.5 percentage points. In contrast, Bucuresti-Ilfov and Praha recorded minimal reductions of 6 and 4 percentage points, respectively. This resulted in convergence among peers, with Bucuresti-Ilfov remaining the only region below the EU average by approximately 25%.Although it ranks lowest in the Innovation pillar (116.8), the evolution across the group is consistent. In the domains of Technological Readiness and Business Sophistication, Bucuresti-Ilfov achieves a score approximately 50% of that of its peers. Praha excels in Readiness, while Oberösterreich demonstrates strength in Sophistication. Bucuresti-Ilfov exhibits upward momentum attributed to efficiency, yet faces challenges in basic services, infrastructure, and institutional frameworks. The innovation gap remains, although the difference with peers such as Praha is decreasing (Figure 3).

Figure 3. Comparative RCI sub-index: Bucuresti-Ilfov vs peer regions (2016 and 2022)

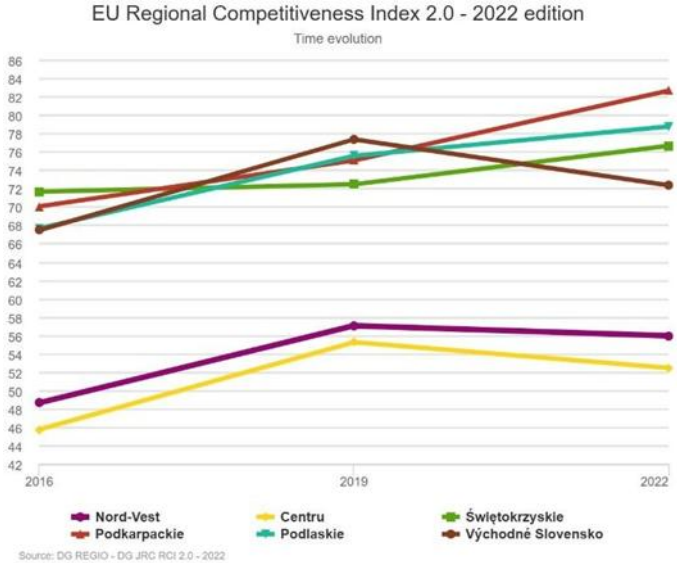


Source: Authors' work based on RCI data

Nord-Vest and Centru

Nord-Vest (RO11) and Centru (RO12) have parallel trajectories comparable to their Central European and Mediterranean peers. The analysis of key peer regions (Swietokrzyskie, Východné Slovensko, Podkarpackie, Podlaskie) reveals two distinct trends. The Romanian regions and Východné Slovensko experienced improvements from 2016 to 2019, followed by a decline by 2022. Notably, the Slovak region exhibited significant volatility, rising from 4th place in 2016 to 1st in 2019, before returning to 4th place. In contrast, the Polish regions (Swietokrzyskie, Podkarpackie, Podlaskie) demonstrated steady growth in all three editions (Figure 4).

Figure 4. Regional Competitiveness Index Evolution – Nord-Vest, Centru & peers



Source: (European Commission, 2022)

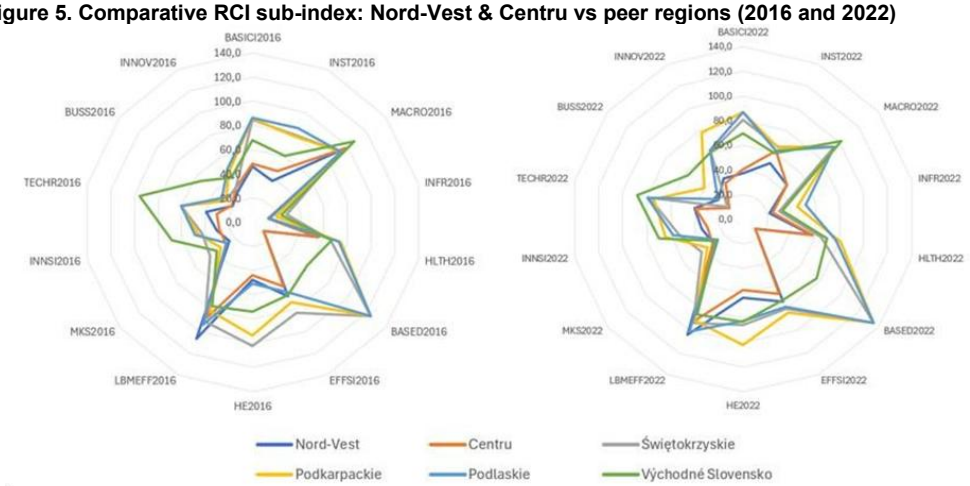
All regions in the Basic sub-index underperform relative to the EU average. Polish regions tend to show convergence toward the mean, with the exception of minor declines

in Podlaskie and Swietokrzyskie. However, Podkarpackie is the only region that improved its score. By contrast, Romania's Nord-Vest and Centru regions experienced the most substantial drops, approximately 10 percentage points. Disparities arise from national pillars rather than from institutions, which reflect balance (50.4–65.2). Macroeconomic analysis indicates that Východné Slovensko exceeds the EU average, while Polish regions are approximately at 94.3, in contrast to Romanian regions, which stand at 45.1. Basic Education suggests an enormous disparity, with Poland scoring 134.8, followed by Slovakia at 76.4 and Romania at 12.3. The hierarchy of Infrastructure and Health is as follows: Poland, Slovakia, Romania.

Over a period of six years, efficiency demonstrated an overall rise, although trends varied among nations. Podlaskie and Podkarpackie regions in Poland witnessed significant growth, whereas Swietokrzyskie had a distinct decline. The Romanian regions experienced growth, with Nord-Vest at the forefront, close to Východné Slovensko. Pillar analysis indicates that Podkarpackie is above the EU average in Higher Education, while Romanian regions lag by approximately 60 percentage points. Nord-Vest is the leading region in the Labor Market, with Podlaskie following closely behind. The market size exhibits "negative convergence," as all regions reveal substantial lag, with scores ranging from 26.5 to 42.8.

Innovation continues to show polarization and is below the EU average, with Východné Slovensko at the top of the list, followed by regions in Poland and Romania. All peers demonstrated improvement, with the exception of Nord-Vest. The Slovak region excels in Business Sophistication and Technological Readiness, while Podkarpackie achieves the highest score in the Innovation pillar. Romanian regions lag, especially in terms of Readiness and Innovation. Polish regions, with the exception of Podkarpackie, face challenges in Business Sophistication. However, they are otherwise contending for leadership within the group (Figure 5).

