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Regional Specialisation and Sectoral Concentration in Romania on Local Administrative Units Level (LAU)

Abstract. *This study provides an in-depth examination of regional specialisation and sectoral concentration within Romania, focusing on Local Administrative Units (LAU). Leveraging data from the National Trade Register Office spanning 2008 to 2021, the research analyses various economic indicators, including turnover, employment, company count, and profit or loss accounts, across different sectors according to the NACE rev. 2 classification. These indicators are synthesised at the LAU level, corresponding with the Nomenclature of Territorial Units for Statistics (NUTS) framework. The study employs a suite of specialised and concentration indexes, such as the Herfindahl-Hirschman and Krugman specialisation indexes, to dissect regional economic structures and identify patterns of economic specialisation, diversification, and stability. This investigation elucidates the complex dynamics of regional economic development, offering critical insights for policy formulation, economic strategy, and scholarly discourse on economic integration and structural transformation within the context of Romanian administrative units and beyond. This contribution is pivotal for understanding regional economic patterns, guiding strategic decision-making in economic planning, and fostering sustainable development.*

Keywords: *industrial concentration, regional specialisation, factor analysis.*

JEL Classification: L60, R12, C380.

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1. Introduction

Entrepreneurship stands as a cornerstone of societal prosperity, fuelling economic growth, technological innovation, and job creation. It is a multifaceted phenomenon, examined through various disciplinary lenses, each providing unique insights into its role within the economic and social fabric. Despite a lack of consensus on a singular definition, the significance of entrepreneurship is universally acknowledged, underpinned by its substantial contributions to economic dynamism and development.

This study embarks on a detailed analysis of the intricate web of economic activities across various localities, employing data sourced from the National Trade Register Office. The data, spanning from 2008 to 2021, encompass key economic indicators such as turnover, employment numbers, company count, and net profit and loss accounts across various sectors, following the NACE rev. 2 classification system. These indicators are aggregated at the Local Administrative Units level, adhering to the Nomenclature of Territorial Units for Statistics (NUTS) framework, providing a granular view of economic dynamics at the locality level.

The study meticulously examines regional economic specialisation and diversification through indices such as the Herfindahl-Hirschman and Krugman specialisation indexes. These measures dissect the economic structure at a regional level, offering insight into the depth of specialisation or diversification across sectors and regions. Additionally, the analysis extends to assess economic concentration and stability, incorporating the Herfindahl-Hirschman concentration index and the Lilien index, to elucidate structural employment shifts and regional economic instability.
By delving into these multifaceted indicators, the research aims to uncover the evolving patterns of economic specialisation, concentration, and stability across different regions. This endeavour not only provides a nuanced understanding of regional economic landscapes, but also sheds light on the broader economic integration and structural transformation processes. The outcome is a comprehensive portrayal of the economic dynamics at play, underpinning informed decision-making for policymakers, economists, and industry stakeholders, as they navigate the complexities of regional economic development and planning.

2. Literature review

Entrepreneurship is frequently associated with economic growth and development, improving living conditions, generating new jobs, and technological progress, in other words, the cause of prosperity in a society. The definition of entrepreneurship by experts in various fields, each with a unique perspective on the definition and factors influencing its economic and social environment, is broad and indistinguishable. Different opinions should not necessarily be conceived as contradictory but rather as providing an interpretation from another point of view, using another "lens" in the observation of entrepreneurship. There is not a single theory that everyone agrees on that can explain entrepreneurship as a separate economic and social phenomenon. This is because entrepreneurship involves many different fields of study and is very complicated. Although there is no unanimously accepted definition of what it represents and how it manifests itself, entrepreneurship is considered important due to its role in economic growth and development. Proof of the importance of the entrepreneur is the increased interest of economists and specialists in other fields, as well as of public initiatives at the regional or national level to support entrepreneurship (Curaj et al., 2021). In the paper written by Reveiu & Dardala (2015) the influence of cluster type business agglomerations is analysed from the perspective of entrepreneurial activities development in Romania. Through the research carried out, we analysed these hypotheses regarding the similarity or concealment of the Romanian industries at the zonal level and their concentration or dispersion.

Over time, regional specialisation and economic concentration in Romania have been explored by several authors. A group of three Romanian researchers, Andrei, Constantin, and Mitruț (2009), concluded through the documentation they did that the regional specialisations are due to several economic effects, such as the transition, regional changes, and privatisations. This transition process that took place in Romania at the beginning of the 21st century divided the interregional work areas while increasing the competition between the companies currently on the market (Andrei et al., 2009). In the paper written by Furtună et al (2013) the spatial concentration of the activity is analysed from the perspective of the energy industry in Romania.

