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A comparative analysis of the socioeconomic development of the Norte Region of Portugal in the European context in the last two decades

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Dissertation

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Abstract

This study explores the application of tensor decomposition to analyze regional dynamics across the European Union. The data is structured into a three-dimensional tensor – geographical regions, socioeconomic indicators, and time. The aim is to find potential patterns, interactions, and temporal trends that form regional development.

Understanding the trajectories of European Union regions across multiple dimensions of sustainable development is increasingly relevant, particularly in the context of regional disparities and the Europe Union's Cohesion Policy. This study aims to explore how regions have evolved over time and how they compare within the European context, analyzing key dimensions of regional development, such as economic growth, competitiveness, innovation, and social progress.

In addition, we use the Norte Region of Portugal as a reference case, comparing its performance with other EU regions to highlight its strengths and challenges. This approach intends to identify regions with similar development trends, offering valuable insights into factors influencing these dynamics.

Keywords: European Union, Regional development, Multidimensional data analysis, Tensor decompositions, Tucker3 model

Resumo

O presente estudo usa a decomposição de tensores, especificamente a decomposição de Tucker, para analisar as dinâmicas de desenvolvimento regional na União Europeia. Os dados são estruturados num tensor tridimensional – composto por regiões, indicadores socioeconómicos e o tempo. Com a presente análise pretende-se aprofundar o conhecimento sobre a evolução das diferentes regiões europeias ao longo das duas últimas décadas, procurando identificar-se eventuais padrões e tendências de desenvolvimento regional.

A análise das trajetórias das regiões da União Europeia nas múltiplas dimensões que integram o desenvolvimento sustentável assume uma importância crescente, especialmente no contexto das disparidades regionais e da Política de Coesão da União Europeia. Este estudo visa analisar a evolução das regiões ao longo do tempo e a sua posição relativa no contexto europeu, explorando dimensões chave do desenvolvimento regional, como o crescimento económico, a competitividade, a inovação e o progresso social.

Adicionalmente, apresenta-se uma análise mais detalhada para o caso da Região do Norte de Portugal, comparando o seu desempenho com o de outras regiões, de forma a destacar os seus pontos fortes e os principais desafios. O objetivo é identificar regiões com trajetórias de desenvolvimento semelhantes, ao mesmo tempo que procura destacar fatores que influenciam estas dinâmicas.

Palavras-chave: União Europeia, Desenvolvimento regional, Análise de dados multidimensionais, Decomposição de tensores, Modelo Tucker3

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Chapter 1

Introduction

This chapter outlines the motivation behind this study and the main reasons for the selected approach. It also presents a brief description of the topic and the problem to be solved, as well as its relevance within the context of regional development. Finally, the chapter provides an overview of the structure of the dissertation, summarizing the content of each subsequent chapter.

1.1 Context and motivation

Understanding the evolution of European Union regions across multiple dimensions of socioeconomic development is a topic of growing relevance in the context of regional analysis (OECD, 2024). This study aims to explore the factors that have shaped regional development over the past two decades. In this context, a set of indicators that cover various dimensions of sustainable development are analyzed, including economic growth, competitiveness, innovation, and social progress. The analysis of those dimensions fosters the knowledge of how regions have evolved over time and how they compare within the European context.

In addition, the Norte Region of Portugal will be used as a reference case and will be compared to other EU regions to highlight its strengths and challenges. The study seeks to identify regions with similar performance trends, contributing to a deeper understanding of regional development patterns. In doing so, the study aims to provide valuable insights about regional disparities, a key theme in the European Union's Cohesion Policy.

1.2 Problem definition

According to the Ninth Report on Economic, Social and Territorial Cohesion (European Commission, 2024), the EU's Cohesion Policy has contributed to significant convergence among regions, although significant disparities still persist. While convergence at national level is evident, it often masks internal disparities, and some regions are facing economic stagnation and slight progress across key dimensions of development.

Using a period of 20 years, this study enables the identification of more robust trends and meaningful comparisons, assessing whether regions with similar baselines have diverged in their trajectories and investigating the factors that may have contributed to these dynamics.

With this in mind, the fundamental questions this study aims to answer are:

- What patterns of development exist among European regions?
- How have they evolved across the multiple dimensions of socioeconomic development over time?

Furthermore, a special aspect of this study is the application of a methodology that has not been widely used in analysis of this nature. Using an approach based on a High-Order Singular Value Decomposition (HOSVD), this study seeks to explore other perspectives, enhancing the tools available for regional development studies and offering an extended understanding of the data and trends identified.

1.3 Dissertation structure

The dissertation is organized into five sections.

Chapter 1 presents the motivation for selecting the subject and outlines the proposed approach. It also includes a brief description of the topic and the problem to be addressed.

Chapter 2 provides the theoretical foundations that form the basis of the dissertation. It begins by demonstrating the increasing importance of these analyses in regional development and the rationale behind the selected indicators. Then, it introduces the foundations of tensor decompositions, including the basic concepts and operations. The relevance of tensor decomposition in multidimensional data analysis is also highlighted.

Chapter 3 addresses the literature review and summarizes the most relevant research related to the subject under study. First, it focuses on comparative territorial analyses using multidimensional data. Then, it highlights studies that apply tensor decomposition techniques, namely the Tucker decomposition.

Chapter 4 explains the methodological approach adopted to conduct the research. This section provides a brief overview of the rationale behind the selection of the variables used in the analysis and then presents the Python tool used to analyse the multidimensional data.

Chapter 5 provides a brief description of the variables selected for the study. In particular, it explains the framework that guided the choice of indicators, regions and time horizon considered. The chapter also includes an exploratory analysis of the data and identifies the main data pre-processing procedures carried out to ensure the continuity of the analysis.

Chapter 6 presents the results of the study. It begins by describing the application of the Tucker decomposition, which was used to obtain the factor matrices that serve as the basis for representing the trajectories of the regions. This is followed by the interpretation of the components associated with the indicators and the regions. Finally, the regional trajectories over the 20 years of the reference period are presented, their meaning is discussed, and the specific case of the Norte Region of Portugal is analysed.

Finally, Chapter 7 offers concluding remarks, summarizing the key points and reflecting on the limitations and possible next steps for research.

Chapter 2

Theoretical Foundations

This chapter presents the theoretical foundations that support the analysis carried out in this study. It is divided into two main sections.

The first highlights the importance of understanding regional dynamics in the context of policy design, and the value of adopting a multidimensional framework for assessing regional development. In line with this approach, the study draws on three different composite indicators developed by the European Commission to evaluate how European regions have evolved across key dimensions of development, namely competitiveness, innovation and social progress.

The second section presents the methodological approach used in the study, which is based on Higher-Order Singular Value Decomposition (HOSVD). It includes a conceptual overview of tensors, explains the fundamentals of tensor decomposition techniques, and discusses their application in visualizing regional trajectories over time.

Together, these sections provide the necessary methodological basis for the subsequent empirical work.

2.1 Comparative regional analysis

2.1.1 The importance of regional dynamics in policy design

The analysis of regional dynamics has emerged as a key pillar to address disparities and promote sustainable growth. More and more, effective cohesion and development policies are needed due to the increasing complexity of socioeconomic interdependencies between regions and the need for customized interventions within the EU.

Recent policy documents end reports underline the critical role of regional analyses in driving strategic cohesion efforts. *The Ninth Report on Economic, Social and Territorial Cohesion*, published by European Commission (2024), highlights how understanding the unique trajectories of EU regions is essential for mitigating disparities and promoting balanced growth.

The European Commission report on Regional Trends for Growth and Convergence in the European Union (2023) also reinforces this perspective, presenting an in-depth analysis of the evolving challenges and opportunities faced by regions. The document provides an analysis of the regional disparities and trends in the EU, stressing that effective policy responses must be made with a thorough knowledge of regional dynamics.

2.1.2 A multidimensional framework for regional development

An integrated approach to regional development requires a focus on multiple dimensions that jointly drive sustainable growth. According to the EU Regional Competitiveness Index (RCI) 2.0 (2022, revised 2023), the concept of sustainability relates to region's capacity to provide an attractive environment in both the short and long term. The RCI is composed of three sub-indices – "Basic", "Efficiency" and "Innovation" – and of eleven pillars that describe the different aspects of competitiveness and provides a comprehensive framework for assessing regional strengths and weaknesses, particularly in areas critical for economic performance and global competitiveness.

Innovation emerges as a central pillar in fostering dynamic and resilient regions. The Regional Innovation Scoreboard (RIS) 2023 emphasizes that regions are important engines of economic development. In this context, to measure innovation performance at the regional level has become ever more important. The RIS provides a comparative assessment of the performance of innovation systems across European regions on 21 indicators grouped into four main types of activities – Framework conditions, Investments, Innovation activities, and Impacts – and twelve innovation dimensions.

Equally important is the dimension of social progress. The EU Regional Social Progress Index (EU-SPI) 2.0 (2024) aims to evaluate EU regions across a wide range of dimensions of social progress, as a complement to traditional measures of economic progress, such as the Gross Domestic Product (GDP). The index is based on 53 socio-economic and environmental indicators, using twelve components that are further aggregated into three broader dimensions describing respectively basic, intermediate, and more advanced aspects of social progress.

The increasing availability of data contributes to a more precise understanding of the interconnections between the various dimensions of sustainable growth. By integrating insights from different sources, policymakers can make interventions that are both effective and adaptive to the evolving needs of regions (eg.: Stiglitz et al. (2018, *Beyond GDP: Measuring What Counts for Economic and Social Performance*). The analysis of regional dynamics serves as the foundation for designing and implementing policies that promote cohesive, competitive and socially progressive regions.

2.2 An approach based on a Higher-Order Singular Value Decomposition (HOSVD)

In order to perform a comprehensive comparative analysis of the socioeconomic development of European Union (EU) regions, we propose to use a methodology based on higher-order tensor decompositions. Given the inherently multidimensional nature of the data to be analyzed, this approach was chosen as a powerful and efficient tool for data representation and analysis (Kolda and Sun, 2008).

This chapter introduces the concept of tensors, gives an overview of the main methods of tensor decompositions, and provides a detailed explanation of Tucker decomposition. In particular, a description of the Higher-Order Singular Value Decomposition (HOSVD) is done. Finally, the application of this method to the present study is outlined.

In this document, we follow the standardized notation and terminology in multiway analysis proposed by Kiers (2000) and the notation used by Kolda and Bader (2009).

2.2.1 An overview of tensors

A tensor is a multidimensional array. Usually, we say that a tensor is an N-way data array, where N is the *order* of the tensor and represents the number of dimensions, also known as *ways* or *modes*. A tensor of order zero is a *scalar* and is denoted by lowercase letters (e.g. a). A tensor of order one is a *vector* and is denoted by lowercase boldface letters (e.g. $\mathbf{a}$). A tensor of order two is a *matrix* and is denoted by boldface capital letters (e.g. $\mathbf{A}$). A higher-order tensor (order three or higher) is denoted by boldface Euler script letters (e.g. $\boldsymbol{\mathcal{X}}$). The ith entry of a vector $\mathbf{a}$ is denoted by a_i, element (i, j) of a matrix A is denoted by a_{ij}, and element (i, j, k) of a third-order tensor $\boldsymbol{\mathcal{X}}$ is denoted by x_{ijk} (Kolda and Bader, 2009). Indices typically range from 1 to their capital version, e.g., $i = 1,..., I$, $j = 1,..., J$, $k = 1,..., K$.

A vector of order I is a tensor in $\mathbb{R}^I$, an $I \times J$ matrix is a tensor in $\mathbb{R}^{I \times J}$, an $I \times J \times K$ three-way array is a tensor in $\mathbb{R}^{I \times J \times K}$, and, more generally, a N-way array is a tensor in $\mathbb{R}^{I_1 \times I_2 \times \ldots \times I_N}$, where $\mathbb{R}$ represents the set of real values and N is the number of dimensions of the tensor (or its *order* or *mode*).

In Figure 4.1 a 3-order tensor is represented. The 3 dimensions of the tensor are denoted as mode A, mode B and mode C. Each mode refers to a set of entities. The entities along the vertical axis are indicated by the first index i and refer to mode A. The entities along the horizontal axis are indicated by the second index j and pertain to mode B. The entities along the depth axis are indicated by the third index k and belong to mode C.

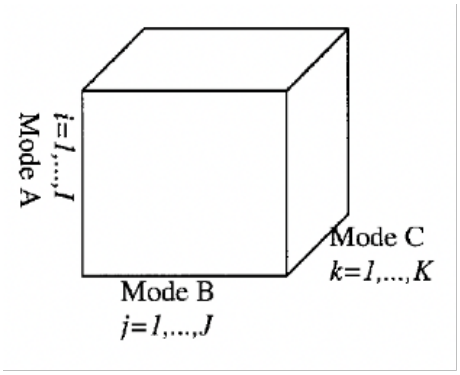


Figure 2.1: A 3-order tensor (adapted from Kiers, 2000).

Tensor common operations

When we fix some modes of a tensor, we can consider only parts of the tensor, like slices and fibers.

A slice of a tensor is a two-dimensional subtensor, obtained by fixing all but two indices. In the case of a 3-way array we can consider it as a set of matrices: the horizontal, lateral and frontal slices, denoted by $X_{i::}$, $X_{:j:}$, and $X_{::k}$, respectively (Figure 2.2).

A fiber of a tensor is a one-dimensional section of a tensor, obtained by fixing every index but one. A fiber is analogue of matrix rows and columns. For a 3-way array we can obtain a set of vectors: column, row, and tube fibers, denoted by $x_{:jk}$, $x_{i:k}$, and $x_{ij:}$, respectively (Figure 2.3).

Although there exists a wide range of standard tensor operations commonly employed in multiway analysis, here we will introduce the most significant operators to understand the process of Tucker decomposition.

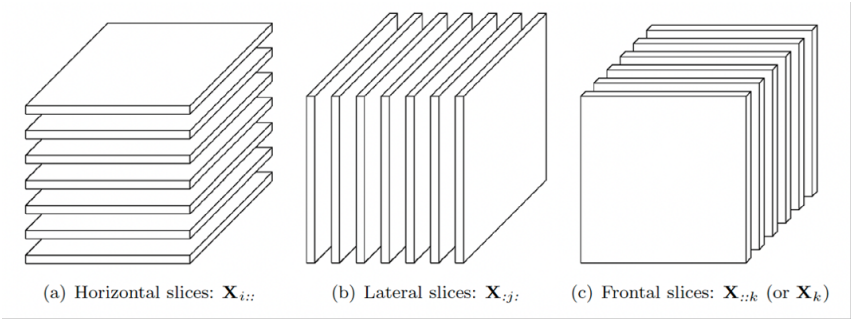


Figure 2.2: Slices of a 3rd-order tensor (from Kolda and Bader, 2009).

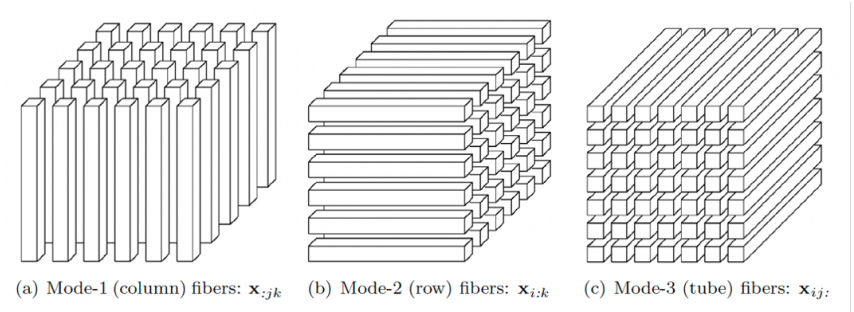


Figure 2.3: Fibers of a 3rd-order tensor (from Kolda and Bader, 2009).

A process particularly useful computationally is *matricization*, through which it is possible to transform a tensor into a matrix (and vice-versa). Matricization, also known as *unfolding* or *flattening*, of an N-way array reorders its elements as a matrix and the total number of elements is unchanged. We can obtain different arranged matrices, depending on the modes that are mapped to the rows (or columns) of the matrix. A matricization of a 3-way tensor $\boldsymbol{\mathcal{X}}$ of size $I \times J \times K$ can result into a matrix $\mathbf{X_a}$ (of size $I \times JK$), $\mathbf{X_b}$ (of size $J \times KI$) or $\mathbf{X_c}$ (of size $K \times IJ$).