Figure 5. Comparative RCI sub-index: Nord-Vest & Centru vs peer regions (2016 and 2022)



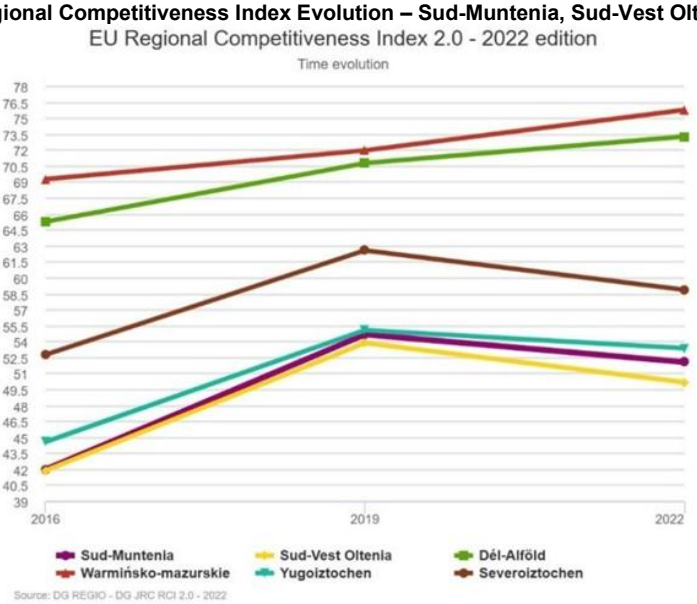
Source: Authors' work based on RCI data

Sud-Muntenia & Sud-Vest Oltenia

Sud-Muntenia (RO31) and Sud-Vest Oltenia (RO41) maintain a consistent peer status in all editions, particularly with Dél-Alföld, Warmińsko-Mazurskie, Yugoiztochen, and

Severoiztochen. RCI trends reveal two distinct patterns: the Central European regions, specifically Dél-Alföld and Warmińsko-Mazurskie, sustained a consistent upward trajectory from 2016 to 2022. The Romanian and Bulgarian regions experienced an important rise from 2016 to 2019, followed by a minor decrease. Notwithstanding the recent decline, these four regions experienced a net overall improvement from 2016 to 2022 (Figure 6).

Figure 6. Regional Competitiveness Index Evolution – Sud-Muntenia, Sud-Vest Oltenia & peers



Source: (European Commission, 2022)

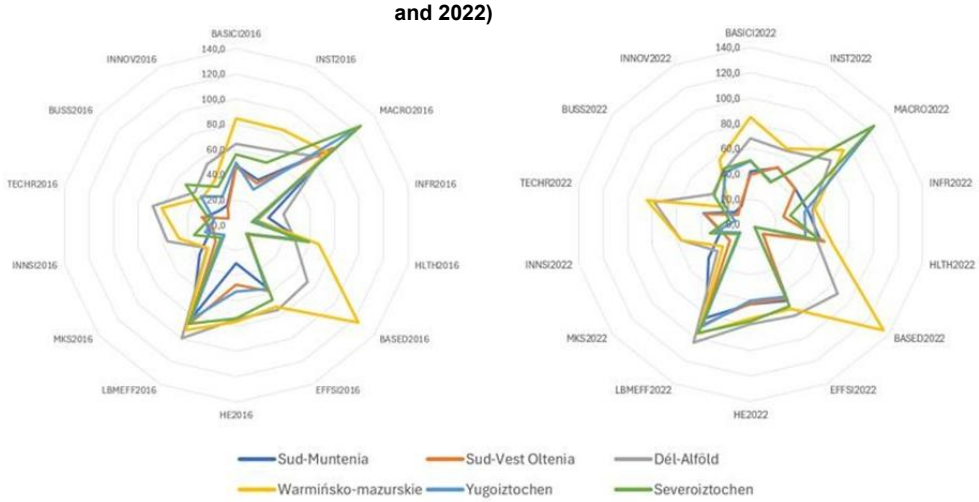
The longitudinal analysis of the Basic sub-index suggests stagnation or a decline in comparison to the EU mean. Sud-Muntenia, Sud-Vest Oltenia, Dél-Alföld, and Severoiztochen experienced major drops, whereas Yugoiztochen and Warmińsko-Mazurskie experienced slight increases. Pillar breakdowns reveal clear hierarchies, with institutions prioritizing Central Europe over Romania and Bulgaria. Bulgaria is positioned at the highest level of macroeconomic performance, exceeding the EU average by 25 percentage points, followed by Central European regions, while Romania lags at 45.1. In terms of infrastructure, Sud-Muntenia achieves nearly double the score of Sud-Vest Oltenia, while Central European regions average around 50, and Yugoiztochen surpasses Severoiztochen. Health results are primarily driven by Warmińsko-Mazurskie, whereas Yugoiztochen exhibits a relative shortage. Basic Education reveals significant disparities: Warmińsko-Mazurskie is 37 times higher than Bulgaria, Dél-Alföld approaches the EU average, whereas Romania (12.3) and Bulgaria (3.7) offer minimal scores.

In contrast, Efficiency demonstrates convergence, with the gap reduced to 17 percentage points, and exhibits universal growth from 2016 to 2022. Leader Dél-Alföld has increased its advantage over Warmińsko-Mazurskie. The growth of Romanian regions surpassed that of comparable Bulgarian regions, with Sud-Muntenia exceeding Sud-Vest Oltenia. Dél-Alföld and Severoiztochen lead in Higher Education and Lifelong Learning, while Romania and Yugoiztochen lag by approximately 15 percentage points. A comparable disparity is present in the Labor Market, with Central European regions and Severoiztochen at the top of the rankings. The market size is generally weak, however,

Sud-Muntenia (42.9) significantly outperforms Central European peers and Sud-Vest Oltenia, while Bulgarian regions exhibit considerable lag (~11-12).

The Innovation sub-index emphasizes changes in leadership dynamics. Warmińsko-Mazurskie passed the previous leader, Dél-Alföld, which experienced a slight decline. Bulgarian regions did not maintain growth. In the context of Romanian regions, Sud-Vest Oltenia has made advances in improving its innovation infrastructure, approaching the level of Sud-Muntenia. Nonetheless, both regions continue to rank as the least effective within this peer group (Figure 7).