In 2016, two Romanian researchers, Neagu, O. and Neagu, M.I (2016), conducted research on the evolution of the dynamics of the degree of specialisation of the regions and of the economic concentration in Romania, having as a time interval the years 2000–2013. They concluded that the Northwest and Center regions (according to the values of the Krugman Index) are closest to the national economic structure, while Bucharest-Ilfov is furthest from it. The differences between regional and national economic structures have increased in recent years. According to the Herfindahl-Hirschman index, the southern regions have become more specialised (South-East, South Muntenia, South-West, and West Oltenia), the North-East and Bucharest-Ilfov regions have diversified their activities, and the Northwest and Center regions have remained almost the same over the years. The values of the Gini coefficient indicated a different dynamic, as follows: the South-East region was the only one more specialised in the period examined; other regions such as the North-West, Center, North-East, and Bucharest-Ilfov have become more diversified; and the regions of the South have remained stable as an economic structure. Using regional employment data to measure specialisation and showing it with the Herfindahl-Hirschman index and the Gini coefficients showed that there was a trend for all regions to become more diverse. Economic entropy increased in all regions, and the similarity between the regional and national economic structure increased in the Center, North-East, West, and Bucharest-Ilfov regions and decreased in the South and North-West regions (Neagu & Neagu, 2016).

According to von Schutz and Stierle (2013) who provide a thorough examination of regional specialisation and sectoral concentration across the

European Union, emphasising the period surrounding the EU's enlargement. The study employs a comprehensive dataset from Eurostat's REGIO database, focusing on Gross Domestic Product (GDP), Gross Value Added (GVA) by different regions and sectors, and utilising the European System of National Accounts (ESA 95). The analysis includes various indicators like the Krugman index (Krugman, P. - 1994) for regional specialisation and various concentration measures, analysing these across EU member states and candidate countries to identify and compare patterns of economic concentration and specialisation. The research aims to contribute to understanding the implications of EU enlargement on regional economic structures, offering insights that are relevant for policymakers and economic strategists seeking to navigate the evolving landscape of European integration.

The Ellison-Glaeser index, also known as the Ellison-Glaeser Coagglomeration Index, is a statistical measure used to quantify the degree of coagglomeration or spatial concentration of economic activities, particularly in the context of urban areas. It was developed by the economists Edward L. Glaeser and Glenn Ellison in their seminal paper "The Geographic Concentration of Industry: Does Natural Advantage Explain Agglomeration?" published in the American Economic Review in 1999. The Ellison-Glaeser index measures the extent to which different industries or economic activities tend to locate near each other within a given geographical area, such as a city or metropolitan region. It compares the observed level of co-location of industries to what would be expected if industries were distributed randomly across space.

The formula for calculating the Ellison-Glaeser index involves comparing the observed co-location of industries to the expected co-location under the assumption of random spatial distribution. The index ranges from -1 to 1, with positive values indicating a higher degree of co-location than expected under randomness, negative values indicating less co-location than expected, and zero indicating random spatial distribution. The Ellison-Glaeser index has been widely used in empirical research to study various aspects of economic geography and urban economics. It has applications to understand the reasons for industrial clustering, the effects of agglomeration economies on productivity and innovation, and the implications for urban planning and policy. One of the strengths of the Ellison-Glaeser index is its simplicity and ease of interpretation. It provides a quantitative measure of spatial concentration that can be readily applied to empirical data, allowing researchers to compare the degree of industry clustering across different regions and industries.

However, the Ellison-Glaeser index also has limitations. For example, it does not account for the intensity of industry clustering or the underlying mechanisms driving agglomeration. Additionally, its calculation relies on certain assumptions, such as the randomness of spatial distribution under the null hypothesis, which may not always hold true in practice.

According to Gabe and Abel (2016), it delves into how various occupations cluster within US metropolitan areas, driven by shared knowledge requirements. It uses the Ellison-Glaeser index to assess coagglomeration levels and identifies a strong correlation between occupations that require similar skills and knowledge, leading to their geographical proximity. This phenomenon is particularly evident in sectors such as engineering, technology, and arts. The study suggests that such coagglomeration fosters job mobility and knowledge spillovers, enhancing innovation and economic development. This research underscores the strategic importance of knowledge sharing in the spatial organisation of occupations, indicating that urban planning and policy development could benefit from considering these knowledge-based relationships.

Another application of this index was made in the article written by Howard et al. (2016), which provides an in-depth analysis of how industries cluster together within specific geographic regions. It introduces a new index for measuring industry coagglomeration, comparing it with the well-established Ellison-Glaeser (EG) index, and uses data from the Vietnamese manufacturing sector for empirical validation. The study examines factors like transport costs, labour market pooling, and technology spillovers to understand their impact on industry clustering. The findings offer valuable insights for policymakers, particularly in developing economies, highlighting how understanding industry coagglomeration can inform strategies to boost economic growth, enhance regional development, and optimise industrial policies. The research not only contributes a new analytical tool to the economic literature, but also provides a nuanced understanding of the spatial dynamics of industrial development, emphasising the significance of coagglomeration patterns in shaping economic landscapes. The conclusion likely underscores the importance of incorporating coagglomeration analysis into economic planning and industrial strategy, suggesting that such insights can lead to more targeted and effective interventions in regional and national economic policies.

Another perspective could be made based on the Lilien Index and the Modified Lilien Index (LI) are both measures used in labour economics to assess structural changes in the labour market. They were developed by the economist George Lilien to quantify the extent of sectoral shifts in employment over time. The Lilien Index measures the dispersion of employment growth rates across different sectors of the economy. The Modified Lilien Index (MLI) adjusts the Lilien Index to account for changes in the overall level of employment in the economy. Both the Lilien Index and the Modified Lilien Index are valuable tools for labour economists and policymakers in understanding the structural dynamics of the labour market. They help identify sectors that experience significant changes in employment patterns, which can inform policy interventions aimed at addressing unemployment or promoting workforce adaptation to evolving economic conditions. Ansari et al. (2014) delve into the intricacies of the Lilien Index (LI) and the Modified Lilien Index (MLI), which are pivotal in assessing structural shifts within the economy and their impact on regional unemployment rates. It elucidates the methodologies used for calculating these indices using Stata, offering a practical guide for economists and researchers.