The other operation highly relevant in the context of Tucker decomposition is the *Kronecker product*, since it provides a mathematical framework to express the relationships between the original tensor and its factor matrices. This mathematical operation on two matrices of arbitrary size is denoted by $\mathbf{A} \otimes \mathbf{B}$, where $\mathbf{A} \in \mathbb{R}^{I \times J}$ and $\mathbf{B} \in \mathbb{R}^{K \times L}$. The result is a matrix of size $(IK) \times (JL)$ and defined by:

$$\begin{aligned} \mathbf{A} \otimes \mathbf{B} &= \begin{bmatrix} a_{11}\mathbf{B} & a_{12}\mathbf{B} & \cdots & a_{1J}\mathbf{B} \\ a_{21}\mathbf{B} & a_{22}\mathbf{B} & \cdots & a_{2J}\mathbf{B} \\ \vdots & \vdots & \ddots & \vdots \\ a_{I1}\mathbf{B} & a_{I2}\mathbf{B} & \cdots & a_{IJ}\mathbf{B} \end{bmatrix} \\ &= \begin{bmatrix} \mathbf{a}_1 \otimes \mathbf{b}_1 & \mathbf{a}_1 \otimes \mathbf{b}_2 & \mathbf{a}_1 \otimes \mathbf{b}_3 & \cdots & \mathbf{a}_J \otimes \mathbf{b}_{L-1} & \mathbf{a}_J \otimes \mathbf{b}_L \end{bmatrix}. \end{aligned} \tag{2.1}$$

2.2.2 Tensor decompositions

Tensor decomposition is a fundamental technique for analyzing multi-dimensional data, enabling the reduction of data complexity while covering latent structures and meaningful

information. By representing tensors in a more compact and interpretable form, tensor decomposition facilitates advanced data analysis and computational efficiency (Liu et al., 2022).

Historically, tensor decompositions were first applied in psychometrics and chemometrics. Over the years, their utility has expanded to encompass a wide range of fields, including signal processing, numerical linear algebra, computer vision, numerical analysis, data mining, graph analysis, neuroscience, financial analysis, social sciences, business market analysis, and machine learning (Kolda and Bader, 2009). These advances reflect the versatility of tensor decompositions in addressing diverse challenges in both theoretical and applied contexts.

Two of the most widely used methods for tensor decomposition are the CANDECOMP/PARAFAC (CP) decomposition and Tucker decomposition. This study focuses on Tucker decomposition, a higher-order generalization of the singular value decomposition (SVD), and a brief introduction to this methodology is presented next.

Tucker decomposition

Introduced by Tucker in 1963 and 1966, its 3-way variant is known as the Tucker3 model. Building on Tucker's foundational work, De Lathauwer (2000) introduced an orthogonality constraint on the component matrices, broadening its applicability and leading to its recognition as the Higher-Order Singular Value Decomposition (HOSVD). Tucker decomposition can be viewed as a high-order extension of Principal Component Analysis (PCA). It deconstructs a tensor into two main components: a core tensor, which represents a compresses version of the original tensor and captures the interactions between different components; a set of factor matrices, which can be thought of as the principal components in each mode of the tensor.

This process enables the efficient representation of multidimensional data while preserving its essential structure. Tucker decomposition is particularly advantageous due to its flexibility in handling data with varying ranks across different modes.

In a three-order tensor $\boldsymbol{\mathcal{X}} \in \mathbb{R}^{I \times J \times K}$, the Tucker decomposition is expressed as:

$$\mathcal{X} \approx \mathcal{G} \times_1 \mathbf{A} \times_2 \mathbf{B} \times_3 \mathbf{C} = \sum_{p=1}^{P} \sum_{q=1}^{Q} \sum_{r=1}^{R} g_{pqr}\, \mathbf{a}_p \circ \mathbf{b}_q \circ \mathbf{c}_r \tag{2.2}$$

where $\boldsymbol{\mathcal{G}} \in \mathbb{R}^{P \times Q \times R}$ is the *core tensor* and $\mathbf{A} \in \mathbb{R}^{I \times P}$, $\mathbf{B} \in \mathbb{R}^{J \times Q}$, and $\mathbf{C} \in \mathbb{R}^{K \times R}$ are the *factor matrices* associated with each mode of the tensor.

The elementwise representation of this decomposition (2.2) is given by:

$$x_{ijk} \approx \sum_{p=1}^{P} \sum_{q=1}^{Q} \sum_{r=1}^{R} g_{pqr}\, a_{ip}\, b_{jq}\, c_{kr} \tag{2.3}$$

Where P, Q, and R denote the number of components (columns) in the factor matrices $\mathbf{A}$, $\mathbf{B}$, and $\mathbf{C}$, respectively. If P, Q, and R are smaller than I, J, and K, respectively, the core tensor $\boldsymbol{\mathcal{G}}$ serves as a compressed representation of $\boldsymbol{\mathcal{X}}$.

The matricized forms of the Tucker decomposition for each mode are represented as follows:

$$\mathbf{X}_{(1)} \approx \mathbf{A}\mathbf{G}_{(1)}(\mathbf{C} \otimes \mathbf{B})^{\mathsf{T}}, \tag{2.4}$$

$$\mathbf{X}_{(2)} \approx \mathbf{B}\mathbf{G}_{(2)}(\mathbf{C} \otimes \mathbf{A})^{\mathsf{T}}, \tag{2.5}$$

$$\mathbf{X}_{(3)} \approx \mathbf{C}\mathbf{G}_{(3)}(\mathbf{B} \otimes \mathbf{A})^{\mathsf{T}}. \tag{2.6}$$

where $\mathbf{X_n}$ represents the mode-*n* unfolding of $\boldsymbol{\mathcal{X}}$, and $\otimes$ denotes the Kronecker product.

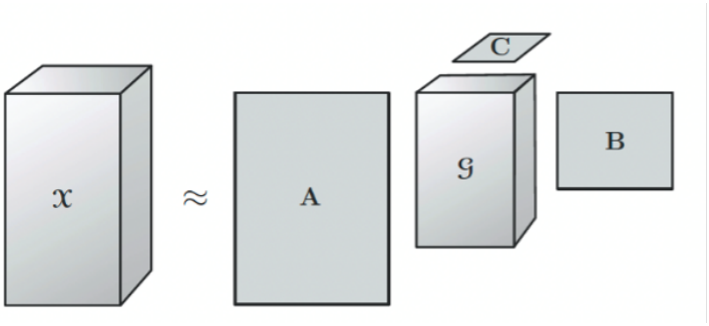


Figure 2.4: Tucker decomposition of a 3-way array (from Kolda and Bader, 2009).

Figure 2.4 illustrates the Tucker decomposition of a 3-way tensor. This visualization highlights the transformation of a tensor into a core tensor and 3 factor matrices, emphasizing its utility in compactly representing high-dimensional data.

For computing a Tucker decomposition, Tucker introduced three methods (Kolda, 2009), one of which is now commonly known as the Higher-Order Singular Value Decomposition (HOSVD), from the work of De Lathauwer (2000). Tucker's original method aimed to capture the variation in each mode independently of the others, but computational limitations at the time restricted its practical use. De Lathauwer (2000) presented HOSVD as a natural extension of the matrix SVD and discussed how to perform the computations in a more efficiently way.

In this study, we utilize a three-dimensional tensor to analyze relationships across the following dimensions (modes): EU regions, socioeconomic indicators and time. By decomposing this tensor, our aim is uncovering latent structures, potential interactions, and temporal patterns, offering insights into regional development and socioeconomic trends in Europe.

2.2.3 Visualization of regional trajectories over time

In the context of comparative regional analysis, visualizing and interpreting the evolution of regions over time is essential. One effective approach is based on the development of trajectories, which can provide an intuitive and compact representation of regional dynamics.

A trajectory is defined as a sequence of time-ordered states of an object in a dynamic system. Oliveira and Gama (2012) present a framework for analyzing the trajectories of countries' economic evolution. We adapt this methodology to our case (regional comparison).

Typically, trajectories are visualized in low-dimensional subspaces, with 2D projections being the most common due to their simplicity and effectiveness in data analysis. The third

dimension is often encoded within the plane to maintain clarity. This allows us to track the evolution of a region's performance in a visually accessible manner.

Trajectories enhance the interpretation of temporal data and facilitate the identification of trends, structural changes, and economic shifts. Furthermore, when multiple trajectories are plotted together, they enable comparative studies by showing the relative positions of different regions over time.

To construct these trajectories, the original three-order tensor is decomposed using a HOSVD. The two most representative components of the decompositions are then used as x and y coordinates for each time point, allowing a clear and meaningful visualization of regional evolution.

The next step of this analysis is the interpretation of a region' trajectory, which can be characterized by a direction (e.g. upwards, downwards, leftwards, rightwards), and an amplitude (higher or lower). A wider trajectory suggests significant changes, whereas a stable one indicates minimal variation over time. Additionally, the shape and the position help identify regions with similar development patterns.

Chapter 3

Literature Review

This chapter reviews the key literature related to both comparative regional analysis and the methodology chosen to develop the proposed study.

The methodology employed in this study is based on the working paper "How We Got Here? A Methodology to Study the Evolution of Economic Indicators" (Oliveira and Gama, 2011), which outlines a framework for examining the temporal evolution of multidimensional data. In this paper, the analysis was conducted through the definition and interpretation of temporal trajectories of countries within a shared two-dimensional space, obtained from a High-Order Singular Value Decomposition (HOSVD). As described in chapter 2, the HOSVD is a method used to perform Tucker decomposition on tensors, imposing orthogonality constraints to ensure interpretability and robust factorization.

3.1 Regional comparative analysis

The study of territorial dynamics has been a critical focus in understanding the spatial and temporal evolution of socio-economic indicators (eg.: OECD (2024), *How's Life?*). Comparative analyses of these dynamics allow identifying patterns, disparities, and trajectories that provide valuable insights for policy-making and planning.

The cited working paper (Oliveira and Gama, 2011) offers a framework for analyzing the evolution of economic indicators by examining temporal trajectories of countries within a common multidimensional space. Instead of focusing on countries, the present study aims to adjust their methodology to explore regional-level dynamics, while extending its application to other dimensions of regional development.

Building on this foundation, recent studies have applied comparative methodologies to understand diverse regional phenomena. Guarascio et al. (2025), for instance, analyze the impact of Artificial Intelligence (AI) technologies on employment across European regions. This study highlights how structural factors such as sectoral specialization, research and development (R&D) capacity, productivity, and workforce skills shape regional adaptation to AI-driven economic shifts. By combining a variety of indicators in a cluster analysis, they identified four groups of regions: high-tech service and capital centers, advanced manufacturing core, southern periphery, and eastern periphery. This classification underscores the heterogeneity of regional dynamics and the need for tailored policy interventions.

Similarly, Rodríguez-Pose and Crescenzi (2008) explore the interplay between innovation, economic growth, and regional disparities in the European Union. Their work demonstrates

that the capacity of regions to generate and absorb innovation is unequal, with core regions benefitting from advanced infrastructure and strong institutional frameworks, while peripheral regions often face structural disadvantages. By employing a combination of econometric models and spatial analyses, their research points to the multidimensional nature of regional disparities and offers insights into fostering balanced regional development. This aligns with studies like Barca et al. (2012), which emphasize the importance of place-based approaches. Their work highlights how tailored strategies can foster inclusive growth and sustainability.

Together, these studies emphasize the value of regional comparative analysis as a way of understanding the complex dynamics that influence the economic development.

At the same time, methodologies for analyzing the evolution of individuals and clusters have also been explored. In their research, Oliveira and Gama (2012) propose the MEC framework to address the problem of monitoring the evolution of clusters over time. The proposed method traces cluster evolution by detecting key transitions such as *births*, *deaths*, *splits* and *merges* of clusters. To demonstrate its applicability and feasibility, the framework was tested in two real-world case studies using datasets from Banco de Portugal and *The Data Page* of New York University – Leonard N. Stern School of Business. In the first case study, they analyze the general evolution trends in the Portuguese activity sectors. In the second case study, the authors identify rare events and unusual financial behavior in European companies.

Building up on the MEC framework, Siddiqui et al. (2012) refines its methodology by introducing a predictive approach to modeling the evolution of perennial objects. Rather than relying on a predefined set of states, their framework dynamically derives *ad hoc* states based on the observed evolution of objects. Operating incrementally, it continuously learns and adapts cluster structures over time, enhancing its ability to predict the mostly likely next state of each object. In addition to tracing evolution through the detection and categorization of cluster transitions, this approach allows the emergence of new clusters as objects evolve. Consequently, unlike MEC, which assumes a single evolutionary pattern, this method captures multiple coexisting evolutionary trajectories, offering a more flexible representation of complex dynamic systems.

These methodologies are particularly relevant to this study, because they provide strong bases for tracing the evolution of multidimensional data over time. Their approaches align with the main goal of this research, which is to analyze and compare the trajectories of regions over time.

3.2 Tensor decompositions

The study of multidimensional data has evolved substantially over the past decades, driven by the increasing complexity of data in modern applications. The aforementioned methodology proposed by Oliveira and Gama (2011) demonstrated the importance of understanding dynamic, multidimensional phenomena using tensor-based approaches for this purpose.

Tensor decompositions, as generalizations of matrix factorizations, have gained growing attention for their ability to model and analyze high-order data efficiently. A comprehensive overview by Acar and Yeber (2008) highlighted the versatility of tensor decompositions for unsupervised multiway data analysis, emphasizing their applications in signal processing, chemometrics, and social network analysis. Kolda and Sun (2008) further explored tensor decomposition methods tailored for large datasets, emphasizing their computational feasibility in real-world scenarios.

The Tucker decomposition, introduced by Tucker (1963), enables the representation of three-mode (or higher) data in a compact form, facilitating interpretability and computational efficiency. A fundamental approach within the Tucker Decomposition is the orthogonality-constrained version, expanded by De Lathauwer (2000), known as Higher Order Singular Value Decomposition (HOSVD).

Kolda and Bader (2009) introduced a general framework of higher-order tensor decompositions, highlighting their application in diverse fields. Regarding to Tucker decomposition, they presented examples from chemical analysis, psychometrics, signal processing, computer vision with TensorFaces and data mining. For instance, Savas and Eldén (2007) employed HOSVD for the automatic classification of handwritten digits.

Other works have further diversified the methodological and application landscapes of tensor decompositions. Bahadori et al. (2014) introduces a method for analyzing multivariate spatio-temporal data, demonstrating that the low-rank tensor learning framework is efficient and robust for analyzing complex, large-scale spatio-temporal data.

Tensor decompositions have proven to be appropriate in addressing regional and domain-specific challenges. For instance, Tucker decomposition has been employed to uncover patterns in grain price dynamics by Correa et al. (2016). In this paper, the authors proposed the use of Tucker decomposition to both analyze the temporal patterns of price indexes of corn and soybeans in Brazil and the United States, and map trajectories that represent their behavior over time in a concise and representative low-dimensional subspace.

Another example is the research conducted by Sangveraphunsiri et al. (2022), which examined the impacts of the COVID-19 pandemic on the spatio-temporal characteristics of a bicycle sharing system in Bangkok. In their study, multidimensional trip data were decomposed into four different modes related to their spatial and temporal dimensions, by a non-negative Tucker decomposition approach, to explain the change in people's transport behavior, especially in pre- and post- pandemic periods.

The utility of tensor decompositions extends across other domains such as hyperspectral imaging (Xu et al., 2020). In their paper, under the dual-camera compressive hyperspectral imaging (DCCHI) system, a new reconstruction algorithm is proposed based on the collaborative Tucker3 tensor decomposition.

Among the different approaches of Tucker decomposition, the Higher Order Singular Value Decomposition (HOSVD), has been widely explored due its ability to efficiently process high-dimensional datasets. Symeonidis (2015) proposed an item recommendation method for social tagging systems, using HOSVD in combination with tag clustering to enhance recommendation accuracy in multi-way data structures.

In context of Big Data processing, Wang et al. (2018) introduced a columnwise HOSVD algorithm, designed for dimensionality reduction, feature extraction, and noise reduction in tensor-represented datasets, demonstrating its effectiveness to handle with large and complex datasets.

More recently, Gonzalez et al. (2021) developed an innovative methodology using tensors and HOSVD for denoising and compressing microseismic and distributed acoustic sensing (DAS) data, providing deeper insights into rock structure.

In relation to temporal evolution, Oliveira and Gama (2013) explored the visualization of evolving dynamic social networks using the concept of temporal trajectories at both the actor and community levels. To achieve this, they represented evolving networks using third-order tensors and applied the Tucker3 model for data decomposition. The projection of the two

most representative components resulted in a two-dimensional space where the trajectories of entities were visualized. Also, by computing the distance between pairs of trajectories, the authors may identify actors with similar/dissimilar trajectories.

These studies highlight the ability of tensor methods to capture latent patterns in data that can be difficult to recognize using traditional approaches. The ongoing expansion of tensor decomposition applications underscores their value in addressing the challenges imposed by increasingly complex datasets.

3.3 Summary of related work

Table 3.1 summarizes the main studies reviewed in this chapter, including their relevance to the present research.