Figure 7. Comparative RCI sub-index: Sud-Muntenia & Sud-Vest Oltenia vs peer regions (2016 and 2022)



Source: Author's work based on RCI data

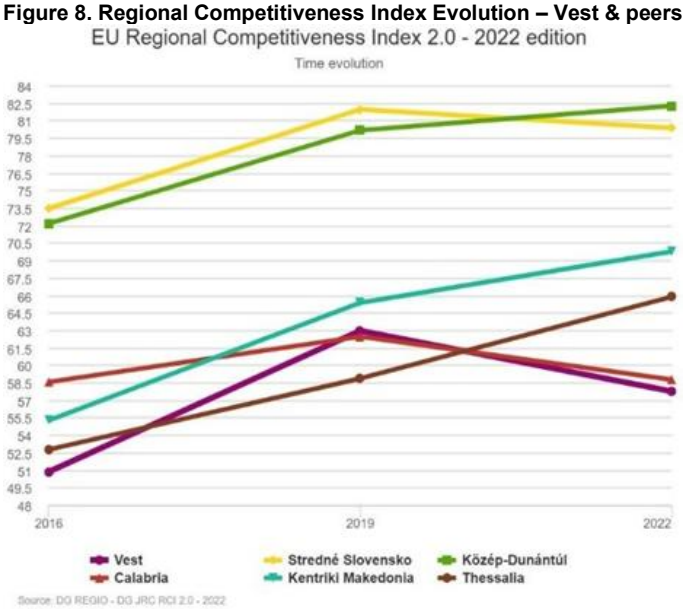
Vest

The Vest region, similar to București-Ilfov, has a unique profile characterized by a lack of domestic peers and significant volatility in its associations across RCI editions. In contrast to other Romanian regions, its peer group includes both Central European and Mediterranean member states. Key peers consist of Stredné Slovensko and Közép-Dunántúl, which remained consistent in 2016 and 2019, as well as Southern European regions such as Calabria (Italy), Kentriki Makedonia, and Thessalia (Greece).

RCI progression indicates significant shifts. In 2016, Vest was ranked last. By 2019, it demonstrated substantial progress, exceeding the advancements made by Calabria and Thessalia. Despite Thessalia's continued rise, Vest experienced an important drop by 2022, falling to last place, just behind Calabria. Calabria demonstrated the most serious decline, dropping from third place in 2016 to last in 2022.

Stredné Slovensko and Közép-Dunántúl show higher absolute competitiveness; however, their trends are diverging. Közép-Dunántúl demonstrated steady growth throughout the periods from 2016 to 2022. In contrast, Stredné Slovensko experienced initial growth but subsequently declined after 2019, ultimately giving its leading position to the Hungarian region (Figure 8).

Figure 8. Regional Competitiveness Index Evolution – Vest & peers



Source: (European Commission, 2022)

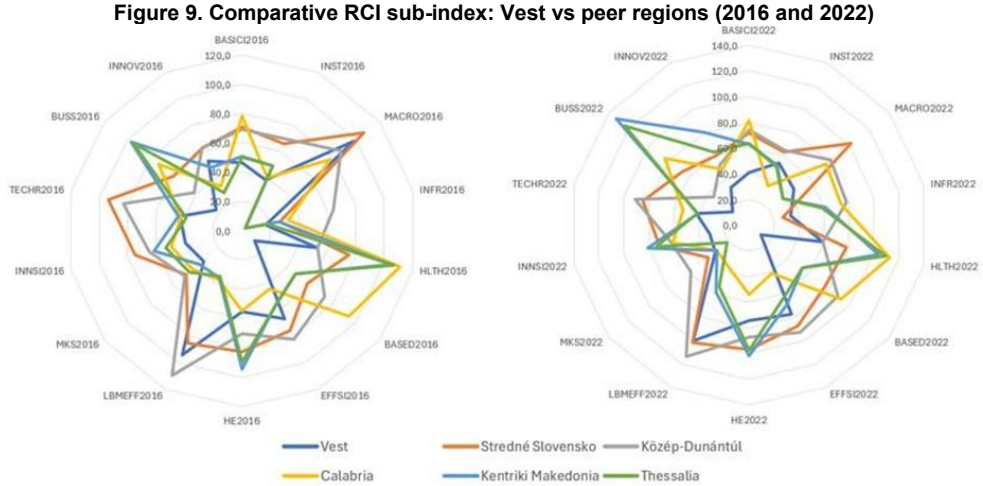
In the Basic sub-index, Vest is the only peer that shows a decline over time, ranking last in absolute terms behind the leaders Calabria, Közép-Dunántúl, and Stredné Slovensko. The competitiveness gap between the Greek regions of Kentriki Makedonia and Thessalia increased significantly, from around 5 percentage points in 2016 to more than 20 in 2022. Pillar analysis indicates a nuanced situation: Vest notably enhanced its Institutions score (increasing from 38.2 to 53.8, achieving a third-place rank), yet faces challenges in other areas. Macroeconomic performance is predominantly driven by Stredné Slovensko, which exceeds the average, whereas Greek regions occupy the lowest rankings. Infrastructure is more developed in Közép-Dunántúl and Calabria, while it is deficient in Vest. Mediterranean regions show performance exceeding the EU average in Health, while Romanian, Hungarian, and Slovak regions lag behind. Basic Education is predominantly led by Calabria and Central European peers. Greek regions fall short of the average by 50 points, with Vest having a significant low of 12.3.

The Efficiency sub-index indicates overall advancement and convergence. The leaders of 2016, Közép-Dunántúl, Stredné Slovensko, and Vest, sustained their leading positions in 2022, showing progress towards the EU average. Greek regions progressed, while Calabria had an unusual divergence linked to a decreasing market size. The Central European and Greek regions align with the average in Higher Education and Lifelong Learning, whereas Vest and Calabria fall behind. In the Labor Market, Vest aligns with Stredné Slovensko and Közép-Dunántúl, positioning itself at the forefront and in line with the average, while Mediterranean regions face challenges. The market size is a notable weakness, with only Közép-Dunántúl achieving a score above 50. Vest and Stredné Slovensko exhibit poor performance, although they outperform the lagging regions of Greece and Calabria.

Innovation trends reveal a distinct conflict. Over time, Vest, Stredné Slovensko, and Közép-Dunántúl experienced a decline, with Vest consistently identified as the

weakest performer across all three pillars. In contrast, the Greek regions and Calabria experienced average increases of 20 percentage points over a period of six years. Technological readiness in Stredné Slovensko and Közép-Dunántúl is nearing the EU average, while other regions are at approximately half that level. Business sophistication exhibits significant polarization: Greek regions surpass the average by 24–32 points, while Calabria lags by 17 points, and Vest records a notably low score of 16.4. The Innovation pillar is predominantly led by the Greek regions and Stredné Slovensko, with Vest occupying the last position once more (Figure 9).