The core of the analysis focuses on the application of LI and MLI to understand sectoral employment changes, particularly within the context of Italy's regional economies. The LI quantifies the dispersion of sectoral employment growth rates, serving as an indicator of structural change in the labour market. It suggests that higher dispersion, reflected by a higher LI, indicates greater sectoral shifts and potentially higher transitional unemployment rates.

Another approach is using Herfindahl-Hirschman Index (HHI), which is a commonly used measure of market concentration in economics, particularly in the context of antitrust and competition policy. It provides a quantitative assessment of the degree of competition or concentration within a market based on the market shares of firms operating within it. The HHI is calculated by summing the squares of the market shares of all firms in the market. It is important to note that the HHI has some limitations. For instance, it does not account for the competitive dynamics within a market or the potential for entry and exit of firms over time. Additionally, the HHI may not fully capture market power in markets with differentiated products or where firms compete on non-price factors.

Despite its limitations, the Herfindahl-Hirschman Index remains a widely used tool for assessing market concentration and informing competition policy decisions. Its simplicity and ease of calculation make it a valuable metric for analysing market structures and potential competitive concerns. Sekur (2020) delves into the evolving landscape of economic concentration and regional specialisation within EU regions, assessing the dynamics from 2005 to 2017 using the Herfindahl-Hirschman Index. This research underscores the importance of nuanced regional analysis in understanding the broader economic integration processes and in formulating targeted interventions to foster balanced regional growth and economic resilience across the EU.

3. Data and Methodology

For this study, data were taken from National Trade Register Office. The data are provided at local administrative units level (about 3181 records), per year, and contain the following indicators: turnover, number of employees, number of companies, net profit or loss account for each activity as described in NACE rev. 2 (Statistical Classification of Economic Activities). The data were summarised at the level of Local administrative units (LAU) according to Nomenclature of Territorial Units for Statistics (NUTS). Any of the above indicators can be used to measure activity. Most studies use employment indicators.

3.1 Specialisation indicators

Herfindahl-Hirschman index measures the absolute level of specialisation for each region. It is calculated as follows (Sekur, 2020):

$HHI_i^s = \sum_{j=1}^{m} {s_{ij}}^2$,

where i is the region, j is the sector, m is number of sector of activities, $s_{ij} = \frac{x_{ij}}{\sum_{j=1}^{m} x_{ij}} = \frac{x_{ij}}{x_{i\cdot}}$, x_{ij} is the employment in region i and sector j, $x_{i.}$ is total employment in region i. The index values can range between 0 and 1. When value is 1, only one sector is represented in region i (regional specialisation).

The Krugman specialisation index compares the economic structure of a region with a reference structure (usually the national structure), as follows:

$KSI_i = \sum_{j=1}^{m} |s_{ij} - s_i|$,

where i, j, m and s_{ij} have the same meaning as the Herfindahl-Hirschman index.

$s_j = \frac{x_{.j}}{\sum_{j=1}^{m} x_{\cdot j}} = \frac{X_{\cdot j}}{X}$, where $x_{.j}$ is the total employment in j activity (national level), X is the total employment (national level) and s_j is the share of j activity in total national.

Regional Diversification index takes values between 0 (total diversification) and 1 (total specialisation). It is calculated as follows: $H_i = \frac{\sum_{j=1}^{m} \frac{x_{ij}}{x_{i.}} \cdot \log \frac{x_{i.}}{x_{ij}}}{\log m}$, where $x_{i.} = \sum_{j=1}^{m} x_{ij}$.

3.2 Concentration indicators

The Herfindahl-Hirschman concentration index measures the degree of concentration for each activity, as follow:

$HHI_j^c = \sum_{i=1}^{n} {S_{ij}}^2$,

where $S_{ij} = \frac{x_{ij}}{x_{.j}}$, n is number of regions, $x_{.j}$ is total employment in sector activity j.

The Krugman concentration index is calculated as follows:

$KSI_i = \sum_{i=1}^{n} |S_{ij} - S_i|$, unde S_{ij} it is calculated in the same way as the Herfindahl-Hirschman index, and $S_i = \frac{x_{i.}}{\sum_{i=1}^{n} x_{i.}}$, is the share of i region in total national. Sectoral dispersion index is calculated according to the formula: $H_j = \frac{\sum_{i=1}^{n} \frac{x_{ij}}{x_{.j}} \cdot \log \frac{x_{.j}}{x_{ij}}}{\log n}$, where $x_{.j}$ is the number of employees in sector j. The index varies between 0 (total, uniform dispersion) and 1 (no dispersion - concentration in a single region).