Authors (Year)	**Main goals / Research questions**	**Methodology**	**Relevance to this study**
Oliveira & Gama (2011)	Analyze the temporal evolution of economic indicators across countries	HOSVD – Tucker3 model, temporal trajectories in a bidimensional space	Provides a methodological basis for adapting tensor techniques to regional analysis
Guarascio et al. (2025)	Assess the impact of AI technologies on employment across regions	Cluster analysis, multidimensional indicators	Highlights that structural characteristics of regions significantly shape the economic and labor impact of AI
Rodríguez-Pose & Crescenzi (2008)	Examine the relationship between innovation and economic growth across European regions	Multiple regression analysis, spatial analysis	Emphasizes the role of local socioeconomic conditions in fostering innovation and transforming it into growth
Barca et al. (2012)	Investigate how local institutions and historical-geographical context affect the effectiveness of development policies	Critical review of economic and regional development literature	Reinforces the importance of place-based approaches
Oliveira & Gama (2012)	Monitor the evolution of cluster structures over time using economic and financial datasets	MEC framework (cluster transitions)	Supports the dynamic analysis of regional development trajectories
Siddiqui et al. (2012)	Predict the dynamic evolution of clusters	Incremental learning (building on the MEC framework)	Enhances understanding of evolving structures in complex dynamic systems
Acar & Yener (2008)	Review key contributions on multiway models, algorithms, and their applications	Overview of Tucker and PARAFAC models	Supports the application of tensor methods to high-dimensional, structured data
Kolda & Sun (2008)	Explore tensor methods for large datasets	Memory-Efficient Tucker (MET) algorithm	Demonstrates the feasibility of tensor decomposition in large-scale data environments
Tucker (1963)	Introduce a method for analyzing multi-way data via tensor decomposition	Tucker decomposition model	Provides the conceptual foundation for the Tucker model used in this study
De Lathauwer (2000)	Extend Tucker's model by introducing orthogonality constraints	Higher-Order Singular Value Decomposition (HOSVD)	Forms the conceptual basis of the HOSVD method applied in this research
Kolda & Bader (2009)	Provide a comprehensive overview of tensor decomposition techniques and their applications	Survey of CANDECOMP/PARAFAC (CP) and Tucker models	Establishes the theoretical framework for applying tensor methods to multidimensional datasets

These studies offer valuable foundations in two key dimensions relevant to this analysis. On one hand, some studies emphasize the critical importance of understanding regional characteristics and temporal dynamics in designing public policies that promote sustainable

Authors (Year)	Main goals / Research questions	Methodology	Relevance to this study
Savas & Eldén (2007)	Classify handwritten digits using tensor decompositions	HOSVD for dimensionality reduction and classification	Demonstrates the effectiveness of HOSVD in extracting latent patterns from high-dimensional data
Bahadori et al. (2014)	Analyze multivariate spatio-temporal data using tensor methods	Fast greedy algorithm for learning low-rank tensors	Highlights the ability of tensor models to capture correlations across variables, space, and time in a scalable way
Correa et al. (2016)	Analyze grain price dynamics over time	Tucker decomposition, spatio-temporal trajectories	Proposes a methodological process to summarize and interpret complex multidimensional datasets
Sangveraphunsiri et al. (2022)	Examine the impacts of COVID-19 on the spatio-temporal characteristics of a bicycle-sharing system	Non-negative Tucker decomposition	Shows the use of tensor decomposition in analyzing evolving mobility patterns
Xu et al. (2020)	Propose a novel reconstruction algorithm for hyperspectral imaging under the DCCHI system	Tucker3 model	Demonstrates the use of tensor decomposition in advanced image processing applications
Symeonidis (2015)	Improve item recommendation in tagging systems	Clustering combined with HOSVD	Shows how tag clustering before tensor construction can reduce dimensionality and sparsity in large datasets
Wang et al. (2018)	Enable dimensionality reduction in Big Data contexts	Columnwise HOSVD algorithm	Validates HOSVD as a robust method for reducing complexity in large-scale datasets
Gonzalez et al. (2021)	Apply tensor decomposition to seismic data for denoising and compression	Tucker decomposition	Illustrates the application of Tucker models to geophysical time-series data
Oliveira & Gama (2013)	Visualize dynamic social network structures	Tucker3 model, spatio-temporal trajectories	Provides a basis for visualizing similarities and differences in regional development paths

Table 3.1: Summary of related work

regional growth. On the other hand, the methodological contributions highlight the growing application of tensor decompositions, particularly the Tucker3 model, in several fields – such as signal processing, chemometrics, image analysis, and social network analysis – proving to be an efficient tool for handling with high-dimensional and complex datasets.

The present study seeks to extend the application of tensor decomposition – specifically the Tucker3 model - to the analysis of economic and social development trajectories at the regional rather than national level. By examining the evolution of all EU regions over an extended time horizon of approximately two decades, this approach allows for a comparative and temporal analysis of regional dynamics. In doing so, it aims to provide deeper insights into persistent regional disparities and to inform more targeted regional policymaking.

Chapter 4

Methodology

The theoretical foundations of Tucker decomposition is the basis for the methodology used in this study, as discussed in the previous chapter. Tucker decomposition is a powerful tensor factorization technique that enables the extraction of latent structures and interactions within multi-dimensional datasets (Liu et al., 2022). Decomposing a tensor in a core tensor and factor matrices facilitates the identification of underlying patterns and relationships across multiple dimensions.

In the context of this research, Tucker decomposition appears as an appropriate methodological choice for analyzing complex socioeconomic data, where multiple factors interact over time and across different geographical regions. Thus, this study employs a three-dimensional tensor to analyze relationships across distinct dimensions (modes), providing a structured approach to examining regional socioeconomic dynamics in Europe. The following three modes define the tensor:

- **Mode A (EU regions)**: This mode represents the geographical scope of the analysis.
- **Mode B (Socioeconomic indicators)**: This mode captures the socioeconomic characteristics of each region. It incorporates a diverse set of indicators relevant to regional development.
- **Mode C (Time)**: This mode offers a temporal perspective to identify trends and changes over time.

The goal is to decompose the tensor, composed from these three modes, extracting structures and interactions among regions, indicators and time.

With this approach it's possible to identify regional development patterns, interactions among socioeconomic indicators and temporal dynamics. This provides us with valuable insights into the factors shaping regional development and socioeconomic trends in the European context.

The total dimensionality of the tensor is given by multiplying the number of variables in each mode (number of regions $\times$ number of indicators $\times$ number of years).

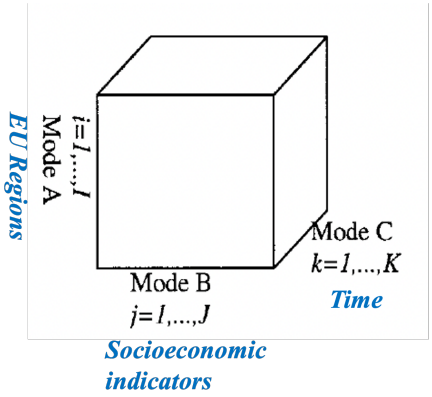


Figure 4.1: Tensor representation of the 3 modes under analysis (adapted from Kiers, 2000).

4.1 Selection of variables for each mode

Mode A – EU Regions (NUTS II classification)

For this study, we utilize the Nomenclature of Territorial Units for Statistics (NUTS) classification, a structure developed by the European Union to reference countries' regions for statistical purposes. The classification consists of three levels:

- NUTS 1 - major socio-economic regions.
- NUTS 2 - basic regions (for regional policies).
- NUTS 3 - small regions (for specific diagnoses).

According to the NUTS 2024 classification at level 2, there are 244 regions in total. These regions provide the geographical scope necessary to analyze socioeconomic trends at regional level.

Mode B – Socioeconomic indicators

The indicators are selected based on well-established EU publications and frameworks that measure regional economic and social performance.

- *EU Cohesion Policy*

Economic, social, and territorial cohesion is one of the European Union's core objectives, as outlined in Article 174 of the Treaty on the Functioning of the EU. It aims to reduce disparities among EU regions and address the challenges faced by less-favored areas. Aligned with this goal, and to foster job creation, business competitiveness, economic growth, and cross-border and interregional cooperation, Cohesion Policy stands as the EU's main investment policy.

In the 2021-2027 programming period of EU policies, Cohesion Policy funding is aimed at contributing to two key objectives: Investment for jobs and growth goal and European territorial cooperation goal (Interreg). Methodology on the allocation of global resources per Member State is set out in Annex XXVI of Regulation (EU) 2021/1060 of 24 June, which

lays down common provisions on the European Regional Development Fund, the European Social Fund Plus, the Cohesion Fund, the Just Transition Fund and the European Maritime, Fisheries and Aquaculture Fund and financial rules for those and for the Asylum, Migration and Integration Fund, the Internal Security Fund and the Instrument for Financial Support for Border Management and Visa Policy.

The prosperity of regions, based in the GDP per capita, measured in PPS is the main criterion for allocating resources for the investment for jobs and growth goal. Also, regions may benefit from additional premium based on their performance in certain indicators, such as unemployment, particularly youth unemployment, education levels, greenhouse gas emissions, and migration flows.

- *European Regional Competitiveness Index (RCI)*

Since 2010, the EU Regional Competitiveness Index (RCI) has been measuring key competitiveness factors across all the NUTS-2 level regions in the European Union. Using a comprehensive set of indicators, the Index evaluates the region's capacity to offer an attractive environment for firms and residents to work and live. The most recent edition, RCI 2.0 (2022, revised 2023), is based on an updated methodology and includes 68 indicators (Appendix A), grouped into eleven pillars and three sub-indices (Basic, Efficiency, and Innovation), offering a detailed perspective on a region's capacity to attract businesses and residents.

The 'Basic' sub-index refers to the foundations of all types of economies. It identifies the key factors for promoting regional competitiveness and includes five pillars: (1) Institutions, (2) Macroeconomic stability, (3) Infrastructures, (4) Health and (5) Basic education.

The 'Efficiency' sub-index focuses on the structural factors that allow regions to allocate their resources more effectively. As regions evolve, a more skilled labour force and a more efficient labour market play a central role in enhancing development. It includes three pillars: (6) Higher education, training and lifelong learning, (7) Labour market efficiency and (8) Market size.

Finally, the 'Innovation' sub-index comprises the three pillars that represent the key competitive factors in the most developed regions: (9) 'Technological readiness', (10) 'Business sophistication' and (11) 'Innovation'.

- *Regional Innovation Scoreboard 2023 (RIS)*

The regional innovation scoreboard (RIS) is an extension of the European innovation scoreboard (EIS), designed to assess and compare the innovation performance of European regions using a selected set of indicators. The first edition was published in 2009, and it provides valuable insights into the strengths and weaknesses of regional innovation ecosystems.

The RIS 2023 evaluates 239 regions of 22 EU countries, Norway, Serbia, Switzerland, and the United Kingdom. By offering a comparative analysis, the RIS helps policymakers, businesses, and researchers identify trends and opportunities. Innovation performance is measured through a composite indicator, known as the Regional Innovation Index (RII), which consolidates data from 21 indicators (Appendix B), grouped into four main types of activities – Framework conditions, Investments, Innovation activities, and Impacts – and twelve innovation dimensions.

The 'Framework conditions' refers to the essential resources for a Regional Innovation System: (1) Human resources, (2) Attractive research system and (3) Digitalization.

'Investments' include the financial resources allocated to R&D activities across both public and private sectors, as well as non-R&D innovation expenditures: (4) Finance and support, (5) Firm investments and (6) Use of information technologies.

'Innovation activities' essentially represent the first tangible outputs of the system (including product or process innovations, patents, and design rights), as well as the collaborative efforts between businesses and research institutions. These are classified into three dimensions: (7) Innovators, (8) Linkages and (9) Intellectual assets.

Finally, the 'Impacts' assesses the contribution of the Regional Innovation System to three specific dimensions: (10) Employment impacts, (11) Sales impacts and (12) Environmental sustainability.

- *EU regional Social Progress Index 2.0*

The EU-Social Progress Index (EU-SPI 2024) is a valuable tool designed to assess the social dimension of regional development across EU regions. It enables benchmarking and helps policymakers and stakeholders identify the regions' strengths and challenges, particularly in social and environmental aspects. By incorporating 52 indicators (Appendix C), the EU-SPI provides a multidimensional perspective on progress beyond economic metrics. The index is structured around twelve components, grouped into three broad dimensions, reflecting different stages of social development: 'Basic needs', 'Foundations of wellbeing' and 'Opportunity'.

The dimension of 'Basic needs' evaluates essential conditions necessary for survival and a minimum standard of living. It includes four components: (1) nutrition and medical care, (2) water and sanitation, (3) housing and (4) safety.

'Foundation of wellbeing' involve those factors that become more important as societies advance. This dimension encompasses (5) basic education, (6) information and communications, (7) health and (8) environmental quality.

The third dimension 'Opportunity' represent the most advanced level of social development, and reflects a society's ability to foster equal opportunities, tolerance and continuous human capital development. It is composed of the following components: (9) trust and governance, (10) freedom and choice, (11) inclusive society and (12) advanced education.

Mode C – Time

Finally, for the third mode, the study considers a long-term period spanning twenty years, beginning in 2000. This temporal scope allows for the identification of both short-term fluctuations and long-term regional development patterns, providing a robust basis for analyzing regional socioeconomic evolution.

4.2 Software and computational framework

To perform the tensor decomposition, the study uses TensorLy, a dedicated Python library designed for tensor learning and decomposition, which was created in 2015 by Jean Kossaifi to make tensor methods accessible and easy.

It provides an efficient and user-friendly framework for implementing various tensor factorization methods, including Tucker decomposition. The functionalities and capabilities of TensorLy are detailed in the work of Kossaifi et al. (2019), where the authors present an

overview of tensor methods and their applications in machine learning. Their study highlights the library's modular design, computational efficiency, and ease of use, demonstrating its relevance for large-scale tensor-based data analysis. It also highlights the significance of tensor methods in a wide range of fields, from computer vision to signal processing, reinforcing the suitability of TensorLy for this study.

Chapter 5

Description of the data

This section provides an overview of the indicators selected to carry out the comparative analysis of the evolution of European regions over the past 20 years. As mentioned previously, the indicators were chosen based on methodologies and frameworks adopted by the European Commission to assess the performance of European regions across different dimensions of socio-economic development, such as economic growth, competitiveness, innovation, social progress, and environmental sustainability.

Indicators included in the study

In total, 153 indicators were initially considered, building on the established references mentioned above, namely the indicators used in the allocation of EU Cohesion Policy funds for the 2021-27 programming period, the EU Regional Competitiveness Index 2.0 (2022 edition), the Regional Innovation Scoreboard (2023 edition), and the European Regional Social Progress Index 2.0 (2024 edition).

Reference framework	Number of indicators
Cohesion Policy 2021-2027	11
RCI 2.0, 2022	68
RIS, 2023	21
EU-SPI 2.0, 2024	53

Figure 5.1: Number of indicators initially considered during the data selection process.

Although a wide variety of sources contribute to the collection of these indicators, Eurostat emerged as the most consistent and accessible database. Many alternative sources either do not provide public access to their data or fail to cover the entire time frame under study (2000-2019). For this reason, Eurostat was prioritized, and of the 153 indicators initially identified, 83 were either directly available or could be derived from its datasets. It means that, in some cases, indicators were not directly downloadable and had to be constructed from available data – for instance, youth unemployment (age group 15-24) was derived from figures on the unemployed and economically active populations by age group.

Regional coverage and time period

Beyond indicators, the two other dimensions that are relevant for defining the analytical framework of this study are the regional and temporal scope of the dataset.

Regarding regional coverage, the analysis is conducted at the NUTS 2 level of the "Nomenclature of Territorial Units for Statistics" (NUTS), the EU's hierarchical classification system for dividing territory into comparable statistical units. While the most recent revision (NUTS 2024) defines 244 NUTS 2 regions, this study adopts the NUTS 2016 classification, which identifies 240 regions and underpins the categorization used in the EU Cohesion Policy for the 2021-2027 programming period. This choice ensures consistency with the policy framework of reference and guarantees that the same codification is applied throughout the analysis. Actually, besides Eurostat and national statistical institutes providing harmonized time series adjusted to updated territorial boundaries, the extended time horizon inevitably results in uneven data availability for some regions and indicators.

The dataset was compiled at the NUTS 2 level, covering all European Union regions. Thus, considering the regional scope of the study, from the 83 indicators accessible through Eurostat, only a subset was suitable for this study. Some indicators were available exclusively at the national level rather than the NUTS 2 regional scale. Furthermore, a few indicators overlapped across the different frameworks, so they were only used once to avoid duplicating information. Taking these constraints into account, a total of 37 distinct indicators were compiled and prepared for analysis.

The temporal dimension spans the period from 2000 to 2019. The year 2020 was deliberately excluded, as the COVID-19 pandemic introduced profound disruptions in several indicators, which would risk biasing the long-term trends that this study seeks to capture.

5.1 Exploratory data analysis and data pre-processing

A preliminary analysis of the data revealed that several indicators and regions contained substantial gaps. To preserve the robustness of the analysis, all regions and indicators with more than 35% missing values were excluded from the study. Furthermore, regions with more than 20% of their observations missing consecutively were also removed, in order to avoid prolonged gaps in the time series. This procedure resulted in a final dataset of 26 indicators and 160 regions. This refined dataset provides the foundation for the comparative analysis of regional development trajectories across European Union.

The 26 indicators adopted in this analysis are briefly described as follows.

- **Population**: Average annual population to calculate regional GDP data.
- **GDP**: Gross domestic product (GDP) at current market prices, in purchasing power standard per inhabitant.
- **Unemployment**: Share of unemployed persons aged 15–74 as a percentage of the labour force (given by the total number of people employed and unemployed).
- **Youth unemployment**: Share of young persons unemployed as a percentage of the economically active population (age group 15-24).
- **Low education rate**: Percentage of population aged 25-64 with low education (less than primary, primary and lower secondary education).
- **Employment**: Percentage of people aged 20–64 that are currently employed.
- **Tertiary educational attainment (30-34)**: Percentage of population aged 30-34 with tertiary education (ISCED 5-8) attainment.
- **Early leavers from education and training**: Percentage of the population aged 18-

24 having attained at most lower secondary education and not being involved in further education or training.