Figure 9. Comparative RCI sub-index: Vest vs peer regions (2016 and 2022)



Source: Author's work based on RCI data

Sud-Est & Nord-Est

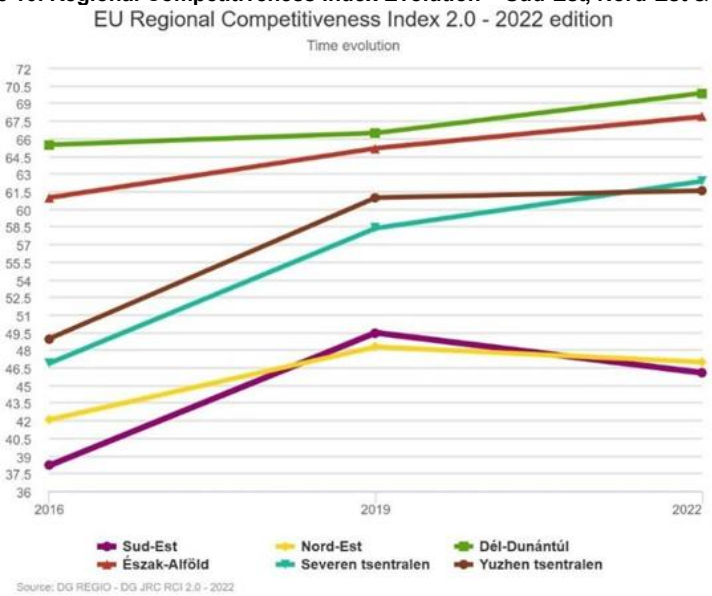
The final evaluation examines the Sud-Est and Nord-Est regions of Eastern Romania. The 2022 RCI Report categorizes them as the least competitive territories within the EU, ranking 234th and 233rd, respectively, which establishes low performance expectations compared to their peers. Analyzing the interaction with counterparts—Dél-Dunántúl and Észak-Alföld (Hungary), and Severen tsentralen and Yuzhen tsentralen (Bulgaria)—is essential for understanding regional drivers and convergence. This group has a balanced geographical distribution, comprising two regions from each country, with the Romanian regions next to both neighboring countries.

Longitudinal analyses indicate three distinct patterns among these paired groups. The Hungarian regions are the leaders in absolute terms, reflecting consistent and stable growth across all phases. The Bulgarian regions experienced upward trends in both periods, with Severen tsentralen showing significant acceleration from 2019 to 2022. Conversely, the Romanian regions demonstrated distinct volatility: while experiencing substantial growth from 2016 to 2019, Sud-Est and Nord-Est were the only regions to experience a decline during the 2019–2022 period, resulting in varying rankings over time (Figure 10).

The Basic sub-index reveals distinct trends: Hungarian regions (Dél-Dunántúl, Észak-Alföld) and Yuzhen tsentralen experienced improvements, whereas Severen tsentralen saw a slight decline (<2 pp) and Romanian regions (Sud-Est, Nord-Est) faced significant reductions (>5 pp). The decline in Romania is primarily attributed to a decrease

of over 40 percentage points in macroeconomic stability. Pillar analysis reveals clear hierarchies. Institutions demonstrate relative homogeneity, with Hungarian regions surpassing Romanian ones, which in turn exceeds Bulgarian peers. In contrast, macroeconomic performance is led by Bulgaria, above the EU average by over 25 percentage points, followed by Hungary, while Romania faces challenges. Infrastructure development is primarily driven by Yuzhen tsentralen and Észak-Alföld, whereas other regions remain stagnant at approximately 30. Health indicators reveal similarities, with Dél-Dunántúl at the forefront and Nord-Est marginally surpassing Sud-Est by 5 percentage points. Basic Education exhibits significant polarization: Hungarian regions are 11.5 points below the EU average, compared to the low scores of Romania (12.3) and Bulgaria (3.7).

Figure 10. Regional Competitiveness Index Evolution – Sud-Est, Nord-Est & peers



Source: (European Commission, 2022)

Trends in the Efficiency dimension illustrate variability. Both Romanian regions improved, with Sud-Est reducing the internal gap from over 11 percentage points in 2016 to less than 2 percentage points in 2022. Bulgaria's Severen tsentralen increased by more than 20 points, securing the group lead. In contrast, both Hungarian regions experienced a decline. The advancements in Romania and Bulgaria are supported by enhancements in Higher Education, Lifelong Learning, and the Labor Market.

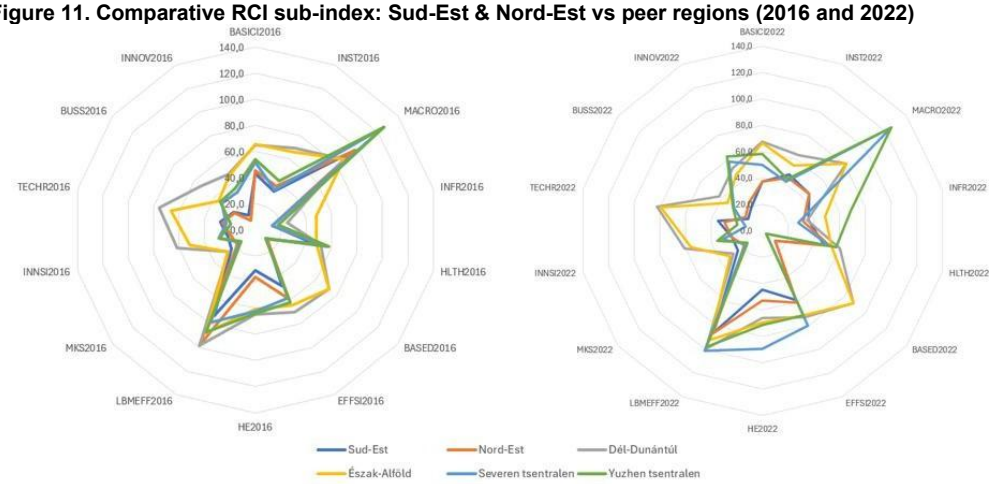
The Innovation sub-index suggested overall enhancement. Romanian and Hungarian developments were influenced by Technological Readiness, whereas Bulgarian regions experienced a twofold increase in their Innovation pillar performance. Nonetheless, this advancement is moderated by a universal decrease in Business Sophistication across all regions (Figure 11).

K-means clustering analysis

This analysis aims at investigating the positioning of Romanian regions within EU regions considering the three main pillars or dimensions of RCI 2.0 – Basic, Efficiency and Innovation. For each pillar we included in the K-means clustering the indicators for the last

three years available – 2016, 2019 and 2022. We first present the clustering results for each pillar and then explore Romanian regions' position in clusters over time and compare it with their peers.