3.3 Regional instability and structural change indicators

To measure regional instability (REI) we used the index proposed by Siegel in (Siegel, R. - 1966), and also used in (Trendle and Shorney, 2003) and (Kort, 1981), as follows:

$$REI = \frac{\sum_{t=1}^{T} \frac{E_{jt} - E_{jt}^{Tr^2}}{E_{jt}^{Tr}}}{T},$$

where: E_{jt} - employment at time t in region j, E_{jt}^{Tr} - the linear prediction for T periods for employment at time t and region j. For linear prediction, we used an autoregressive time series model (*AutoReg* class from *statsmodels* package Python).

In order to measure the structural changes of employment, we used the Lilien index (Lilien, 1982). The Lilien index reflects the speed of sectoral reallocation of employment in the economy, as the main factor of specialisation differences. The Lilien index is calculated for each region as follows:

$$L_i = \sqrt{\sum_{j=1}^{m} \frac{x_{ij}^t}{x_{i.}^t}\left(\ln\frac{x_{ij}^t}{x_{ij}^{t-1}} - \ln\frac{x_{i.}^t}{x_{i.}^{t-1}}\right)^2},$$

where i is the region, x_{ij}^t is the employment în regiunea i, activity j at time t and $x_{i.}^t$ is the total employment în region i at time t.

The minimum value of the index is 0, if there are no structural changes in a period.

4. Data Analysis and Results Interpretation

4.1 Exploratory factor analysis of specialisation indicators

In order to highlight the changes produced in the specialisation of the activity for the analysed period, we have applied factor analysis by years of the specialisation indicators, with administrative-territorial units as instances. As expected, using the model without factor rotation does not lead to the identification of multiple factors, the variables being well correlated. The differences from one year to another are small. Figure 1 shows the correlations between the observed variables (years) and the common factors after factor rotation. The factor extraction method is the Minimal Residual Method (MINRES). The model is applied to the Herfindahl-Hirschman and Krugman indices with a VARIMAX rotation. The number of significant factors can be determined by the following criteria: Kaiser, Cattell, cumulative percent of variance extracted as well as Bartlett's significance test to determine the number of factors.

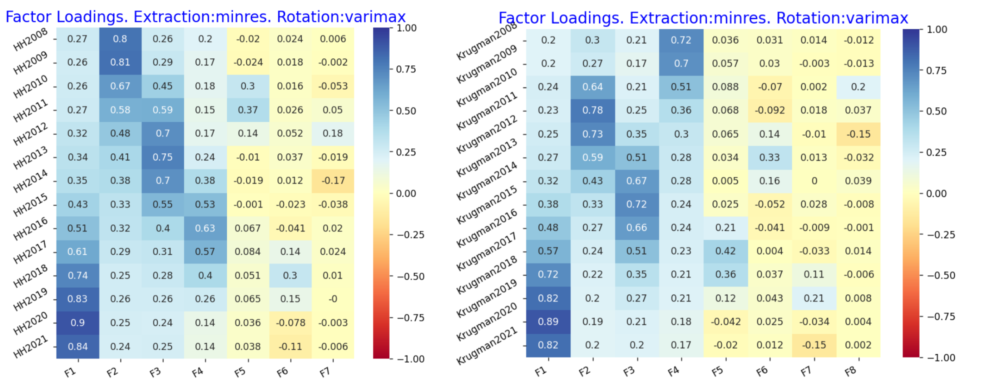

Figure 1. Factor Loadings for Herfindahl-Hirschman and Krugman indices with varimax rotation

Source: Authors` own creation.

For the results interpretation and scores calculation, we used the most restrictive criterion, the Cattell criterion. Figure 2 shows the scree plots for both analyses, highlighting the relevance criteria.

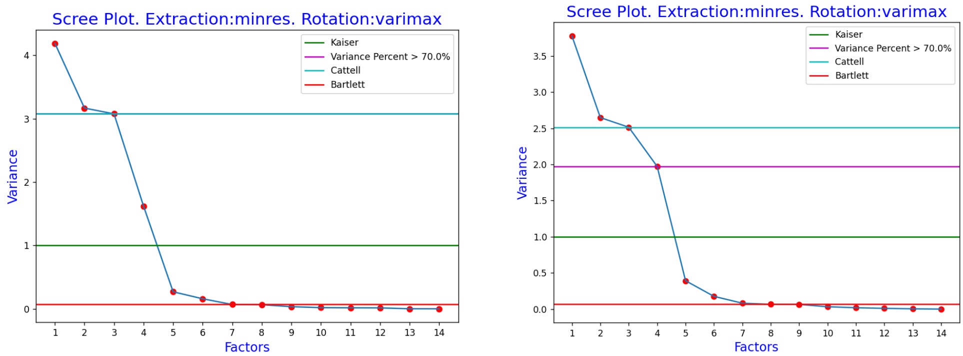

Figure 2. Scree plots of retained factors for Herfindahl-Hirschman and Krugman indices

Source: Authors` own creation.

The factor variance information, including the amount of variance, proportion of variance, and cumulative variance for each factor are presented in Table 1. Interpretation is the process of examination and selection of variables that are correlated with each individual factor. A factor corresponds to a pattern, a construct that can be labelled. The labelling of patterns is a theoretical, subjective, and intuitive process.

Table 1. Factor variance information

Factor	Herfindahl-Hirschman index			Krugman index		
	Variance	Proportional Variance	Cumulative Variance	Variance	Proportional Variance	Cumulative Variance
F1	4.187	0.299	0.299	3.776	0.27	0.27
F2	3.166	0.226	0.525	2.647	0.189	0.459
F3	3.075	0.22	0.745	2.514	0.18	0.638

Source: Authors` own creation.