- **Road fatalities**: Number of deaths in road accidents per million inhabitants.
- **Life expectancy**: Number of years of life expected.
- **Infant mortality**: Number of deaths of children under 1 year of age during the year to the number of live births in that year (per 1000 live births).
- **Lifelong learning**: Adult population participation (% of population aged 25–34) in lifelong learning (i.e. received education or training in the 4 weeks preceding the survey).
- **Employment rate (excluding agriculture)**: Percentage of people aged 15–64 that are currently employed in all economic sectors excluding agriculture.
- **Long-term unemployment**: Percentage of unemployed people actively looking for a job (in the last 12 months or more).
- **Labour productivity**: GDP (in terms of PPS) relative to the number of hours worked.
- **Gender balance unemployment**: Difference between female and male unemployment rates (in absolute value) as an indicator of the distance from gender parity (age group 15-74).
- **Gender balance employment**: Difference between female and male employment rates (in absolute value) as an indicator of the distance from gender parity (age group 15-64).
- **NEET (aged 15-29)**: Young people neither in employment nor in education and training (% of population aged between 15–29).
- **Temporary employment**: Temporary employees as a percentage of the total number of employees aged 20–64.
- **Disposable income per capita**: Net adjusted disposable household income in purchasing power consumption standards (PPCS) per capita.
- **Employment (K-N sectors)**: Employment in the 'Financial and insurance activities; real estate activities; professional, scientific and technical activities; administrative and support service activities' sectors (K-N) as % of total employment (age group 15-64).
- **Gross value added (K-N sectors)**: Gross value added (GVA) in the 'Financial and insurance activities; real estate activities; professional, scientific and technical activities; administrative and support service activities' sectors (K-N) as % of total GVA.
- **Human Resources in Science and Technology**: Share of persons with successfully completed tertiary education and/or those without tertiary education but employed in a science and technology occupation where tertiary education normally required (% of population in the labour force).
- **Employment in technology and knowledge-intensive sectors**: Employment in technology and knowledge-intensive sectors (% of total employment).
- **Teenage pregnancy**: Ratio between births by mothers aged 15-19 years old and the female population of the same age cohort.
- **Tertiary education attainment**: Percentage of population aged 25-64 with tertiary education (ISCED 5-8) attainment.

The final number of regions from each country included in the study is presented below, while a complete table with all 240 EU regions (NUTS 2016) is provided in Appendix D.

Country	NUTS 2 Regions included	Country	NUTS 2 Regions included	Country	NUTS 2 Regions included
AT (Austria)	4 regions	ES (Spain)	17 regions	NL (Netherlands)	10 regions
BE (Belgium)	8 regions	FI (Finland)	1 region	PL (Poland)	8 regions
BG (Bulgaria)	5 regions	FR (France)	19 regions	PT (Portugal)	3 regions
CY (Cyprus)	1 region	HU (Hungary)	6 regions	RO (Romania)	8 regions
CZ (Czechia)	8 regions	IT (Italy)	15 regions	SE (Sweden)	6 regions
DE (Germany)	26 regions	LU (Luxembourg)	1 region	SK (Slovakia)	3 regions
EE (Estonia)	1 region	LV (Latvia)	1 region		
EL (Greece)	8 regions	MT (Malta)	1 region		
Total			**160 regions**		

Figure 5.2: Number of NUTS 2 regions retained for the final analysis.

A univariate exploratory analysis of the data was carried out to provide an initial overview of the main characteristics of each indicator. Figures 5.3 and 5.4 present the main descriptive statistics for the years 2000 and 2019, while the detailed results are provided in Appendix E.

Indicator name	N(valid)	N(missing)	%(missing)	Min.	Max.	Mean	Median	Std.Dev	CV	Skewness	Kurtosis
Population	160	0	0.00	274500.00	11066900.00	2155449.00	1689095.00	1594887.45	0.74	2.24	7.62
GDP	152	8	5.00	3400.00	45700.00	17238.16	17700.00	7569.10	0.44	0.40	0.63
Unemployment	154	6	3.75	1.95	27.35	9.52	7.74	5.66	0.60	1.04	0.51
Youth unemployment	141	19	11.88	3.50	64.09	20.03	17.67	12.71	0.63	1.07	1.09
Low education rate	154	6	3.75	6.40	84.50	36.92	34.55	17.89	0.48	0.49	-0.55
Employment	154	6	3.75	43.18	80.14	65.12	65.96	7.64	0.12	-0.69	0.44
Tertiary educational attainment (aged 30-34)	154	6	3.75	5.70	46.30	20.97	21.40	9.07	0.43	0.32	-0.51
Early leavers from education and training	131	29	18.12	6.00	54.20	18.76	16.30	9.14	0.49	1.35	2.05
Road fatalities	153	7	4.38	22.00	347.00	132.69	128.00	52.77	0.40	0.83	1.46
Life expectancy	115	45	28.12	71.00	81.00	77.43	78.50	2.90	0.04	-0.93	-0.42
Infant mortality	123	37	23.12	2.10	23.00	6.37	4.90	4.04	0.63	2.08	4.05
Lifelong learning	131	29	18.12	0.50	24.00	5.71	4.60	4.93	0.86	1.94	3.44
Employment rate (excluding agriculture)	150	10	6.25	31.77	72.59	56.15	58.22	9.83	0.18	-0.51	-0.58
Long-term unemployment	151	9	5.62	0.50	17.60	4.71	3.60	3.43	0.73	1.44	2.25
Labour productivity	152	8	5.00	12.99	191.95	95.34	104.15	39.22	0.41	-0.27	-0.79
Gender balance unemployment	151	9	5.62	0.08	19.87	4.63	3.48	4.50	0.97	1.41	1.49
Gender balance employment	154	6	3.75	0.46	41.87	18.67	16.71	8.53	0.46	0.62	-0.13
NEET (aged 15-29)	133	27	16.88	4.70	39.80	14.52	12.50	7.19	0.50	1.18	1.42
Temporary employment	153	7	4.38	1.39	40.75	13.74	11.16	8.75	0.64	1.02	0.86
Disposable income per capita	160	0	0.00	19.63	182.24	97.57	107.94	37.44	0.38	-0.46	-0.67
Employment (K-N sectors)	154	6	3.75	0.91	23.65	8.98	8.52	4.03	0.45	0.89	1.40
Gross value added (K-N sectors)	152	8	5.00	11.42	41.91	20.32	20.22	5.81	0.29	0.75	0.71
Human Resources in Science and Technology	154	6	3.75	11.50	55.40	30.26	29.75	8.61	0.28	0.03	-0.25
Employment in technology and knowledge-intensive sectors	143	17	10.62	0.70	10.90	3.88	3.80	1.88	0.49	0.72	0.62
Teenage pregnancy	124	36	22.50	2.95	59.02	14.43	10.81	10.39	0.72	1.79	3.73
Tertiary education attainment (aged 25-64)	154	6	3.75	5.40	38.70	17.75	18.15	7.41	0.42	0.34	-0.70

Figure 5.3: Descriptive statistics of the selected indicators in 2000, summarizing their distribution across the regions included in the study.

The initial examination of the data and the key descriptive statistics, shows that the indicators under study follow distinct trajectories over time.

The mean and the median of several indicators increased gradually throughout the period analysed. This is the case of the proportion of human resources in science and technology (Figure 5.5), as well as the population with tertiary education attainment and adults participation in lifelong learning.

In contrast, some indicators exhibited a negative trajectory, with both the mean and the median declining over the period considered. This pattern is observed, for instance, in the

Indicator name	N(valid)	N(missing)	%(missing)	Min.	Max.	Mean	Median	Std.Dev	CV	Skewness	Kurtosis
Population	160	0	0.00	314400.00	12336340.00	2256346.38	1800265.00	1774077.58	0.79	2.50	8.83
GDP	160	0	0.00	11100.00	78700.00	28726.25	27050.00	10288.79	0.36	1.33	3.65
Unemployment	160	0	0.00	1.31	24.14	6.83	5.45	4.97	0.73	1.44	1.67
Youth unemployment	140	20	12.50	2.68	51.07	18.56	17.32	11.84	0.64	0.81	-0.01
Low education rate	160	0	0.00	2.80	53.70	21.52	18.80	11.69	0.54	0.86	0.14
Employment	160	0	0.00	45.16	85.02	72.42	73.63	8.02	0.11	-0.99	1.16
Tertiary educational attainment (aged 30-34)	160	0	0.00	15.50	63.40	37.83	37.60	10.61	0.28	0.16	-0.46
Early leavers from education and training	157	3	1.88	1.90	27.20	10.42	9.70	4.79	0.46	1.02	0.93
Road fatalities	160	0	0.00	6.00	111.00	54.21	51.50	21.78	0.40	0.58	0.14
Life expectancy	159	1	0.62	74.40	85.80	81.13	82.00	2.74	0.03	-0.96	-0.03
Infant mortality	160	0	0.00	1.10	9.40	3.44	3.20	1.35	0.39	1.62	4.08
Lifelong learning	160	0	0.00	0.60	35.80	10.68	8.80	7.53	0.71	1.30	1.79
Employment rate (excluding agriculture)	158	2	1.25	36.70	80.24	65.37	66.81	9.93	0.15	-0.89	0.39
Long-term unemployment	155	5	3.12	0.30	18.20	3.07	1.90	3.26	1.06	2.24	5.21
Labour productivity	160	0	0.00	33.12	170.55	93.86	99.38	28.91	0.31	-0.01	-0.41
Gender balance unemployment	160	0	0.00	0.00	13.76	1.70	0.91	2.27	1.34	2.78	8.83
Gender balance employment	160	0	0.00	0.89	28.66	10.96	9.24	5.65	0.52	0.80	0.21
NEET (aged 15-29)	160	0	0.00	4.20	38.00	12.53	11.40	6.16	0.49	1.41	2.71
Temporary employment	159	1	0.62	1.12	53.62	17.91	17.43	11.26	0.63	0.90	0.98
Disposable income per capita	160	0	0.00	45.66	159.54	95.99	99.42	24.22	0.25	-0.08	-0.63
Employment (K-N sectors)	160	0	0.00	3.10	23.60	11.62	11.66	4.12	0.35	0.50	0.53
Gross value added (K-N sectors)	160	0	0.00	13.60	47.06	23.57	23.20	5.72	0.24	0.82	1.49
Human Resources in Science and Technology	160	0	0.00	15.90	66.70	42.90	45.30	9.58	0.22	-0.31	-0.31
Employment in technology and knowledge-intensive sectors	158	2	1.25	0.80	10.30	3.61	3.40	1.77	0.49	1.02	1.58
Teenage pregnancy	134	26	16.25	1.83	80.19	10.71	6.40	12.31	1.15	2.77	9.04
Tertiary education attainment (aged 25-64)	160	0	0.00	11.70	53.00	30.33	30.65	9.08	0.30	0.22	-0.52

Figure 5.4: Descriptive statistics of the selected indicators in 2019, summarizing their distribution across the regions included in the study.

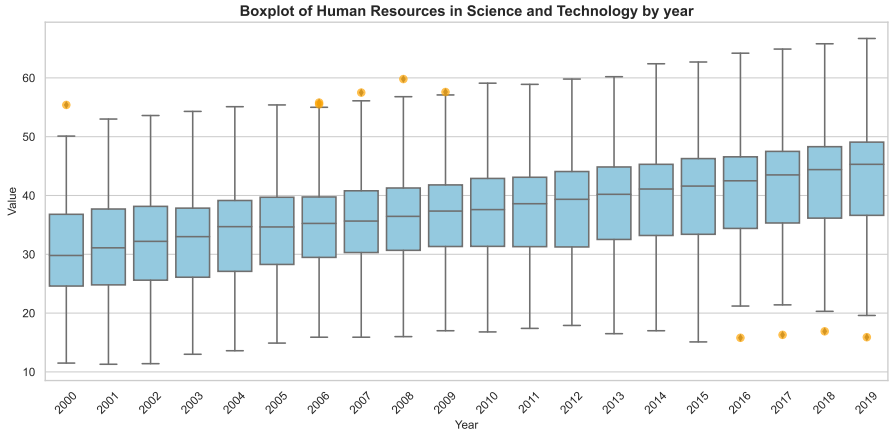


Figure 5.5: Boxplot of an indicator showing a positive trend over the period under analysis. Each box summarizes the distribution of values across the regions included in the study for a given year.

share of population with low education attainment (Figure 5.6), as well as in the early leavers from education and training, the number of road fatalities, and the infant mortality rate.

A third group of indicators displays a more asymmetric pattern of evolution over time, as illustrated in Figure 5.7. It typically correspond to variables that are sensitive to cyclical economic conditions, showing less favourable developments during periods of recession and more positive outcomes during phases of economic expansion. This behaviour is evident in labour-market indicators, such as the unemployment rate, and in the share of young people not in employment, education, or training (NEET).

Boxplots also allow the identification of outliers. Outliers are observations that deviate from the rest of the data and are represented by points located above the upper whisker or below the lower whisker of the boxplot. Formally, they lie outside the interval [Q1 – 1.5*IQR,

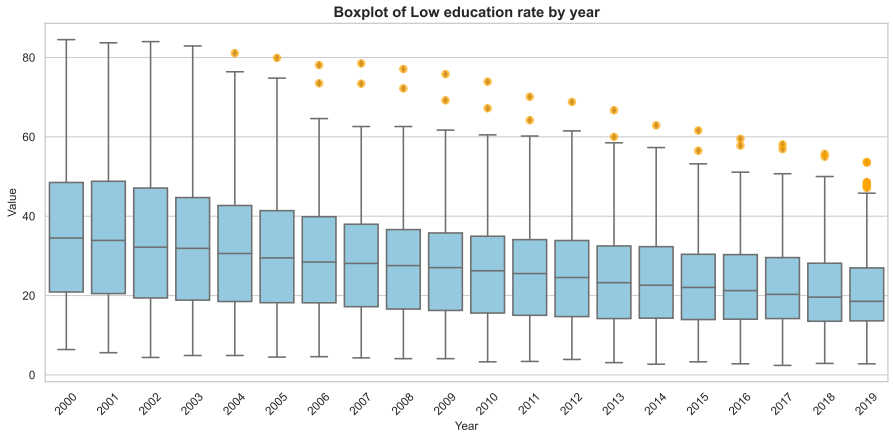


Figure 5.6: Boxplot of an indicator showing a negative trend over the period under analysis. Each box summarizes the distribution of values across the regions included in the study for a given year.

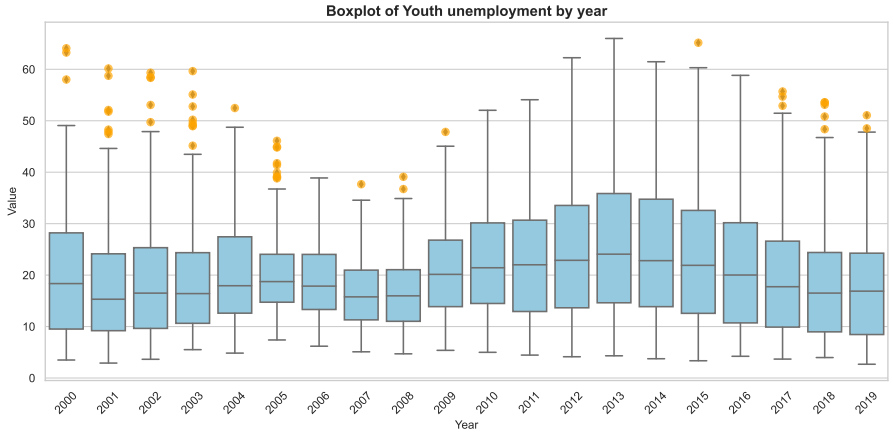


Figure 5.7: Boxplot of an indicator showing an asymmetric distribution over the period under analysis. Each box summarizes the distribution of values across the regions included in the study for a given year.

Q3 + 1.5*IQR], where the interquartile range (IQR) is defined as Q3 – Q1. Observations falling within this interval are classified as moderate outliers, while those lying in the interval [Q1 – 3*IQR, Q3 + 3*IQR] are considered severe outliers.

Outliers are detected across all indicators analysed, with the majority being upper outliers. Only six indicators have lower outliers, namely the employment rate, life expectancy, the employment rate (excluding agriculture), disposable income per capita, employment in sectors K-N, and the share of human resources in science and technology. It is worth noting that some indicators display outliers in the early years of the period under study, which tend to disappear over time, whereas others exhibit the emergence of outliers only in the most recent years.

Another measure is the coefficient of variation (CV), which allows for a comparison of the relative dispersion of the data around their mean. Figures 5.3 and 5.4 show that some indicators have a high CV, such as gender balance in unemployment, while others exhibit much

lower values, such as life expectancy. This implies that indicators with a higher CV present more pronounced regional disparities compared with those whose CV remains relatively low.

Looking at skewness and kurtosis, it is possible to observe that their values vary considerably between the different variables. These two measures capture important aspects of the shape of the distribution. When skewness and kurtosis are close to zero, the distribution tends to resemble the normal distribution, whereas large absolute values typically indicate the presence of outliers.