Figure 11. Comparative RCI sub-index: Sud-Est & Nord-Est vs peer regions (2016 and 2022)



Source: Author's work based on RCI data

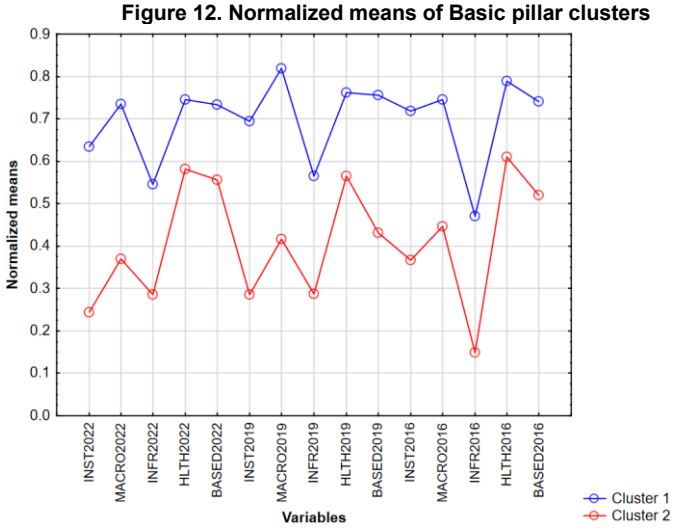
For each pillar only two clusters were identified by the amalgamation; however, there is important variation within each cluster. At the same time, the distances between the clusters are different for the three amalgamations – 1.166 for Basic, 0.860 for Efficiency, and 0.953 for Innovation -, suggesting that the regions tend to be, on average, most diverse in terms of fundamental economic development factors, included in the Basic pillar, and least diverse in terms of Efficiency, while Innovation drivers lay in between. It is also important to mention that ANOVA indicates that all variables are relevant for clustering, for all 3 amalgamations (results are available from authors).

Figure 12 shows the normalized means for the Basic pillar clustering. The algorithm included 102 regions in Cluster 1 and 122 regions in Cluster 2, for 45.53% and 54.46% of the total number of regions, respectively. Cluster 1 clearly dominates Cluster 2 on all variables, but the differences between normalized means vary across variables: the smallest are recorded for HTLH in all years, while the highest are recorded for INFR in 2016, followed by INST in all years. This suggests that regions are more homogeneous when health indicators are considered but least homogeneous on an institutional basis – also note that HLTH is a sub-pillar constructed only from regional level indicators, while INST considers both regional and country-level indicators. However, it is worth noting that the differences between the two clusters diminished between 2019 and 2022, and between 2016 and 2022 for all variables, although in 2019 BASED and INST recorded a higher difference in normalized means compared to 2016.

At the same time, the variation within each cluster across the variables, illustrated in Figure 13, is remarkable. For cluster 1, the highest variation is encountered for INFR2016, followed by INFR2019 and INFR2022, suggesting that EU regions, even the more developed ones, differ importantly in terms of infrastructure. Other high variations are found for INST and BASED, while, at the opposite end, the lowest variations are found for HLTH. For cluster 2, which includes the least developed regions, the highest variation is

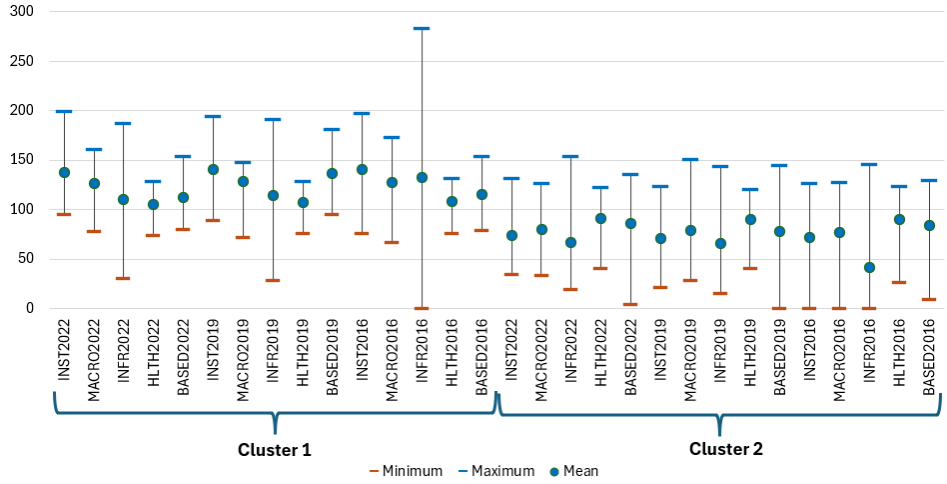
for INFR2016 – however, this within-cluster variation declines in 2019 and 2022 – and BASED2019 and BASED2022, on a rise from 2016. When within-cluster variation is considered for cluster 1 against cluster 2, this is larger for most variables except for INST2022, INFR2022, and INST2019, suggesting a more intense convergence process for less developed regions, possibly because of the lower levels of these variables in 2016.

Figure 12. Normalized means of Basic pillar clusters



Source: Authors' work in Tibco Statistica

Figure 13. Within-cluster variation - Basic pillar clusters

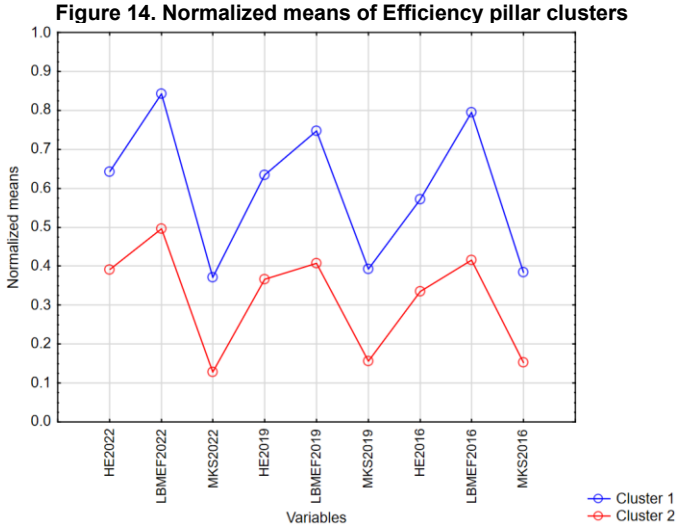


Source: Authors' work on Tibco Statistica output

For the Efficiency pillar, Figure 14 presents the normalized means for the two clusters, showing also the superiority of cluster 1 for all considered variables. In this amalgamation, cluster 1 includes 135 regions (or 60.3% of total regions) and cluster 2 includes 89 regions (39.7% of total regions). As in the case of Basic pillar clustering, the difference between the means varies across variables: the highest is for MKS in all years and the lowest is for LBMEF2019, lowest from 2016 but rising again in 2022. Over time, the difference in normalized means for cluster 1 against cluster 2 was lower in 2022 than in

2019 for HE and LBMEF, but larger for MKS, suggesting a strong and increasing efficiency gap between the regions included in the two clusters.