The first factor (F1), in the exploratory factor analysis of the Herfindahl-Hirschman indices, is related to the years 2019, 2020 and 2021. These are the years that overlap with the COVID-19 pandemic and the energy crisis. The second factor (F2) is related to the great financial crisis of 2008-2009. Factor scores are presented as maps. Figure 2 shows the scores for factors 1 and 2.

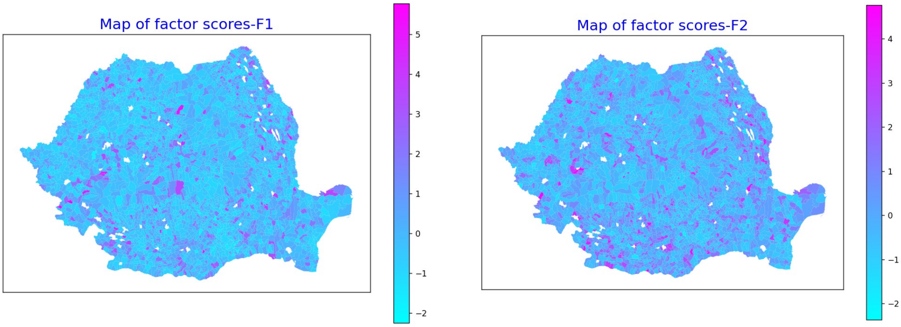

Figure 2. Factor scores map for first and second factor
Source: Authors` own creation.

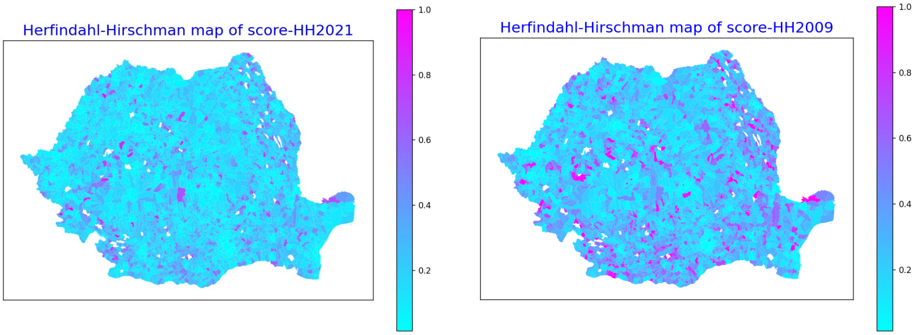

Figure 3. Herfindahl-Hirshman index in 2020 and 2009
Source: Authors` own creation.

The trend in the period 2008-2021 was of a continuous decrease of regional specialisation and a permanent increase of diversification. Despite the fact that there are country-specific characteristics, the general conclusion of most of studies indicates a negative correlation between regional specialisation and regional GDP per capita and unemployment rates. The factors reveal those local administrative units that do not follow this pattern in certain periods. In order to better highlight not only the representative units for each factor, but also the increase in diversification, we presented in figure 3 the Herfindahl-Hirschman indices for the most representative years of the periods 2008-2009 and 2019-2021. For some units, the period of the financial crisis of 2008-2009 and the period of the pandemic meant a significant decline in economic activity in many industries. Each period affected different units, which is reflected by the existence of different common factors. To highlight this, we presented on a heat map the Herfindahl-Hirschman indices for 5 administrative units with the highest scores for factors F1 and F2 (Figure 4). Generally, high values can be seen in the period 2019-2021 for the F1 factor and in the period 2008-2009 for the F2 factor.

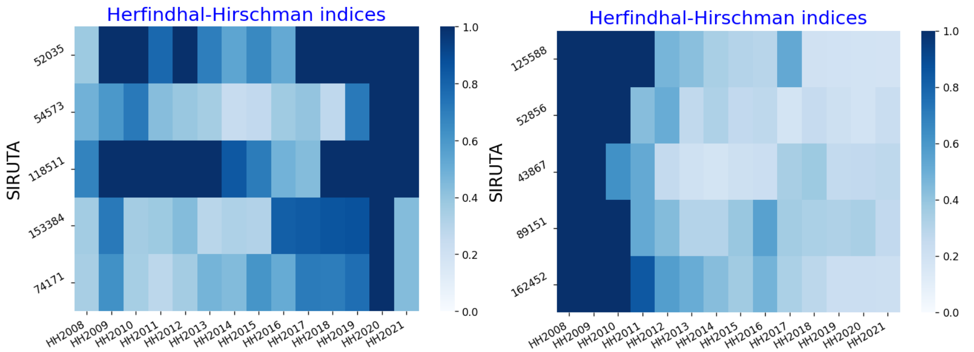

Figure 4. Herfindahl-Hirschman indices for some representative units of F1 and F2

Source: Authors` own creation.

For example, in Figure 5 a Herfindahl-Hirschman heatmap for two representative local units for factors F1 and F2 are represented. In CIUDANOVITA commune, the diversification is reduced to a single industry in 2019-2020 (F1), while in FOROTIC commune the same thing is observed but in 2008, 2009 and 2010 (F2).