Skewness assesses the degree of symmetry of the data around their mean. A positive (negative) skewness value indicates that observations are more concentrated on the left (right) side of the distribution. The histograms for each indicator show that most distributions tend to be left-concentrated, a pattern often associated with the presence of upper outliers. For instance, in 2019, the highest positive skewness value was recorded for teenage pregnancy. As illustrated in Figure 5.8, most observations lie on the left side, accompanied by many severe upper outliers (on the right side).

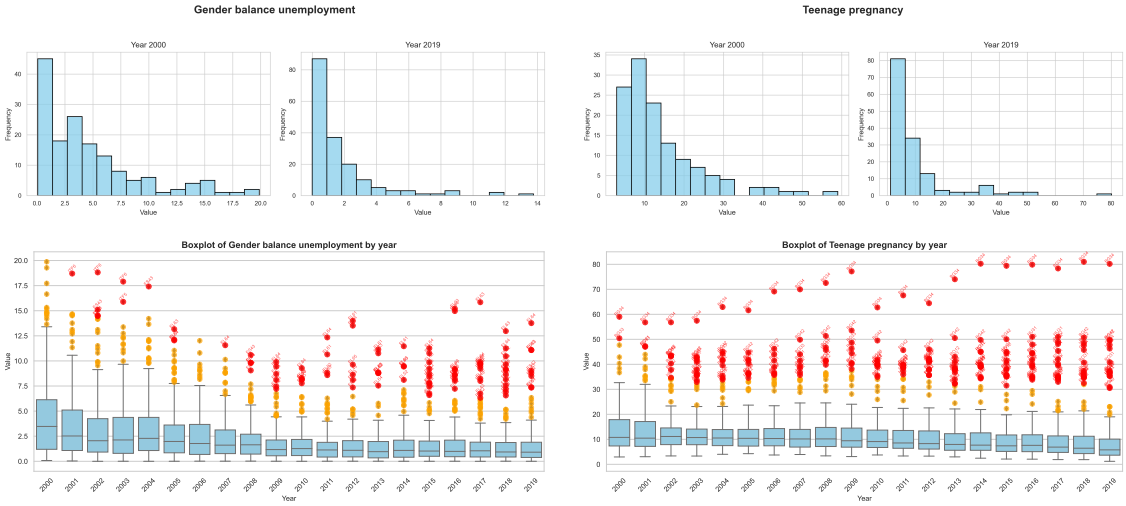


Figure 5.8: Distribution of indicators with high skewness and kurtosis. Histograms show the frequency of values, while boxplots summarize their dispersion and extreme observations across the regions included in the study.

Overall, these findings highlight the strong heterogeneity that characterizes regional development patterns across Europe. The results obtained from this univariate analysis provides a robust basis for the subsequent comparative study, underscoring the need for multidimensional analytical techniques, such as tensor decomposition, to capture the complexity and dynamics of regional trajectories over time.

To proceed with the analysis, a tree-dimensional tensor was constructed using the TensorLy library in Jupyter Notebook. The resulting tensor has the dimensions 160 x 26 x 20, corresponding respectively to the number of regions, indicators, and years included in the study. This data structure provides a compact and systematic representation of the dataset, enabling the application of tensor decomposition methods.

Although the most critical indicators and regions with substantial missing data had already been excluded, some gaps persisted within the retained dataset (Figure 5.9).

Before proceeding with the analysis, these missing values were treated in order to ensure the internal consistency of the tensor. Two complementary methods were applied: First, in-

Indicator	N (Total)	N (Valid)	N (Missing)	% Missing
Population	3200	3200	0	0.00%
GDP	3200	3176	24	0.75%
Unemployment	3200	3183	17	0.53%
Youth unemployment	3200	3059	141	4.41%
Low education rate	3200	3184	16	0.50%
Employment	3200	3184	16	0.50%
Tertiary education attainment (aged 30-34)	3200	3184	16	0.50%
Early leavers from education and training	3200	3137	63	1.97%
Road fatalities	3200	3174	26	0.81%
Life expectancy	3200	3092	108	3.38%
Infant mortality	3200	3128	72	2.25%
Lifelong learning	3200	3134	66	2.06%
Employment rate (excluding agriculture)	3200	3140	60	1.88%
Long-term unemployment	3200	3118	82	2.56%
Labour productivity	3200	3176	24	0.75%
Gender balance unemployment	3200	3159	41	1.28%
Gender balance employment	3200	3184	16	0.50%
Young people neither in employment nor in education and training (aged 15-29)	3200	3151	49	1.53%
Temporary employment	3200	3174	26	0.81%
Disposable income per capita	3200	3200	0	0.00%
Employment (K-N sectors)	3200	3181	19	0.59%
Gross value added (K-N sectors)	3200	3176	24	0.75%
Human Resources in Science and Technology	3200	3184	16	0.50%
Employment in technology and knowledge-intensive sectors	3200	3103	97	3.03%
Teenage pregnancy	3200	3086	114	3.56%
Tertiary education attainment (aged 25-64)	3200	3184	16	0.50%
Total	**83200**	**82051**	**1149**	**1.40%**

Figure 5.9: Missing values for the selected indicators. The table shows, for each indicator, the total number of observations, the number of valid and missing values, and the corresponding percentage of missing values.

ternal gaps between observed values were filled using linear interpolation, ensuring continuity without affecting the endpoints of the time series. Second, when missing values occurred at the extremes of the series, they were estimated through linear regression based on the available observations for that region and indicator.

After this procedure, 98.60% of the observations remained original, 0.33% were filled by internal interpolation, and 1.06% were imputed using regression at the series boundaries. This approach allows a complete data tensor suitable for subsequent tensor decomposition analysis.

Finally, since the selected indicators are expressed in heterogeneous units of measurement, all values were normalized using the z-score standardization methods, thereby allowing meaningful comparisons across variables and preventing those with larger scales from disproportionately influencing the analysis.

Chapter 6

Results

6.1 Tucker decomposition

The processed data were structured into a three-way tensor $\boldsymbol{\mathcal{X}} \in \mathbb{R}^{160\times26\times20}$, where the modes correspond to 160 regions (I=160), 26 indicators (J=26), and 20 years (K=20). This representation of the data preserves the inherent multiway structure of the data and allows for the joint analysis of cross-sectorial, thematic, and temporal dimensions within a unified framework. To extract the main structural patterns while reducing dimensionality, we employed a Tucker decomposition to find a core tensor $\boldsymbol{\mathcal{G}} \in \mathbb{R}^{P\times Q\times R}$ and the factor matrices $A \in \mathbb{R}^{I\times P}$, $B \in \mathbb{R}^{J\times Q}$, and $C \in \mathbb{R}^{K\times R}$, each one associated with regions, indicators, and years, respectively. The factor matrices summarize each original mode into a reduced number of components, while the core tensor captures the strength of interactions among components across modes.

The decomposition was computed using a Higher-Order Singular Value Decomposition (HOSVD). In this approach, singular value decompositions are applied independently to the mode-wise unfoldings of the data tensor, and the leading singular vectors are retained in each mode according to the selected multilinear rank. This procedure results in orthonormal factor matrices and a deterministic, non-iterative Tucker decomposition. Although the HOSVD does not guarantee the optimal low-rank approximation of a tensor in a least-squares sense, it provides a quasi-optimal solution that is well suited for exploratory and structural analysis (Ballard and Kolda, 2025).

The selection of the multilinear rank (P, Q, R) in a Tucker decomposition is an important modelling decision, as it determines the balance between dimensionality reduction and approximation accuracy. As discussed in the literature (Ballard and Kolda, 2025), Tucker decompositions can be tuned either towards data compression or towards more accurate reconstruction of the original tensor.

In this study, the goal was to identify a multilinear rank that achieves a substantial reduction in dimensionality while preserving interpretability and ensuring that the most relevant structural patterns in the data remain detectable. For a given multilinear rank, the original tensor can be reconstructed from the Tucker model, and the quality of the approximation can be assessed by comparing the reconstructed tensor to the original one. In general, lower ranks lead to larger reconstruction errors and reduced explanatory power, whereas higher ranks improve approximation accuracy at the cost of increased model complexity. The rank selection was therefore guided by a data-driven exploratory approach, comparing the percent-

age of explained variation across a range of rank combinations, as depicted in figure 6.1.

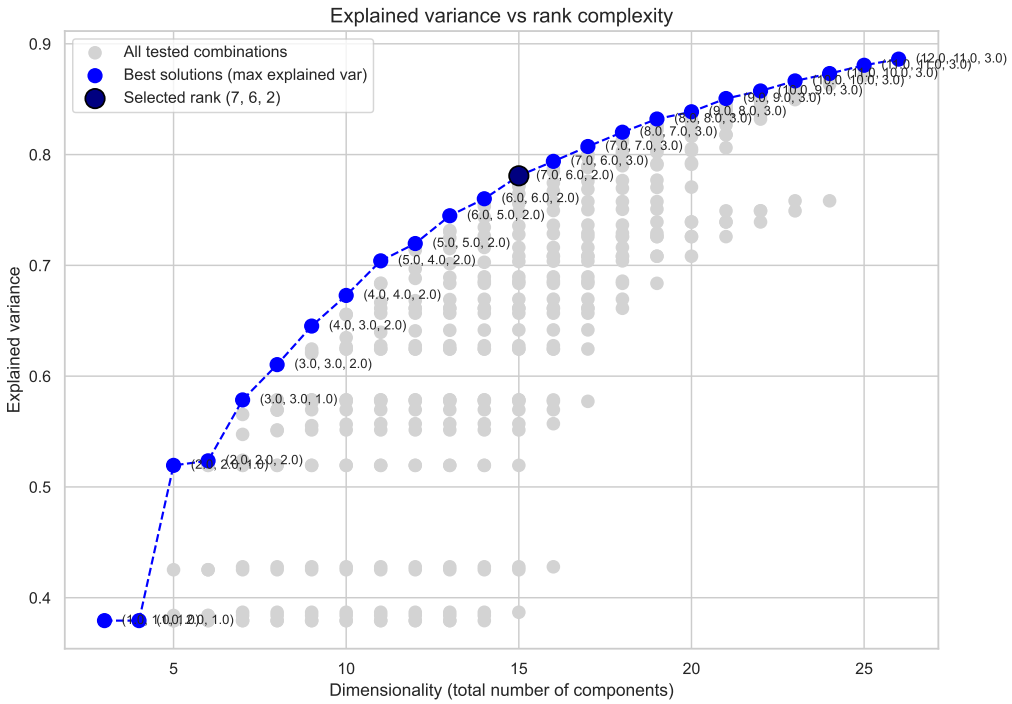


Figure 6.1: Explained variation for alternative Tucker rank configurations. The horizontal axis represents the sum of ranks retained across the three modes, and the vertical axis shows the explained variation.

The scree plot shows a smooth, concave relationship between total model dimensionality and explained variation, with improvements becoming progressively smaller as the rank increases. Rather than exhibiting a sharp elbow, the curve displays a gradual transition from substantial gains at low-dimensional models to clearly diminishing returns at higher levels of complexity.

To further support the rank selection, marginal gains in explained variation along the upper-envelope curve were computed, quantifying the incremental benefit of increasing model complexity. The results indicate that gains are substantial for low-dimensional models, reflecting the extraction of the dominant structure of the data, but decrease steadily as the total rank increases. Beyond a certain point, additional components yield only small improvements in explained variation, indicating diminishing returns.

Based on this analysis, a multilinear rank $(7, 6, 2)$ was selected. This model explains 78.08% of the total variation in the data while maintaining a level of complexity that remains interpretable across the three dimensions under analysis. For robustness, results were compared with the nearby lower-complexity solution $(6, 5, 2)$. The main indicator and regional patterns are stable across both specifications, but $(7, 6, 2)$ yields a better fit and a clearer thematic separation in the factor structure. Therefore, $(7, 6, 2)$ was retained as the baseline specification for the interpretation and the temporal trajectory analysis.

In the following section, we present and interpret the results of the selected Tucker decomposition. We begin by analysing the factor matrices associated with regional and indicator modes: matrix A summarizes the regional dimension into seven latent regional profiles, while

matrix B captures six latent socio-economic dimensions. The entries of these factor matrices represent the weights (or scores) of each region and indicator on the corresponding components. We then examine the core tensor $\mathcal{G}$ to assess the relative importance of cross-mode interactions and to identify the dominant structural relationships underlying the data. The factor matrix C identifies two dominant temporal components and is also analysed.

6.2 Interpreting Structural Components and Core Interactions

This section focuses on the interpretation of the components extracted by the Tucker decomposition, namely the regional factor matrix A, the indicator factor matrix B, as well as the core tensor ($\mathcal{G}$) that summarises cross-mode interactions across regions, indicators, and time. Using the selected ranks $(P, Q, R) = (7, 6, 2)$, the model provides a compact representation of the original tensor while retaining a substantial part of the overall variability (78.08%). Interpretation proceeds in two steps. First, the core tensor $\mathcal{G}$ is analysed to understand which combinations of regional and indicator components – modulated by the temporal components – constitutes the dominant interaction patterns in the data. Second, the factor matrices A and B are examined to find possible socio-economic meaning to the indicator themes and regional profiles. Together, these results provide insight into the main patterns present in the data.

Core tensor interactions and the role of the temporal mode

The core tensor $\boldsymbol{\mathcal{G}} \in \mathbb{R}^{7\times6\times2}$ identifies which combinations of regional profiles (matrix A) and indicator themes (matrix B) contribute most to the reconstruction of the observed tensor, and how these contributions are distributed across the two temporal components. In practical terms, large $|G_{pqr}|$ values indicate that regional component A_p and indicator component B_q are strongly coupled, with their join affect primarily channelled through temporal component C_r.

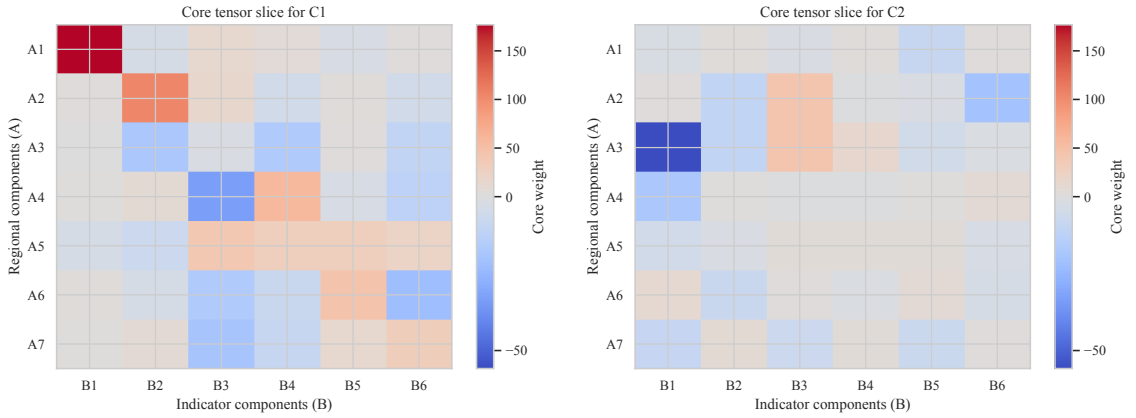


Figure 6.2: Heatmaps of the core tensor slices associated with temporal components C1 and C2. Rows correspond to regional components (A1-A7), columns to indicator components (B1-B6), and colors represent the sign and magnitude of the core weights.

An important feature of the solution is its concentration: there is a small number of A-B parings that account for most of the core interaction strength. The largest entry is $(A1, B1, C1)$ with G=176.78, indicating that the B1 is the dominant indicator dimension associated with the regional profile captured by A1, and that this relationship is primarily expressed by C1. The next most important coupling is $(A2, B2, C1)$ with G=104.57, followed by $(A4, B4, C1)$ with G=57.99. Then, the interaction $(A3, B1, C2)$ shows a relatively high core value in absolute terms (G=-55.85). This suggests that the association between A3 and B1 plays an important role in the temporal pattern captured by C2

Interaction	A_comp	B_comp	C_comp	G_value
(1, 1, 1)	A1	B1	C1	176.78
(2, 2, 1)	A2	B2	C1	104.57
(4, 4, 1)	A4	B4	C1	57.99
(3, 1, 2)	A3	B1	C2	-55.85
(6, 5, 1)	A6	B5	C1	44.91
(2, 3, 2)	A2	B3	C2	42.36
(3, 3, 2)	A3	B3	C2	42.33
(5, 3, 1)	A5	B3	C1	37.3
(4, 3, 1)	A4	B3	C1	-33.33
(7, 6, 1)	A7	B6	C1	30.58

Figure 6.3: Top 10 dominant core tensor interactions ranked by absolute core weight $|G|$. The table shows the top interactions between regional components (A), indicator components (B), and temporal components (C), together with their corresponding G values.

The temporal factor matrix C helps distinguish persistent structural gradients from time-dependent shifts. In the estimated temporal factors, C1 remains positive and varies only modestly over time, whereas C2 changes sign around 2009-2010, separating the 2000s from the 2010s (Figure 6.4). This pattern supports interpreting C1 as a baseline structural time profile, and C2 as a longer-term change between sub-periods.