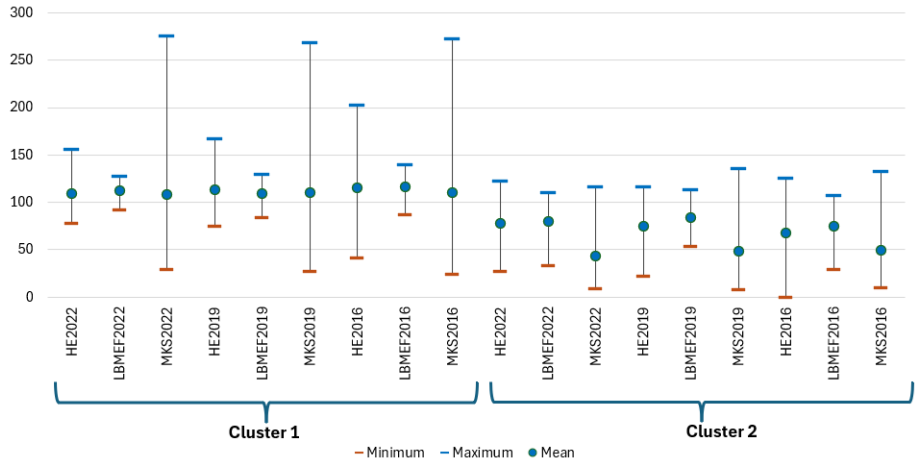
Figure 14. Normalized means of Efficiency pillar clusters



Source: Authors' work in Tibco Statistica

Figure 15 shows the within-cluster variation for all variables in the clustering. MKS in all years is the variable with the highest variation for cluster 1, indicating that the most efficient EU regions differ importantly when their size is considered – measured as disposable income, GDP and population. HE2016 also shows high variability in 2016, but it significantly decreases in 2019 and further in 2022, suggesting more homogeneous regions and higher investments in education. For cluster 2, MKS2019 and HE2016 are the most heterogenous variables, followed by MKS2016 and MKS2022. Considering the within-cluster variation for cluster 1 against cluster 2, this is very large and positive for MKS – this means that MKS heterogeneity is higher for more efficient than for less efficient regions – and for HE2016, but is negative for all the other variables, indicating an encouraging convergence process at EU level.

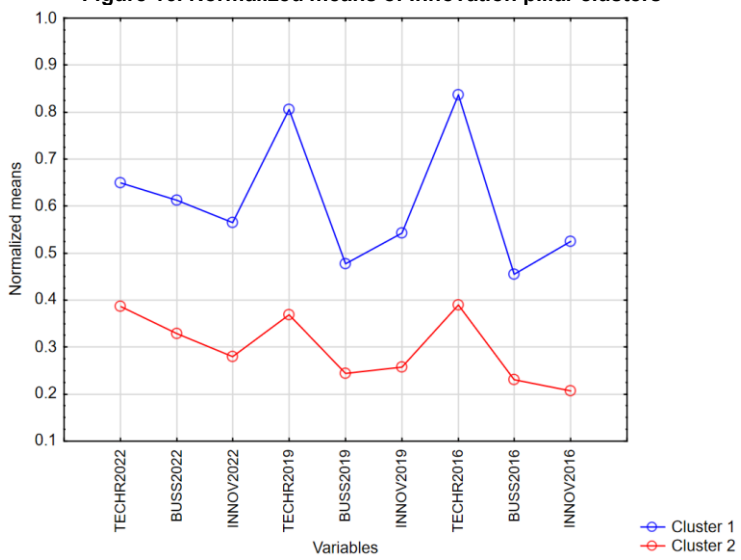
Figure 15. Within-cluster variation - Efficiency pillar clusters



Source: Authors' work on Tibco Statistica output

The normalized means for the Innovation pillar clustering are shown in Figure 16. As for the previous pillars, the k-means amalgamation results in two clusters – cluster 1 includes 118 regions or 52.7% of total, and cluster 2 includes 106 regions or 47.3% of total -, of which cluster 1 clearly dominates cluster 2 on all variables. However, the distance between the means differs across variables; it is highest for INNOV2016 but it declines until 2022, followed by TECHR2016, also on a decline until 2022. For all variables, the distance in means between the two clusters drops in 2019 compared to 2016 and further in 2022, suggesting a lower innovation gap between the more and less innovative regions in EU.

Figure 16. Normalized means of Innovation pillar clusters



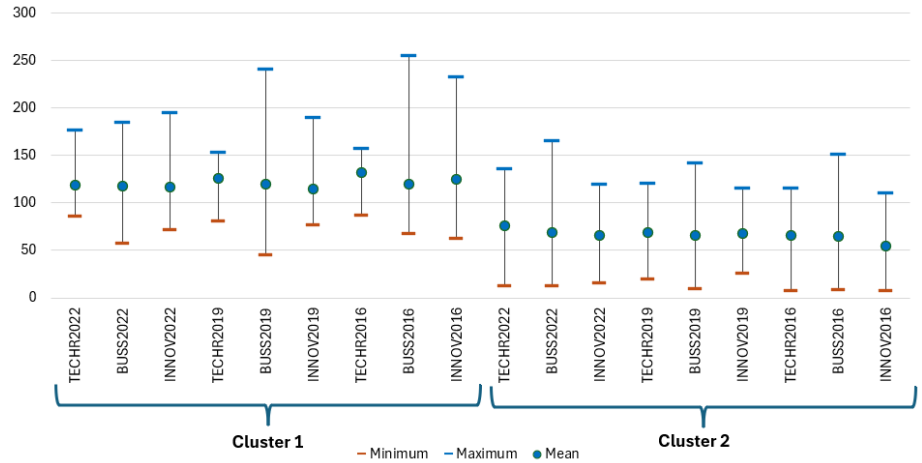
Source: Authors' work in Tibco Statistica

The two clusters show also important variations for each variable included in the amalgamation – see Figure 17. For cluster 1, the largest variation is for BUSS in 2016 and 2019, but also INNOV2016. Similarly, BUSS is the variable with the highest variation in all years for cluster 2, indicating that important regional differences are present when employment and value added in the innovative and high-tech sectors are considered, as well as collaboration between innovative SMEs. For cluster 1, TECHR is the most homogeneous variable in all years, while INNOV is the counterpart for cluster 2 – it is worth noting that for TECHR the homogeneity increases from 2016 to 2019 and further to 2022, suggesting that the more innovative regions tend to be more diverse from this perspective. INNOV's homogeneity declines in 2019 only to rise again in 2022, indicating that the least innovative regions went through a convergence process until 2019, but the pandemic most likely reversed it.