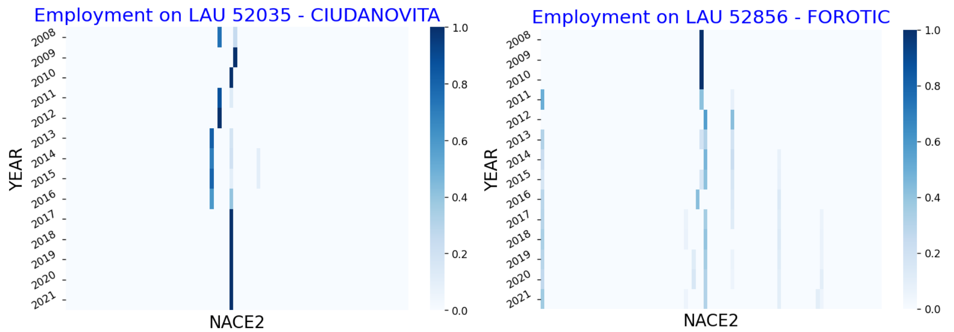

Figure 5. Industry diversification in CIUDANOVITA and FOROTIC communes

Source: Authors` own creation.

4.2 Exploratory factor analysis of concentration indicators

The factor analysis of the concentration indicators reveals the differences between the years of the analysed period regarding industry concentration. The differences are small and can only be highlighted by factor rotation. Figure 6 shows the factor loadings matrix with and without factor rotation.

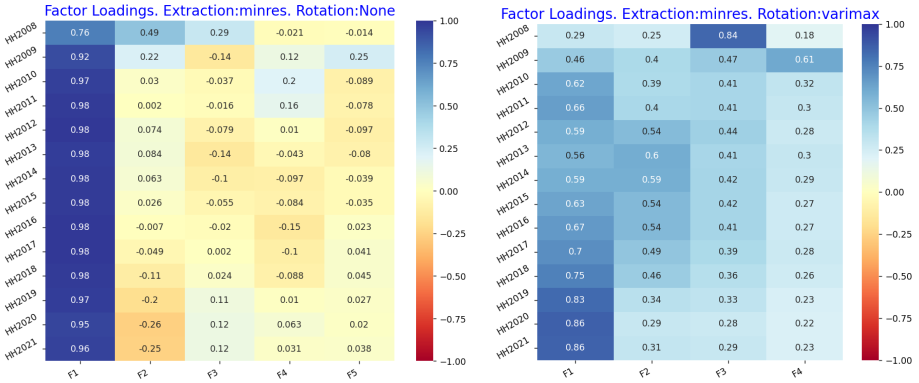

Figure 6. Factor loadings heatmap with and without factor rotation

Source: Authors` own creation.

Almost the same associations between the common factors and the analysed variables (years) are identified, as in the factor analysis of the specialisation indicators. Factor 1 is related to the period of the COVID-19 pandemic, factors 3 and 4 to the period of the financial crisis, and factor 2 is not clearly outlined for a specific period.

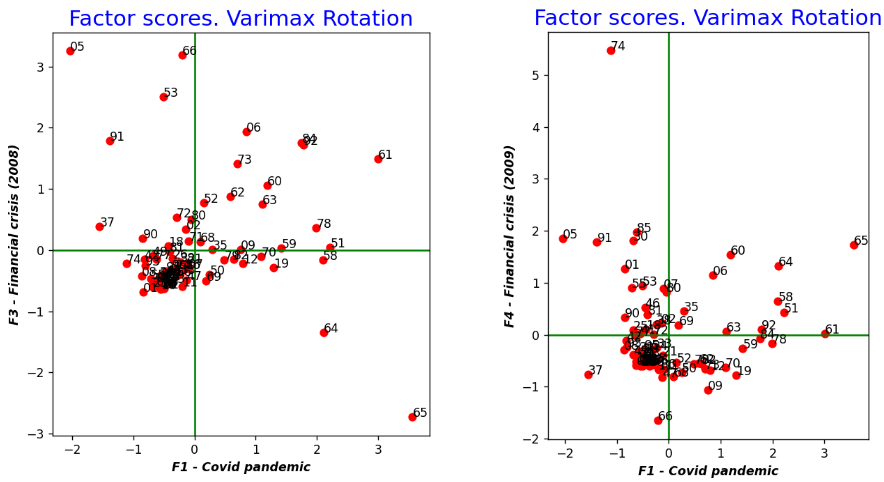

Figure 7. Factor scores for factor 1 and factor 3, factor 4 respectively

Source: Authors` own creation.

The estimated factor scores by the MINRES method highlight, through their extreme values, the relevant activities for each factor. Therefore, for factor 1, high values are observed for activities with NACE identifiers 65 ("Insurance, reinsurance and pension funding, except compulsory social security"), 61 ("Telecommunication"), and so on. High values of scores indicate a greater degree of sectoral concentration of these activities for the period associated with that factor. In opposite, low scores such as those recorded for activity 05 ("Mining of coal and lignite"), highlight a greater spread of the activity in the territory, so a lower sectoral concentration. Figure 8 shows the map of the Herfindahl-Hirschman concentration indices calculated at the level of local administrative units for NACE activity 65, in the years 2008 and 2021. Concentration indices are noticeably higher in 2021. In 2008 the activity was more territorially dispersed.