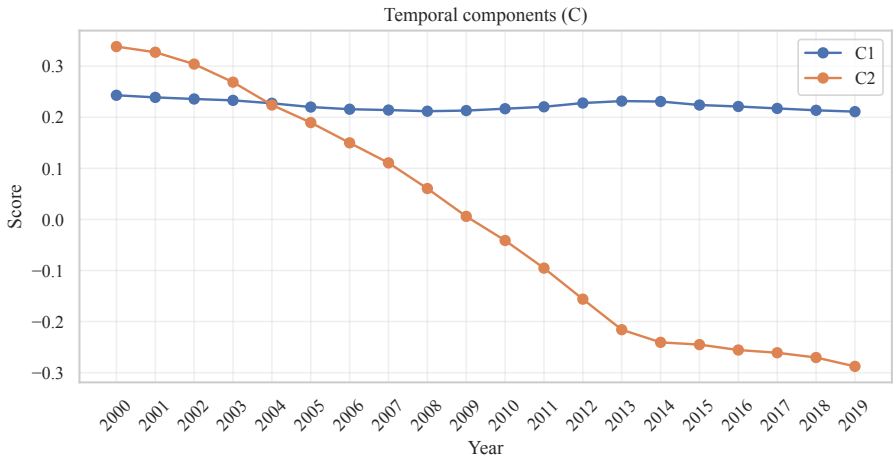


Figure 6.4: Temporal coefficients of components C1 and C2. The horizontal axis represents the years, and the vertical axis represents the coefficients associated with each temporal component.

The results in Figure 6.3, show that most of the strongest combinations are overwhelmingly associated with C1, indicating that the main regional-indicator relationships are structural and persistent over the sample period. In turn, the largest interactions involving C2 highlight dimensions where the association between regional and indicator components are time dependent. The most prominent C2-driven effects include interactions linking A3 with B1 and interactions linking A3 and A2 with B3.

Indicator components

The factor matrix B (26×6) summarizes the indicator mode into six latent components, each representing a distinct socio-economic dimension underlying the original set of indicators. The loadings associated with these components reveal groups of indicators that vary between regions and over time, providing a compact representation of the main thematic structures in the data. The discussion below focuses on indicators with the largest absolute loadings in each component (top positive and top negative), as these are the ones contribute most to the formation and meaning of the factor.

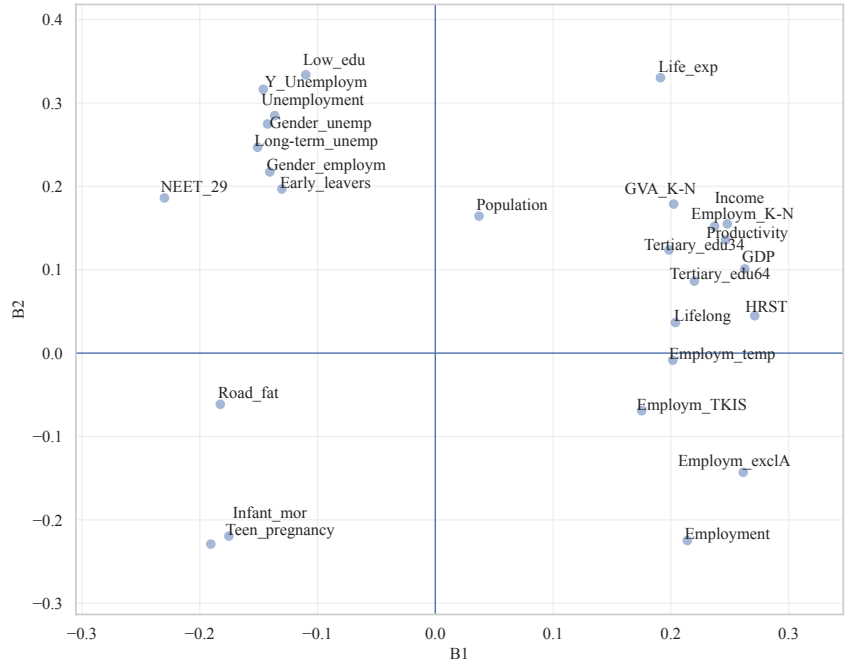


Figure 6.5: Projection of the selected indicators in the B1-B2 component space. The horizontal and vertical axes represent the coefficients (weights) of the indicators on components B1 and B2, respectively, and each point corresponds to one indicator.

The first component (B1) of matrix B covers a broad axis of economic performance, productivity and skilled employment, in contrast to indicators of socioeconomic vulnerability. The highest scores are observed for Human Resources in Science and Technology (0.271), Gross Domestic Product per inhabitant (0.263), Employment rate excluding agriculture (0.261), Employment in K–N sectors (0.248) and Labour productivity (0.247). On the other side, the indicators with the largest negative loadings are young people (aged 15-29) neither in employment nor in education and training (-0.230), teenage pregnancy (-0.191),

road fatalities (-0.183), and infant mortality (-0.175). Therefore, this component seems to reflect a gradient of economic development and competitiveness. Regions scoring high tend to combine strong economic output and productivity with a high-skilled workforce, while low scores are associated with regions with lower economic growth and social vulnerabilities.

The second component (B2) reflects low educational attainment and labour-market vulnerabilities, along with a high life expectancy. The strongest positive loadings are low education rate (0.334), life expectancy (0.330), youth unemployment (0.316), unemployment (0.285) and gender unemployment gap (0.275). The most negative loadings are smaller than positive scores and include teenage pregnancy (-0.229), employment (-0.225) and infant mortality (-0.219). This component captures an axis where low educational attainment aligns with labour market fragilities, opposing regions with lower educational levels and higher unemployment, against regions with greater educational levels and less unemployment. The presence of life expectancy among the strongest positives suggest that this component captures a specific pattern in the data, positioning regions with a higher life expectancy on the positive side of B2 as well.

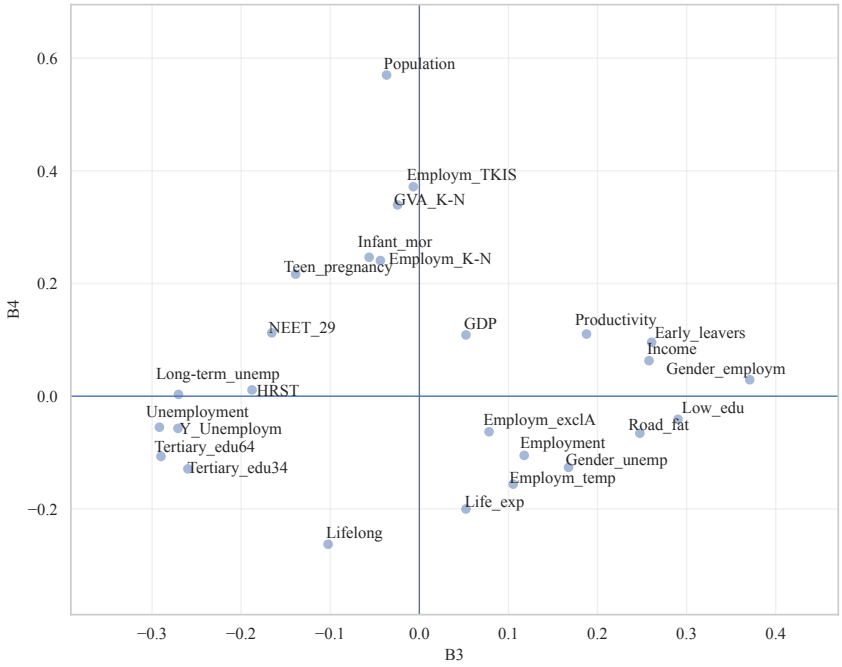


Figure 6.6: Projection of the selected indicators in the B3-B4 component space. The horizontal and vertical axes represent the coefficients (weights) of the indicators on components B3 and B4, respectively, and each point corresponds to one indicator.

The third component (B3) seems to reflect a particular socioeconomic profile that brings together, on one side of the axis, gender disparities in employment, low educational attainment, and high disposable household income. The opposite side of the axis, in turn, appears to be associated with higher unemployment and greater levels of tertiary education. The largest positive loading is gender employment gap (0.371), followed by a lower importance for low education rate (0.290), early leavers from education and training (0.261), and disposable income per capita (0.258). On the negative side, the largest loadings correspond to unemployment (-0.292), tertiary education attainment 25-64 (-0.290), youth unemployment (-0.271), and long-term unemployment (-0.270). This indicates a contrasting profile

where higher levels of education are accompanied by larger unemployment pressures (including youth and long-term unemployment). The component B3 appears in the fourth strongest core interactions, and it involves C2. This indicates that B3 could be important for differentiating some regional profiles, particularly for patterns that vary between the two decades captured by C2, which can be driven by specific conjunctural, social or economic factors.

The fourth component (B4) is strongly dominated by population size, with the highest positive loading in population (0.570). On the positive side, the next highest scores are employment in technology and knowledge-intensive sectors (0.372) and gross value added in K–N sectors (0.340). On the negative side, the largest loadings include lifelong learning (-0.263) and life expectancy (-0.200). This component can be interpreted as a size/urbanisation gradient capturing differences between large/urban economic areas and smaller territories.

The fifth component (B5) seems to be associated to regions with social risk and educational disadvantage, since the strongest positive loading is early leavers from education and training (0.509). On the positive side, the next indicators are low education rate (0.354), infant mortality (0.347), and teenage pregnancy (0.284). On the negative side, the loadings are significantly lower and include the employment in technology and knowledge-intensive sectors (-0.273). This component separates regions with a relatively higher percentage of population having attained at most lower secondary education and not being involved in further education or training, from regions with a relatively lower proportion of early leavers. It may be relevant for interpreting regional profiles where weak educational trajectories are associated with adverse social outcomes.

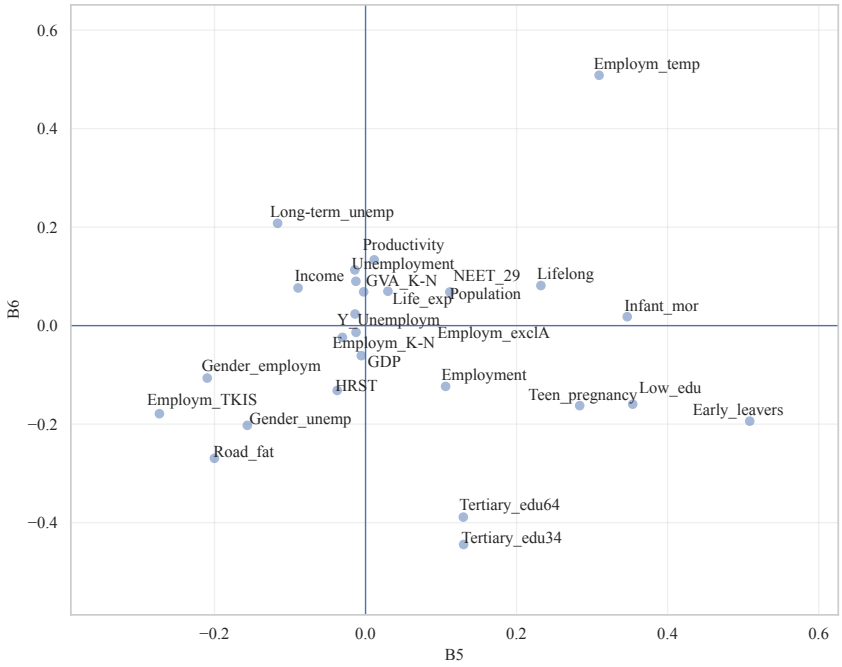


Figure 6.7: Projection of the selected indicators in the B5-B6 component space. The horizontal and vertical axes represent the coefficients (weights) of the indicators on components B6 and B6, respectively, and each point corresponds to one indicator.

Finally, the sixth component (B6) seems to be associated with the precariousness of the labour market and a low-skilled workforce. The highest positive loading is temporary employment (0.508), followed by a second, significantly smaller positive result for long-term

unemployment (0.208). On the other hand, the most negative scores are tertiary educational attainment aged 30-34 (-0.444) and tertiary educational attainment aged 25-64 (-0.389). This component therefore contrasts regions where employment is more precarious and the population is less qualified, with regions characterised by more stable jobs and a more qualified population.

Regional components

The regional factor matrix A (160×7) provides the scores of each region on the seven latent regional components. Each component can be interpreted as a regional profile, and its interpretation should be guided by the core tensor. Specifically, dominant entries in the core tensor G_{pqr} indicate which regional component A_p is most strongly coupled with which indicator component B_q, and through which temporal component C_r.

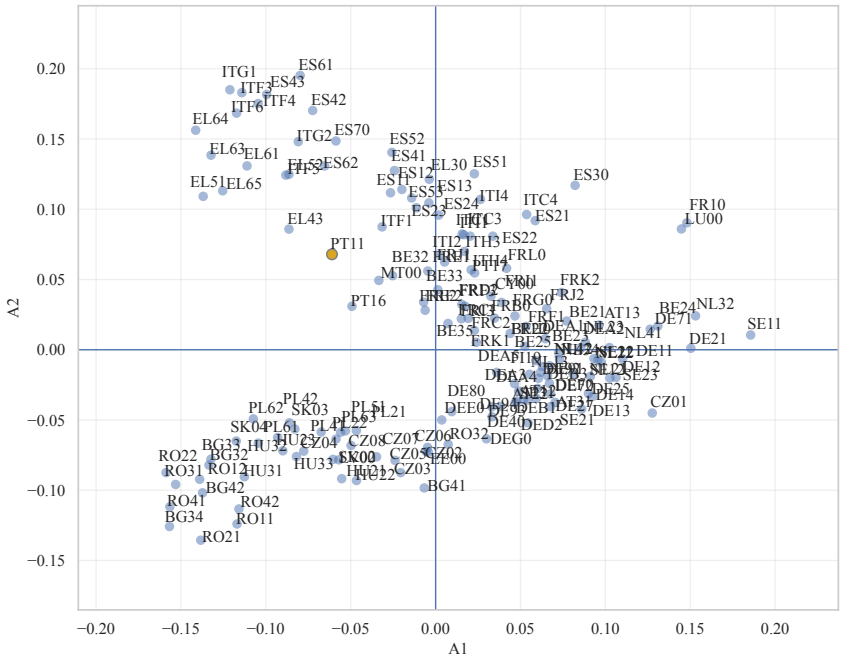


Figure 6.8: Projection of the selected NUTS 2 regions in the A1-A2 component space. The horizontal and vertical axes represent the coefficients (weights) of the regions on components A1 and A2, respectively, and each point corresponds to one NUTS 2 region. The point highlighted in yellow represents Norte (PT11).

The strongest core interaction is $(A1, B1, C1)$, indicating that regions scoring high on A1 tend to be those with great economic performance, higher productivity and high-skill employment (aligned with B1). The regions with the highest scores on A1 include mainly northwestern European regions (SE11 – Stockholm, NL32 - Noord-Holland, DE21 - Oberbayern), while the lowest scores appear especially in parts of eastern Europe (RO22 - Sud-Est, BG34 - Yugoiztochen, RO41 - Sud-Vest Oltenia, RO31 - Sud – Muntenia) and southern Europe, as illustrated in Appendix F. This configuration is consistent with a broad development and competitiveness gradient across European regions: high values identify regions combining higher productivity and knowledge-related labour market structures, whereas low values tend to coincide with less developed economies and more adverse social outcomes.

NUTS 2 code	NUTS 2 label	Country	Capital regions	EU accession	Category region 2021–2027	Geographic area	RIS	RCI	SPI	Loading
Top 5 positive										
SE11	Stockholm	Sweden	Capital region	1995	More developed	North-western	Top 10	Top 10	Top 10	0.1856
NL32	Noord-Holland	Netherlands	Non-capital region	1958	More developed	North-western	Above EU_avg	-	Above EU_avg	0.1531
DE21	Oberbayern	Germany	Non-capital region	1958	More developed	North-western	Top 10	Above EU_avg	Above EU_avg	0.1503
FR10	Ile-de-France	France	Capital region	1958	More developed	North-western	Above EU_avg	Top 10	Above EU_avg	0.148
LU00	Luxembourg	Luxembourg	Capital region	1958	More developed	North-western	-	Above EU_avg	Above EU_avg	0.1448
Top 5 negative										
RO22	Sud-Est	Romania	Non-capital region	2007	Less developed	Eastern	Bottom 10	Bottom 10	Bottom 10	-0.1588
BG34	Югоизточен	Bulgaria	Non-capital region	2007	Less developed	Eastern	Bottom 10	Bottom 10	Bottom 10	-0.1568
RO41	Sud-Vest Oltenia	Romania	Non-capital region	2007	Less developed	Eastern	Bottom 10	Bottom 10	Bottom 10	-0.1566
RO31	Sud-Muntenia	Romania	Non-capital region	2007	Less developed	Eastern	Bottom 10	Bottom 10	Bottom 10	-0.1532
EL64	Στερεά Ελλάδα	Greece	Non-capital region	1981	Less developed	Southern	Below EU_avg	Bottom 10	Below EU_avg	-0.1413

Figure 6.9: NUTS 2 regions with the largest positive and negative coefficients (weights) on component A1. The table shows the A1 loading values and regional characteristics, helping to identify common features among regions with similar positions on this component.