Romanian regions are unfavourably placed in clusters 2 in all amalgamations, with the notable exception of Bucureşti-Ilfov region that belongs to cluster 1 in the Efficiency clustering. Table 2 presents this placement along with the distance to centroid (normalized mean) for each region, with the aim of observing the differences between them. For the Basic amalgamation, Bucureşti-Ilfov is the closest to centroid, followed by Sud-Muntenia and Nord-Est, while Nord-Vest and Vest regions are the farthest from the centroid. For

Efficiency clusters, the closest regions to centroid are Sud-Muntenia and Sud-Vest Oltenia, while the farthest are Nord-Vest and Vest regions. In the case of Innovation clusters, Bucureşti-Ilfov, Nord-Vest and Vest are closest to centroid, while Nord-Est and Sud-Est are the farthest.

Figure 17. Within-cluster variation - Innovation pillar clusters



Source: Authors' work based on Tibco Statistica output

When comparing closer the positioning of Romanian regions against the centroids of the clusters they belong to – see Figure 18 -, a few interesting conclusions emerge. First, in the Basic and Innovation pillars clustering, Romanian regions are worse performers than the average of their group (marked by the centroid) in all variables, with very few exceptions – these are RO42 (Vest) in INST2016 and RO32 (Bucuresti-Ilfov) in INNOV2016, INNOV2019, INNOV2022 and BUSS2016. The only better than centroid position that is preserved from 2016 and 2019 in for INNOV and RO32 region.

Table 2. Placement of Romanian regions in clusters and distance to centroid

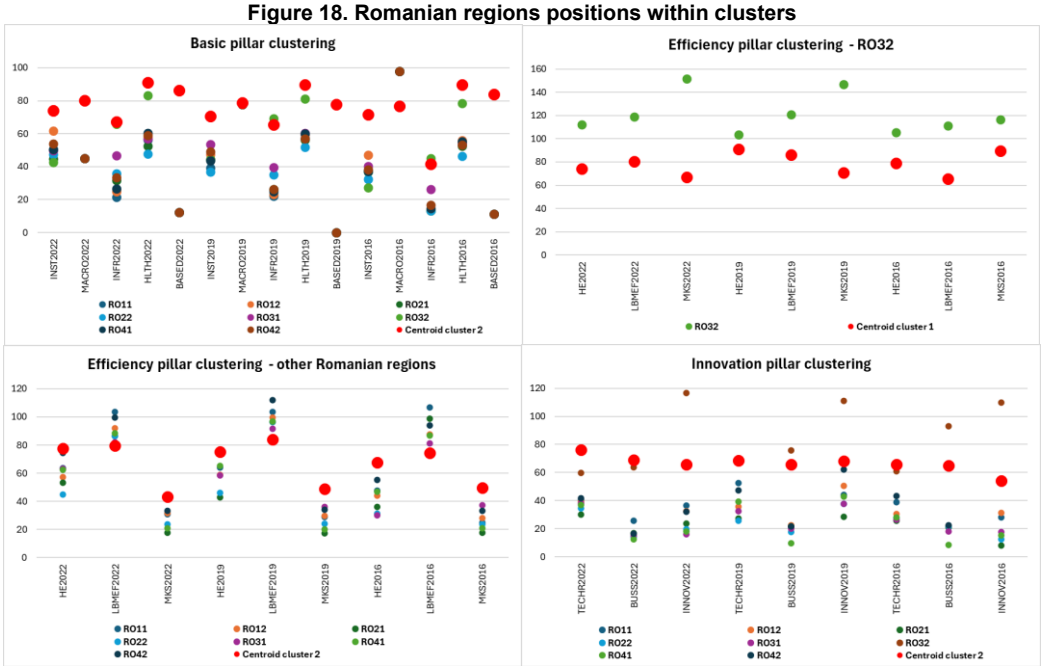
Region code	Region name	Basic clusters		Efficiency clusters		Innovation clusters	
		Cluster	Distance to centroid	Cluster	Distance to centroid	Cluster	Distance to centroid
RO11	Nord-Vest	2	1.194	2	0.512	2	0.539
RO12	Centru	2	1.153	2	0.372	2	0.626
RO21	Nord-Est	2	1.204	2	0.479	2	0.755
RO22	Sud-Est	2	1.255	2	0.441	2	0.741
RO31	Sud-Muntenia	2	1.127	2	0.282	2	0.715
RO32	Bucureşti-Ilfov	2	0.963	1	0.292	2	0.492
RO41	Sud-Vest Oltenia	2	1.156	2	0.333	2	0.720
RO42	Vest	2	1.160	2	0.475	2	0.539

Source: Authors' work in Tibco Statistica

In the Efficiency pillar amalgamation, though, region RO32 is positioned above the centroid for all variables and years, indicating that the capital region is among the leaders

in efficiency within EU regions, but also that there is a significant gap between RO32 and the remaining Romanian regions in efficiency. However, LBMEF is the variable in whose case we see a better positioning than the average for all Romanian regions included in cluster 2. At the same time, all these regions performed worse than the cluster average in MKS and HE for all years.

Figure 18. Romanian regions positions within clusters



Source: Authors' work based on Tibco Statistica output

Last, but not least important, we explore the position in clusters across the three RCI pillars for the peers of Romanian regions. According to the Scorecards associated with RCI 2016, there were 52 EU regions considered as peers for Romanian regions: 11 from Poland, 8 from Germany, 7 from Greece, 5 from Bulgaria and Hungary each, 3 from Italy, 2 from Slovakia, and 1 from Austria, Czechia, Spain, France and Netherlands. Also, 6 Romanian regions were peers for other regions in the country, except for RO31 (Bucuresti-Ilfov) and RO42 (Vest). It is also interesting to see that RO32 does not share any peers with the other Romanian regions, which is explainable by its higher level of development and competitiveness.

For RO32 (Bucuresti-Ilfov), all peers, except for Prague and surrounding areas (CZ_C), Comunidad de Madrid (ES30) and Lombardia (ITC4) share the same cluster 1 for Efficiency pillar. On the other hand, for the other two pillars, Efficiency and Innovation, Prague, Comunidad de Madrid, Lombardia and Provincia Autonoma din Trento (ITH2) are the only regions in the same cluster as RO32, cluster 2. This makes these four regions the closest peers to Bucuresti-Ilfov. For the other seven Romanian regions, their 2016 peers are in general included in the same clusters for all pillars, but there are some exceptions: (i) Dél-Dunántúl (HU23), Opolskie (PL52), Zachodniopomorskie (PL42), Stredné Slovensko (SK03), and Yuzhen tsentralen (BG42) are in cluster 1 in the Efficiency pillar,

while sharing cluster 2 for the Basic and Innovation pillars; (ii) Közép-Dunántúl (HU21) is in cluster 1 in the Efficiency and Innovation pillars; and (iii) Malopolskie (PL21) and Severozapaden (BG31) are in cluster 1 in all pillar amalgamations.