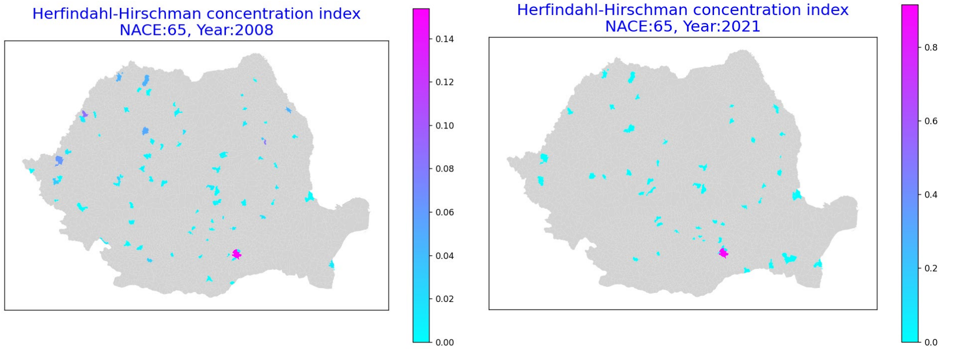

Figure 8. Concentration indices to LAU level for NACE 65, 2008 and 2021
Source: Authors` own creation.

Factor 3 indicates high concentrations of activities 05, 66 ("Activities auxiliary to financial services and insurance activities"), 53 ("Postal and courier activities") in opposite to activities 65, 64. This is well shown in the maps from Figure 9, where the concentration indices for activity 53 in the years 2008 (factor 3) and 2020 (factor 1) are plotted.

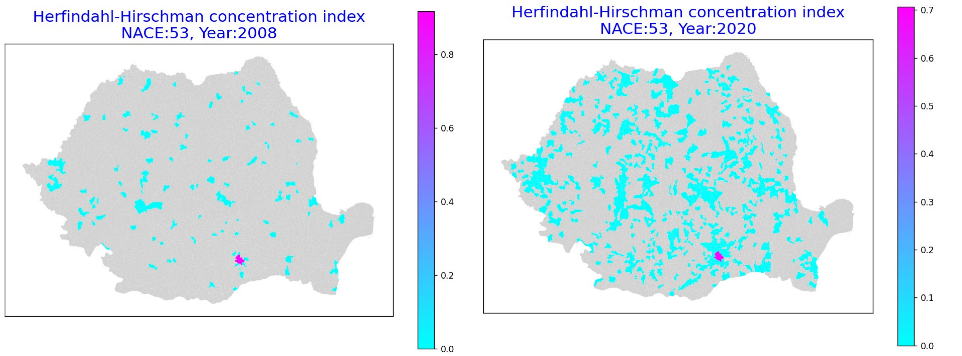

Figure 9. Concentration indices to LAU level for NACE 53, 2008 and 2020
Source: Authors` own creation.

The biggest contribution to the creation of the factor 4 is the activity 74. The activity concentration in 2009 and 2021 is shown in figure 10. The concentration is higher in 2009 (factor 4), the Herfindahl-Hirschman indices are higher and the number of localities where the activity is located is lower.

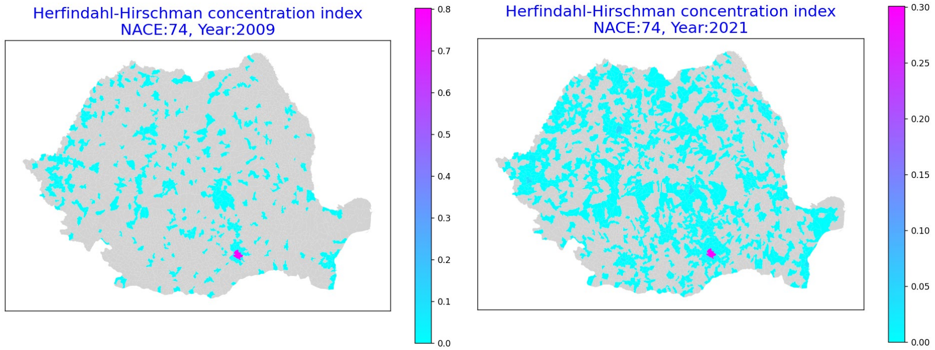

Figure 10. Concentration indices to LAU level for NACE 74, 2009 and 2021
Source: Authors` own creation.

4.3 Analysis of structural changes and regional instability in the period 2008-2021

Many studies show that regional instability has a strong negative effect on a country's economic performance. The calculations made for the period 2008-2021 indicate greater stability in the urban area, in the big cities and their hinterlands in particular. Many rural regions are characterised by unstable economies. This characteristic is visible in the first map in figure 11. It is important to analyse the link between instability, structural changes, and industrial diversification. Pearson's linear correlation coefficient is not relevant. The relationship between these indicators is not linear. Figure 12 shows in more detail the connection between these aspects, also highlighting their spatial autocorrelation.