The second most representative interaction is $(A2, B2, C1)$. As discussed above, B2 is mainly associated with the educational attainment of the population and labour-market structure, while also exhibiting a strong association with life expectancy. Regions with the highest scores on the positive side of A2 tend to have a low educational attainment level and higher life expectancy, which correspond predominantly to southern regions, such as ES61 – Andalucía, ITG1 – Sicilia and ITF3 - Campania. In turn, regions on the negative side of A2 are mainly located in Eastern Europe, including RO21 - Nord-Est, BG34 - Yugoiztochen and RO11 - Nord-Vest. This pattern is illustrated in Appendix G. These regions tend to have a less pronounced proportion of the population with low levels of education and lower life expectancy. At first glance, the coexistence of lower education levels with higher life expectancy may seem counterintuitive, but it should not be interpreted as a direct causal relationship. In a multivariate regional context, life expectancy reflects a broader set of structural determinants—including behavioral and lifestyle factors (including dietary patterns), environmental and climatic conditions, and family or social support structures—that do not necessarily show a direct relationship with indicators of formal education.

NUTS 2 code	NUTS 2 label	Country	Capital regions	EU accession	Category region 2021–2027	Geographic area	RIS	RCI	SPI	Loading
Top 5 positive										
ES61	Andalucía	Spain	Non-capital region	1986	Less developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	0.1952
ITG1	Sicilia	Italy	Non-capital region	1958	Less developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	0.185
ITF3	Campania	Italy	Non-capital region	1958	Less developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	0.183
ES43	Extremadura	Spain	Non-capital region	1986	Less developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	0.1816
ITF4	Puglia	Italy	Non-capital region	1958	Less developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	0.1752
Top 5 negative										
RO21	Nord-Est	Romania	Non-capital region	2007	Less developed	Eastern	Bottom 10	Bottom 10	Bottom 10	-0.1355
BG34	Югоизточен	Bulgaria	Non-capital region	2007	Less developed	Eastern	Bottom 10	Bottom 10	Bottom 10	-0.1258
RO11	Nord-Vest	Romania	Non-capital region	2007	Less developed	Eastern	Bottom 10	Bottom 10	Below EU_avg	-0.124
RO42	Vest	Romania	Non-capital region	2007	Less developed	Eastern	Bottom 10	Below EU_avg	Below EU_avg	-0.1133
RO41	Sud-Vest Oltenia	Romania	Non-capital region	2007	Less developed	Eastern	Bottom 10	Bottom 10	Bottom 10	-0.1118

Figure 6.10: NUTS 2 regions with the largest positive and negative coefficients (weights) on component A2. The table shows the A2 loading values and regional characteristics, helping to identify common features among regions with similar positions on this component.

The next principal pairing is $(A4, B4, C1)$, indicating that A4 is primarily associated with B4, the component dominated by population size, with relevant links to technology and knowledge-intensive employment and gross value added by advanced service activities. Regions with the highest A4 scores include regions where European capitals are located, such as FR10 - Ile-de-France, ES30 - Comunidad de Madrid, RO32 - Bucureşti - Ilfov and BG41 - Yugozapaden, while the lowest sores include NL34 - Zeeland, NL13 - Drenthe, and SE21 - Småland med öarna. This pattern is consistent with a size or urbanisation gradient: high values tend to characterise large regions, where scale effects are stronger and the presence of knowledge-intensive activities is larger.

The core tensor indicates that A3 is primarily a time-differentiating regional profile, as its most relevant pairings occur through C2. In particular, the interactions $(A3, B1, C2)$, and $(A3, B3, C2)$, show that A3 identifies regions whose relative profile changes between sub-periods along the development-competitiveness dimension captured by B1 and the paradoxical education-unemployment-income dimension captured by B3. The negative sign in $(A3, B1, C2)$ reflects an inverse association with B1 under the C2 pattern. The association with C2 indicates that A3 may not primarily represent a structural profile but rather seems to highlight regions whose relative positioning is reconfigured over time, mainly through dimensions B1 and B3. Regions with the highest A3 scores include LV00 - Latvija, ES23 - La Rioja, EE00 - Eesti, and PT16 – Centro, while the lowest include ITF3 - Campania, ITG1 - Sicilia, and FR10 - Ile-de-France.

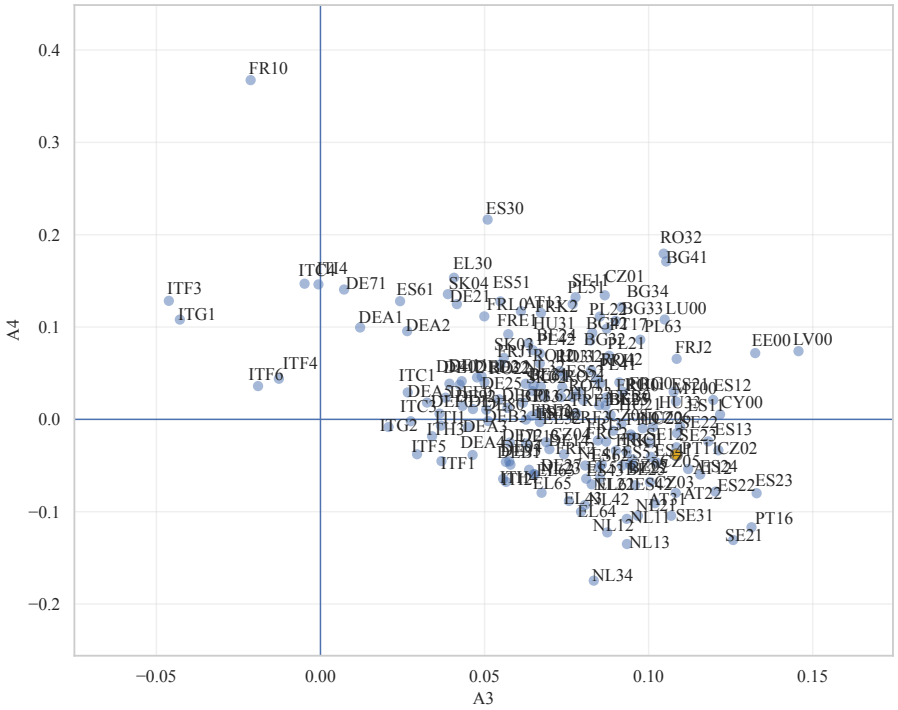


Figure 6.11: Projection of the selected NUTS 2 regions in the A3-A4 component space. The horizontal and vertical axes represent the coefficients (weights) of the regions on components A3 and A4, respectively, and each point corresponds to one NUTS 2 region. The point highlighted in yellow represents Norte (PT11).

NUTS 2 code	NUTS 2 label	Country	Capital regions	EU accession	Category region 2021–2027	Geographic area	RIS	RCI	SPI	Loading
Top 5 positive										
FR10	Ile-de-France	France	Capital region	1958	More developed	North-western	Above EU_avg	Top 10	Above EU_avg	0.3674
ES30	Comunidad de Madrid	Spain	Capital region	1986	More developed	Southern	Above EU_avg	Above EU_avg	Above EU_avg	0.2163
RO32	Bucureşti-Ilfov	Romania	Capital region	2007	More developed	Eastern	Below EU_avg	Below EU_avg	Below EU_avg	0.1795
BG41	Югозападен	Bulgaria	Capital region	2007	Transition	Eastern	Below EU_avg	Below EU_avg	Below EU_avg	0.171
EL30	Αττική	Greece	Non-capital region	1981	Transition	Southern	Below EU_avg	Below EU_avg	Below EU_avg	0.1534
Top 5 negative										
NL34	Zeeland	Netherlands	Non-capital region	1958	More developed	North-western	Above EU_avg	Above EU_avg	Above EU_avg	-0.1747
NL13	Drenthe	Netherlands	Non-capital region	1958	Transition	North-western	Above EU_avg	Above EU_avg	Above EU_avg	-0.135
SE21	Småland med öarna	Sweden	Non-capital region	1995	More developed	North-western	Above EU_avg	Above EU_avg	Above EU_avg	-0.1307
NL12	Friesland (NL)	Netherlands	Non-capital region	1958	Transition	North-western	Above EU_avg	Above EU_avg	Above EU_avg	-0.1224
PT16	Centro (PT)	Portugal	Non-capital region	1986	Less developed	Southern	Below EU_avg	Below EU_avg	Above EU_avg	-0.1168

Figure 6.12: NUTS 2 regions with the largest positive and negative coefficients (weights) on component A4. The table shows the A4 loading values and regional characteristics, helping to identify common features among regions with similar positions on this component.

NUTS 2 code	NUTS 2 label	Country	Capital regions	EU accession	Category region 2021–2027	Geographic area	RIS	RCI	SPI	Loading
Top 5 positive										
LV00	Latvija	Latvia	Non-capital region	2004	Less developed	Eastern	-	Below EU_avg	Above EU_avg	0.1457
ES23	La Rioja	Spain	Non-capital region	1986	Transition	Southern	Below EU_avg	Below EU_avg	Above EU_avg	0.1329
EE00	Eesti	Estonia	Capital region	2004	Transition	Eastern	-	Above EU_avg	Above EU_avg	0.1325
PT16	Centro (PT)	Portugal	Non-capital region	1986	Less developed	Southern	Below EU_avg	Below EU_avg	Above EU_avg	0.1313
SE21	Småland med öarna	Sweden	Non-capital region	1995	More developed	North-western	Above EU_avg	Above EU_avg	Above EU_avg	0.1258
Top 5 negative										
ITF3	Campania	Italy	Non-capital region	1958	Less developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	-0.0462
ITG1	Sicilia	Italy	Non-capital region	1958	Less developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	-0.0428
FR10	Ile-de-France	France	Capital region	1958	More developed	North-western	Above EU_avg	Top 10	Above EU_avg	-0.0213
ITF6	Calabria	Italy	Non-capital region	1958	Less developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	-0.019
ITF4	Puglia	Italy	Non-capital region	1958	Less developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	-0.0127

Figure 6.13: NUTS 2 regions with the largest positive and negative coefficients (weights) on component A3. The table shows the A3 loading values and regional characteristics, helping to identify common features among regions with similar positions on this component.

The fifth largest interaction is $(A6, B5, C1)$. Since the highest values of B5 are associated to early educational disadvantage and social risk (early school leaving, low education rate, infant mortality, teenage pregnancy), the highest scores in component A6 identifies regions with human capital and social inclusion challenges. Regions with the highest scores include BG34 - Yugoiztochen, ES62 - Región de Murcia, BG42 - Yuzhen tsentralen, and RO21 - Nord-Est, whereas the lowest scores include CZ02 - Střední Čechy, ITI4 – Lazio, CZ07 - Střední Morava, and SK02 - Západné Slovensko.



Figure 6.14: Projection of the selected NUTS 2 regions in the A5-A6 component space. The horizontal and vertical axes represent the coefficients (weights) of the regions on components A5 and A6, respectively, and each point corresponds to one NUTS 2 region. The point highlighted in yellow represents Norte (PT11).

NUTS 2 code	NUTS 2 label	Country	Capital regions	EU accession	Category region 2021–2027	Geographic area	RIS	RCI	SPI	Loading
Top 5 positive										
BG34	Югоизточен	Bulgaria	Non-capital region	2007	Less developed	Eastern	Bottom 10	Bottom 10	Bottom 10	0.2051
ES62	Región de Murcia	Spain	Non-capital region	1986	Transition	Southern	Below EU_avg	Below EU_avg	Below EU_avg	0.1303
BG42	Южен централен	Bulgaria	Non-capital region	2007	Less developed	Eastern	Below EU_avg	Below EU_avg	Bottom 10	0.129
RO21	Nord-Est	Romania	Non-capital region	2007	Less developed	Eastern	Bottom 10	Bottom 10	Bottom 10	0.1229
ES70	Canarias	Spain	Non-capital region	1986	Transition	Southern	Below EU_avg	Below EU_avg	Above EU_avg	0.115
Top 5 negative										
CZ02	Střední Čechy	Czechia	Non-capital region	2004	Transition	Eastern	Below EU_avg	-	Above EU_avg	-0.1704
ITI4	Lazio	Italy	Non-capital region	1958	More developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	-0.1519
CZ07	Střední Morava	Czechia	Non-capital region	2004	Less developed	Eastern	Below EU_avg	Below EU_avg	Above EU_avg	-0.1512
SK02	Západné Slovensko	Slovakia	Non-capital region	2004	Less developed	Eastern	Below EU_avg	Below EU_avg	Below EU_avg	-0.151
ITF5	Basilicata	Italy	Non-capital region	1958	Less developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	-0.1501

Figure 6.15: NUTS 2 regions with the largest positive and negative coefficients (weights) on component A6. The table shows the A6 loading values and regional characteristics, helping to identify common features among regions with similar positions on this component.

The component A5 is in the eighth most relevant core coupling $(A5, B3, C1)$, which indicates that the regional profile captured by A5 is primarily associated with the component represented by B3, and through C1. Regions with the highest scores on A5 include RO21 - Nord-Est, ITC4 – Lombardia, RO31 - Sud-Muntenia, RO22 - Sud-Est and the Portuguese region PT11 – Norte. In contrast, the lowest A5 scores are observed in ES21 – País Vasco, FI19 – Länsi-Suomi, EL52 - Kentriki Makedonia, EE00 – Eesti, and CZ01 – Praha. This component A5 seems to separate regions according to the paradoxical socio-economic situation represented by B3, distinguishing those with low levels of education and high income aligned on the positive side of B3, from those regions aligned on the opposite side, where higher education and unemployment pressures are more evident.

NUTS 2 code	NUTS 2 label	Country	Capital regions	EU accession	Category region 2021–2027	Geographic area	RIS	RCI	SPI	Loading
Top 5 positive										
RO21	Nord-Est	Romania	Non-capital region	2007	Less developed	Eastern	Bottom 10	Bottom 10	Bottom 10	0.2325
ITC4	Lombardia	Italy	Non-capital region	1958	More developed	Southern	Below EU_avg	Above EU_avg	Below EU_avg	0.2227
RO31	Sud-Muntenia	Romania	Non-capital region	2007	Less developed	Eastern	Bottom 10	Bottom 10	Bottom 10	0.1958
RO22	Sud-Est	Romania	Non-capital region	2007	Less developed	Eastern	Bottom 10	Bottom 10	Bottom 10	0.181
PT11	Norte	Portugal	Non-capital region	1986	Less developed	Southern	Below EU_avg	Below EU_avg	Above EU_avg	0.1766
Top 5 negative										
ES21	País Vasco	Spain	Non-capital region	1986	More developed	Southern	Above EU_avg	Above EU_avg	Above EU_avg	-0.139
FI19	Länsi-Suomi	Finland	Non-capital region	1995	Transition	North-western	Above EU_avg	Above EU_avg	Top 10	-0.1358
EL52	Κεντρική Μακεδονία	Greece	Non-capital region	1981	Less developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	-0.1243
EE00	Eesti	Estonia	Capital region	2004	Transition	Eastern	-	Above EU_avg	Above EU_avg	-0.1163
CZ01	Praha	Czechia	Capital region	2004	More developed	Eastern	Above EU_avg	-	Above EU_avg	-0.1141

Figure 6.16: NUTS 2 regions with the largest positive and negative coefficients (weights) on component A5. The table shows the A5 loading values and regional characteristics, helping to identify common features among regions with similar positions on this component.

Finally, the interaction $(A7, B6, C1)$ indicates that A7 is mainly associated with B6, which contrasts temporary employment and less qualified employment with a more stable and high-skilled labour force. Regions with the highest A7 scores correspond to ITF6 - Calabria, ITG1

- Sicilia, and SK04 - Východné Slovensko, whereas the lowest scores include eastern European regions, such as CZ01 - Praha, HU21 - Közép-Dunántúl, CZ02 - Střední Čechy, and RO32 - Bucureşti-Ilfov. This component (A7) captures a labour-market profile related to job stability and skills. High A7 scores are associated with regions where temporary employment is more common. Low A7 scores, in contrast, characterise regions combining higher tertiary attainment, together with relatively more stable employment patterns. Because the dominant core interaction for A7 is channelled through C1, this dimension could be interpreted as structural and persistent over the period analysed.

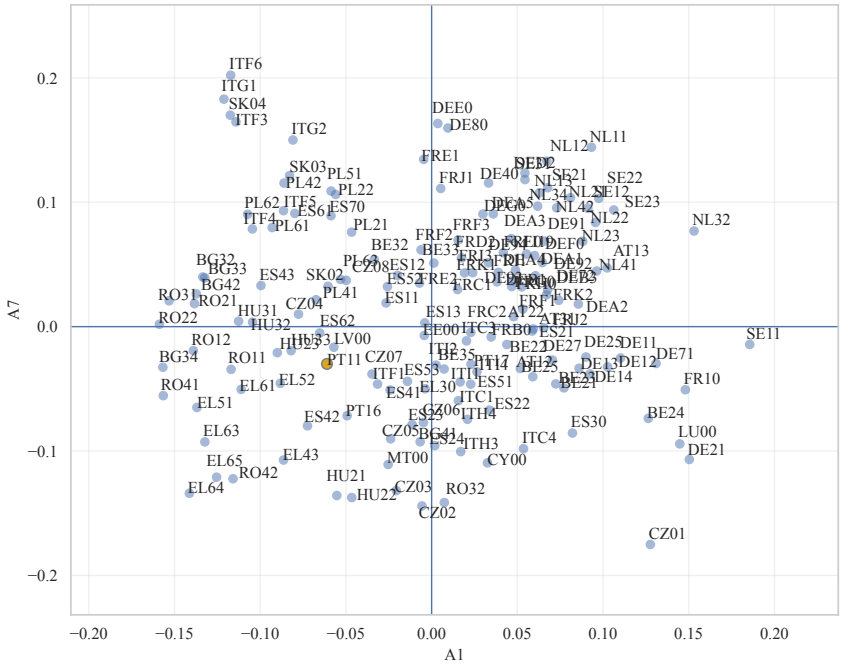


Figure 6.17: Projection of the selected NUTS 2 regions in the A1-A7 component space. The horizontal and vertical axes represent the coefficients (weights) of the regions on components A1 and A7, respectively, and each point corresponds to one NUTS 2 region. The point highlighted in yellow represents Norte (PT11).