These clustering patterns reveal two distinct layers among Romanian regions: (1) the Bucuresti-Ilfov region demonstrates convergence with high-performing Central European capitals and innovation hubs, while the remaining Romanian regions cluster mostly with Eastern European peers that are facing similar developmental challenges. The partial overlap in cluster membership across pillars, particularly the shift between Efficiency and Basic or Innovation pillars for regions like HU23, PL52, and PL42, suggests differential development paths where certain regions are superior in specific competitiveness dimensions. This revealed heterogeneity stresses the importance of pillar-centred analysis when identifying appropriate policy benchmarks for Romanian regional development strategies.

5. Discussions

The examination of regional competitiveness in Romanian NUTS 2 regions from 2016 to 2022 indicates a complex "two-speed" developmental pattern that both aligns with and complicates existing theoretical frameworks in the literature. The synthesis of benchmarking results with K-means clustering analysis reveals major trends concerning the distinction of static and dynamic competitiveness, the influence of institutions, and the ongoing structural heterogeneity within the European Union.

The empirical findings validate the presence of significant regional polarization, in accordance with the "cluster" perspective stated by Porter (1990). București-Ilfov serves as a noteworthy outlier, aligning with competitive Western regions like Praha and Lombardia in the Efficiency pillar, whereas the other seven development regions fall considerably behind, clustering with Eastern European peers.

București-Ilfov demonstrates impressive efficiency in market size and higher education. Nevertheless, its performance in the basic pillars of institutions and infrastructure is remarkably low when compared to Western regions. This corroborates the caution expressed by Tödtling and Trippl (2005) that economic agglomerations may develop through localized knowledge spillovers while struggling to address basic institutional weaknesses. The capital seems to have attained a degree of economic convergence, yet it lacks the "social cohesiveness" and quality of life enhancements identified by Camagni (2002) as essential for dynamic competitiveness. The disparity between the capital and other regions indicates that the advantages of agglomeration are not adequately dispersed. The clustering results for the "Basic" pillar indicate that Romanian regions are the most distant from their cluster centroids, meaning they are underperformers relative to other less competitive regions.

The literature review differentiates between static competitiveness, characterized by cost and labor factors, and dynamic competitiveness, which includes innovation and institutional elements. The findings indicate that Romanian regions besides the capital are significantly influenced by static factors, resulting in competitiveness volatility between 2016 and 2022. The regions of Nord-Vest, Centru, and Sud-Vest Oltenia witnessed significant improvements from 2016 to 2019, followed by declines by 2022. In contrast,

their Polish peers (e.g., Podkarpackie) maintained consistent and sustained growth during the period. The observed volatility in Romanian regions confirms the institutional theory proposed by Rodrik et al. (2002), which asserts that institutional quality is a more critical factor for long-term development than geographic endowment. The failure of Romanian regions to maintain growth during the 2019–2022 crisis period reflects a deficiency in resilience, likely resulting from the structural weaknesses observed in the Basic pillar.

Becker (1993) identifies human capital as a factor contributing to convergence. Nevertheless, the findings show a "disconnect" in this respect. Romanian regions present good performance in Higher Education, but they have considerably lower performance in Basic Education, with scores as low as 12.3 in contrast to the EU baseline of 100. This imbalance indicates an absence of human capital accumulation that might restrict future Smart Specialization strategies, as essential skills necessary for broad absorptive capacity are absent to a large extent (Angeletopoulou et al., 2025).

An important result is that Infrastructure and Institutions are the primary factors inhibiting convergence. The clustering analysis indicated that regions have the lowest homogeneity regarding institutions. This supports North's (1990) argument that institutions function as the "rules of the game" that shape economic outcomes. The persistent underperformance of Romanian regions in the Institutional sub-pillar, despite rising economic output, demonstrates that economic gains are not being effectively converted into administrative capacity or rule of law, both of which are essential for dynamic competitiveness. Moreover, the "Basic" pillar clustering revealed the greatest variation in Infrastructure. In contrast to peers in Hungary and Poland, Romanian regions, excluding the capital, have a plateau or decline in relative infrastructure scores. The absence of physical connectivity limits the "two-way street" effect articulated by Puga (2002), therefore isolating these regions from the benefits of the Single Market.

6. Conclusions

The analysis validates the existence of a polarized "two-speed" developmental model in Romania. București-Ilfov has successfully diverged from national trends, achieving alignment with Western counterparts such as Praha regarding efficiency. However, it still displays imbalances due to considerable weaknesses in institutions and infrastructure. The other seven regions are situated within a low-competitiveness cluster, indicating fragility and volatility, as shown by the performance decline from 2019 to 2022, in contrast to their more resilient Polish peers. This divergence is primarily influenced by significant structural bottlenecks in the Basic pillar, especially in basic education and infrastructure, preventing these regions from transitioning from static to dynamic competitiveness.

Addressing this disparity requires an integrated policy approach instead of a uniform strategy. In the seven lagging regions, investments should focus on boosting "absorptive capacity" by concentrating on basic education and improving hard infrastructure connectivity, rather than pursuing premature high-tech objectives. Addressing the education gap is essential for overcoming low-cost labor advantages and achieving integration into the Single Market. In contrast, București-Ilfov should shift its focus from economic growth toward improving quality of life, particularly through the

improvement of health services and institutional frameworks, in order to mitigate the adverse effects of agglomeration and maintain its status as an innovation center. To address the volatility experienced during the 2019–2022 crisis period, it is essential for national reforms to strengthen local administrative capacity and guarantee the rule of law. This approach will ensure that regional growth is resilient to external shocks rather than reliant on temporary cost advantages.

The findings are marked by the inherent limitations of the RCI dataset, including the dependence on national-level data for macroeconomic and basic education indicators, which may hide particular regional realities. Moreover, territorial reorganizations in other EU member states restricted the continuity of data for specific peers. Future research should incorporate sub-regional indicators to overcome national-level data limitations, however depending on availability. Mixed-methods approaches that combine quantitative analysis with qualitative case studies could also reveal the distinct mechanisms driving competitiveness divergence. Moreover, extending this framework to other Eastern European member states would assess whether Romania's pattern of "two-speed" regional development is broader or it remains highly specific to the country.

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