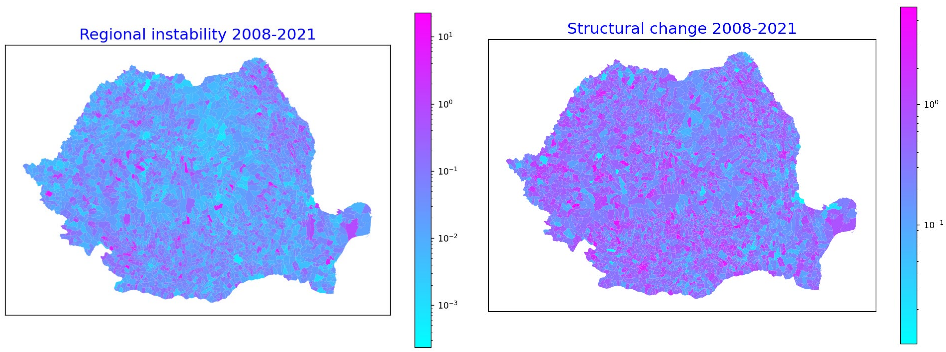

Figure 11. Regional instability and structural change indices in logarithmic scale
Source: Authors` own creation.

The values taken by the indicators were classified as follows: L (Low) - below average values, H (High) - average and above average values. To compare two indicators, each territorial unit will be classified as follows: LL (Low for both indicators), LH (Low for first indicator and High for the second), LH and HH. We applied The Chi-Square test of independence, using the *chi2_contingency*() function in Scipy, Python, between regional instability and structural change on the one hand,

and between regional instability and industry diversification on the other hand, and the result is:

Chi2ContingencyResult(statistic=113.51412185370476, ***pvalue=1.6649134058919307e-26***, dof=1, expected_freq=array([[135.1354494, 267.8645506],[931.8645506, 1847.1354494]]))
Chi2ContingencyResult(statistic=64.72548210024858, ***pvalue=8.609423927297207e-16***, dof=1, expected_freq=array([[184.6343917, 217.3656083], [1276.3656083, 1502.6343917]]))
The results indicate a strong connection between these indicators.

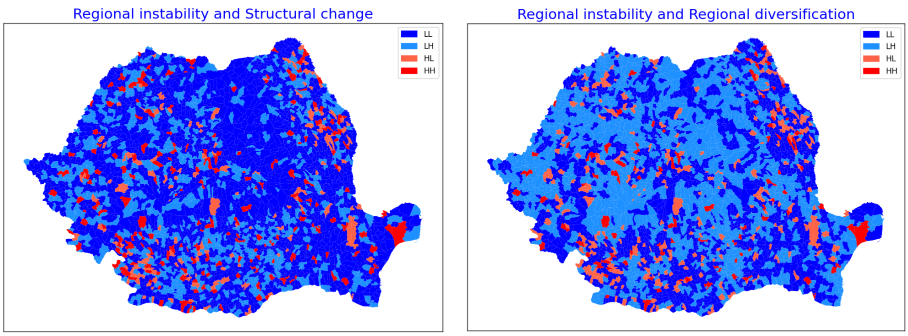

Figure 12. The link between regional instability, structural change and regional diversification
Source: Authors` own creation.

In the first map, the regions coloured in intense blue have stability without structural changes. Most rivets belong to this category. Light blue indicates stability and structural changes. In these regions, instability is avoided precisely by structural changes. Employment in this locality is slightly affected. It is the second situation in the number of regions encountered. Regions colored red indicate instability with or without structural changes. In the second map, the dominant category is LH, stability, and industrial diversity. The regions with stability but less diversity follow. Predominant in this category are rural localities with few but relatively stable activities.

5. Conclusions

While not conducting an in-depth long-term analysis, the findings of this current research remain applicable. Following an extended period of economic transition during the 1990s and 2000s, due to privatisation, liberalisation, and regulatory changes, the industry embarked on a phase of settlement, consolidation, and stabilisation. This study specifically examines this period from the late 2000s to the present. The analysed timeframe commences with a crisis and concludes with another. The factor analysis carried out at the years level has shown that there were no major changes, neither at the level of specialisation nor at the level of industrial concentration. In order to capture differences between years or smaller periods within the analysed timeframe, various procedures of orthogonal factor rotation were employed. The VARIMAX method best captured these differences. After axis rotation, at least two factors are highlighted, regardless of the specialisation index used. The main two factors are strongly correlated with the years 2019-2021 and 2008-2009, respectively. Therefore, the factors highlight the two crisis periods, the financial crisis and the COVID-19 pandemic. The most affected administrative units were communes and small towns. To better understand changes in industrial specialisation and concentration, we supplemented the study with an analysis of instability and structural change. The link between industrial diversity, employment instability, and structural changes in employment in the period 2008-2021 is summarised in the following table:

Table 2. The link between industrial diversity, instability and structural changes

Quadrant	UAT_No	Average employment
HLH	1352	2843.137944
HHH	110	802.693634
LLL	1427	130.445790
LHH	293	97.295465

Source: Authors` own creation.

where:
HHH - administrative territorial units with high industrial diversity, low instability, and high structural changes. Here is where the majority of employment is concentrated. The average employment rate is around of 2843.
LLL - administrative territorial units with high industrial diversity, low instability, and low structural changes. It is about small administrative-territorial units, such as small towns and communes.
LLL - administrative territorial units with low industrial diversity, low instability, and low structural changes. It concerns regions with specific industrial specialisations that have remained unaffected by crises.
LHH - administrative territorial units with low industrial diversity, high instability, and high structural changes. It refers to regions with weak economic activity affected by unemployment and instability.

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