Overall, the regional components provide a compact typology of regional socio-economic profiles, while the core tensor clarifies which indicator dimensions are most relevant for each regional profile and whether the corresponding relationships are more structural (C1) or time-differentiated (C2).

NUTS 2 code	NUTS 2 label	Country	Capital regions	EU accession	Category region 2021–2027	Geographic area	RIS	RCI	SPI	Loading
Top 5 positive										
ITF6	Calabria	Italy	Non-capital region	1958	Less developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	0.2021
ITG1	Sicilia	Italy	Non-capital region	1958	Less developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	0.1829
SK04	Východné Slovensko	Slovakia	Non-capital region	2004	Less developed	Eastern	Below EU_avg	Below EU_avg	Below EU_avg	0.17
ITF3	Campania	Italy	Non-capital region	1958	Less developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	0.1646
DEE0	Sachsen-Anhalt	Germany	Non-capital region	1958	Transition	North-western	Below EU_avg	Above EU_avg	Above EU_avg	0.1633
Top 5 negative										
CZ01	Praha	Czechia	Capital region	2004	More developed	Eastern	Above EU_avg	-	Above EU_avg	-0.1751
CZ02	Střední Čechy	Czechia	Non-capital region	2004	Transition	Eastern	Below EU_avg	-	Above EU_avg	-0.1441
RO32	Bucureşti-Ilfov	Romania	Capital region	2007	More developed	Eastern	Below EU_avg	Below EU_avg	Below EU_avg	-0.1414
HU22	Nyugat-Dunántúl	Hungary	Non-capital region	2004	Less developed	Eastern	Below EU_avg	Below EU_avg	Below EU_avg	-0.1374
HU21	Közép-Dunántúl	Hungary	Non-capital region	2004	Less developed	Eastern	Below EU_avg	Below EU_avg	Below EU_avg	-0.1357

Figure 6.18: NUTS 2 regions with the largest positive and negative coefficients (weights) on component A7. The table shows the A7 loading values and regional characteristics, helping to identify common features among regions with similar positions on this component.

6.3 Temporal Trajectories

By examining the temporal trajectories of regions, different dynamics become visible, indicating that evolution over time is not homogeneous across regions. Some regions follow relatively smooth paths, while others exhibit more irregular trajectories. When the movement is gradual, it usually suggests a steady process of development, whereas more irregular paths may point to sharper changes between specific years. These differences highlight the heterogeneity of regional development paths and suggest that temporal trajectories are shaped by both persistent structural factors and more context-specific adjustments.

The magnitude of the trajectories is also informative. Shorter trajectories indicate limited change over the period, whereas longer ones suggest a more significant evolution over time. This distinction is particularly useful for identifying regions that remained structurally similar throughout the entire period under analysis and those that experienced more pronounced transformations.

Additionally, the direction of each trajectory provides further insight into how the process of regional economic, social, and territorial cohesion evolved over time. It helps to clarify how each region arrived at its current position, revealing whether its path was characterized by progress, with improvements in key economic and social indicators, or instead by stagnation or even deterioration across different dimensions of regional development.

Taken together, the comparison of regional trajectories makes it possible to identify groups of regions that followed similar paths, as well as those whose patterns of evolution were markedly divergent. This perspective also offers an important contribution to understanding how the initial position of European regions, together with their performance across socioeconomic indicators, may shape their subsequent development paths.

Temporal trajectories are visualized by projecting the observations onto the plane defined by the two most representative components of matrix B (B1 and B2). As described in Chapter 2, the coordinates of each region for a given year are obtained by computing the dot product between the values associated with that region in that year and the scores of the two components of matrix B. Connecting the points corresponding to successive years then makes it possible to trace the trajectory of each region in the two-dimensional space spanned

by B1 and B2. Given the large number of regions included in the study (160), representing all trajectories in a single chart does not allow for a clear examination of individual regional trajectories (Figure 6.12).

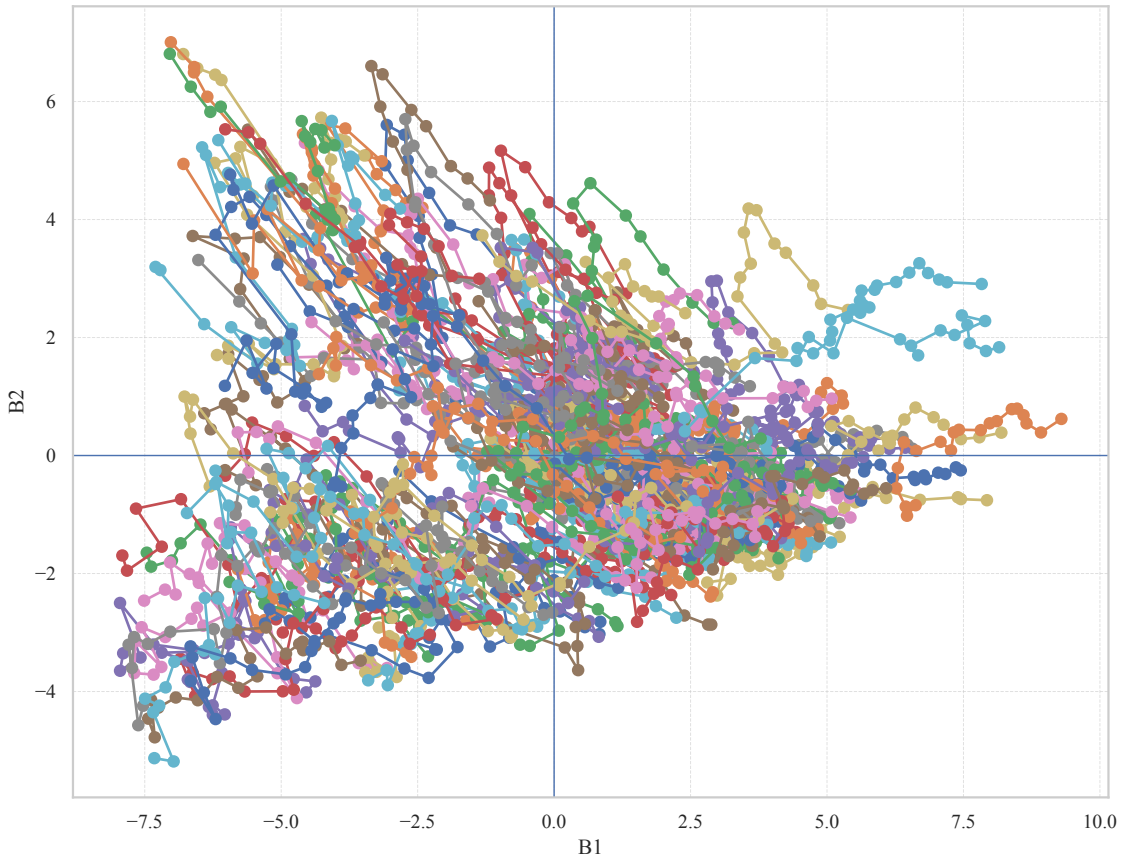


Figure 6.19: Regional trajectories in the B1-B2 component space. Each line connects consecutive years over the period under analysis for each NUTS 2 region.

So, to facilitate the interpretation of the graphical representations, the following figures focus on illustrative cases located in each of the four quadrants of the factorial plane under analysis.

As discussed earlier, component B1 tends to distinguish regions with a higher proportion of human resources employed in science and technology, higher employment rates (excluding agriculture), and greater levels of prosperity and productivity, from regions displaying weaker performance in these indicators and, at the same time, with risks of social vulnerabilities, namely a higher share of NEETs, a higher incidence of teenage pregnancy, and more road accident fatalities.

Component B2, in turn, contrasts regions characterised by a higher proportion of the population with low educational attainment (less than primary, primary and lower secondary education), higher life expectancy, and higher youth unemployment, with regions displaying lower shares of low educational attainment, lower life expectancy, and lower youth unemployment. Therefore, rather than reflecting a simple development profile, this component appears to capture a specific combination of educational, demographic, and labour market characteristics.

Under this interpretation of the factorial plane, regions located in the first quadrant tend to combine stronger performance in the socioeconomic dimension associated with B1, with the less favourable characteristics captured by the positive side of B2, particularly a larger share of the population with low educational attainment and higher youth unemployment. Thus, these regions may display higher levels of prosperity and productivity, while also being characterised by educational weaknesses and pressures in the labour market. The regions whose trajectories remain entirely within this quadrant are some more developed regions of Southern Europe, such as ES30 - Comunidad de Madrid, and ITC4 - Lombardia, as well as in Western Europe, including DE71 - Darmstadt, FR10 - Île-de-France, FRK2 - Rhône-Alpes, and LU00 – Luxembourg.

These cases are consistent with broader evidence on regional development in the EU. All regions whose trajectories remain entirely within the first quadrant were covered by the Regional Competitiveness and Employment Objective in the period 2007-2013 and were categorized as more developed regions for the 2014-2020 and 2021-2027 cohesion policy periods (Appendix H). In addition, some of these regions correspond to capital regions. This is in line with the Eighth Cohesion Report (European Commission, 2022), whose reference period is closer to the 2000-2019 period analysed here, which highlights that capital metropolitan regions performed better than other regions between 2001 and 2019. It also shows that skills endowments are concentrated in more developed regions and especially capital regions. At the same time, the Report also notes that pockets of deprivation may persist even in prosperous regions and that, on average, the highest unemployment rates were found in southern EU regions.

The fourth quadrant tends to include regions occupying relatively favourable positions with respect to both B1 and B2. These are generally more developed regions with lower proportions of population with low educational attainment and lower youth unemployment. Most regions whose trajectories are entirely concentrated in this quadrant belong to Western Europe, particularly Austria, Belgium, Germany, and the Netherlands.

These cases are also consistent with broader patterns of regional development in the EU. In particular, the Eighth Cohesion Report shows that more developed regions tend to perform better in terms of employment and innovation. In addition, the regions located in this quadrant tend to occupy comparatively stronger positions in the Regional Innovation Scoreboard (RIS), Regional Competitiveness Index (RCI), and Social Progress Index (SPI), which supports their interpretation as regions combining stronger socioeconomic performance with more favourable educational and labour-market conditions (Appendix H).

By contrast, the second and third quadrants are associated with less positive regional profiles, although with distinct geographical patterns and development dynamics. All regions whose trajectories remain entirely within the second quadrant belong to Southern Europe, particularly Greece, Spain, and Italy. This is consistent with the Eighth Cohesion Report, which notes that several middle-income and less developed regions, particularly in the southern EU, experienced economic stagnation or decline between 2000 and 2019, suggesting the presence of a development trap. In this sense, the second quadrant appears to reflect a less favorable combination of economic performance, social vulnerability, and educational disadvantage, despite relatively higher life expectancy.

The third quadrant, in turn, is composed exclusively of Eastern European regions, including Bulgaria, the Czech Republic, Hungary, Poland, Romania, and Slovakia. It is also worth noting that these regions belong to countries that joined the European Union more recently,

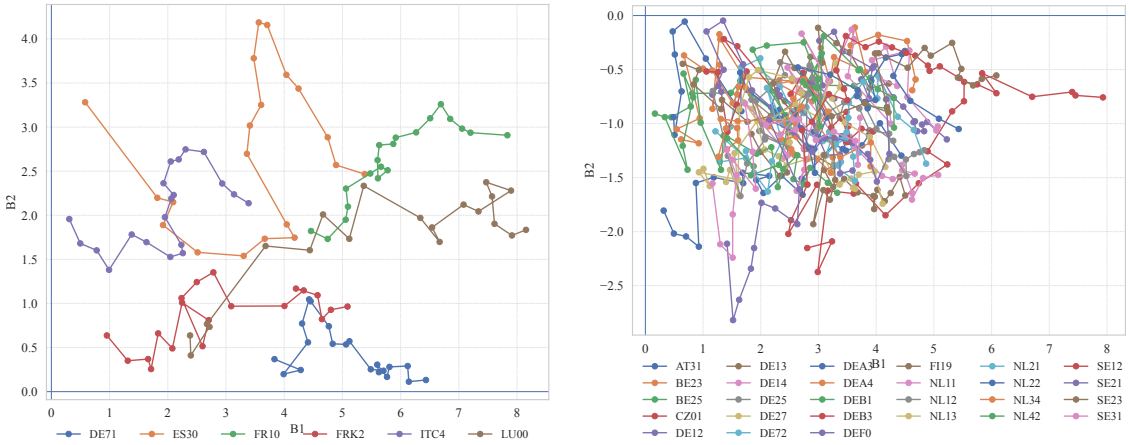


Figure 6.20: Regional trajectories located in the first and fourth quadrants of the B1-B2 component space. Each line connects consecutive years over the period under analysis for each NUTS 2 region.

namely in 2004 and 2007. Their position suggests a different pattern from that observed in the second quadrant. Although these regions remain classified as less developed for the 2021-2027 cohesion policy period and continue to display weaker positions in the socioeconomic dimension captured by B1, they tend to perform relatively better in the characteristics associated with B2, particularly in terms of educational attainment and labor market outcomes. This interpretation is consistent with the trajectory of several Eastern European regions, which experienced substantial catching-up after EU accession, while still remaining below the EU average in overall levels of development. Accordingly, the third quadrant appears to capture a pattern of partial convergence: these regions remain structurally less developed but seem to have achieved comparatively more favorable outcomes in selected social and labor market dimensions.

In addition, regions in both the second and the third quadrants tend to occupy clearly weaker recent positions in the Regional Innovation Scoreboard (RIS), Regional Competitiveness Index (RCI) and Social Progress Index (SPI), than those located in the first and fourth quadrants, which reinforces the interpretation of these quadrants as being associated with less favorable development profiles (Appendix H).

In this sense, regions whose trajectories move from left to right across the factorial plane, following the axis defined by component B1 and occupying either the first or the fourth quadrant, can be interpreted as regions that experienced a process of economic growth with improvements in competitiveness and productivity.

In turn, regional trajectories moving from top to bottom capture changes in the educational and labour market conditions represented by component B2. In particular, this movement may indicate a decrease in the share of the population with low educational attainment and a reduction in youth unemployment. By contrast, trajectories moving in the opposite direction, from bottom to top, suggest a deterioration in those same conditions, reflecting a relative worsening in educational attainment and unemployment.

The following section examines the regional trajectory of the Norte Region of Portugal.

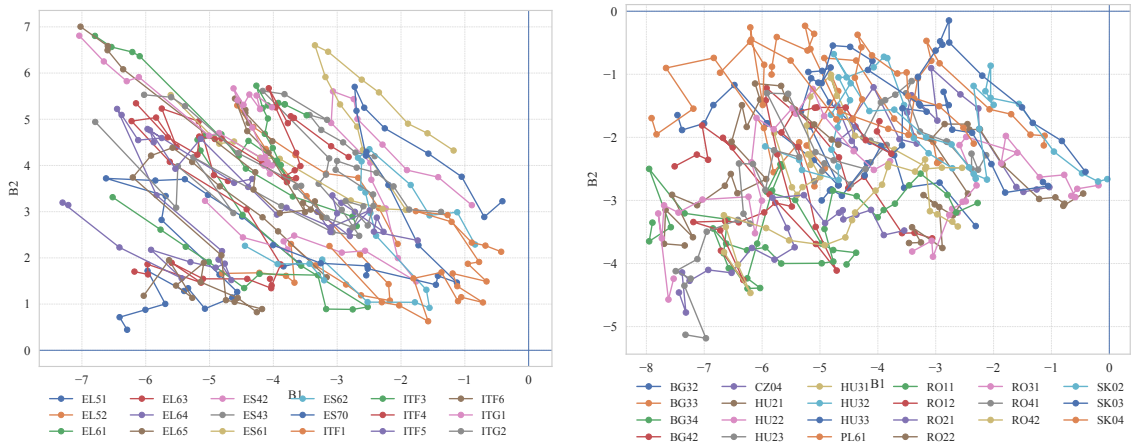


Figure 6.21: Regional trajectories located in the second and third quadrants of the B1-B2 component space. Each line connects consecutive years over the period under analysis for each NUTS 2 region.

6.3.1 Norte Region of Portugal

The individual trajectory of Norte remained in the second quadrant for most of the period analysed in this study. In the first three years, the region was located in the third quadrant. It then moved into the second quadrant, where it stayed for fifteen years, before ending the period, in 2018 and 2019, in the fourth quadrant, close to the horizontal axis.

This trajectory should be interpreted according to the meaning of the two components. Component B1 is mainly associated with economic performance, competitiveness and productivity. Negative scores on this component therefore indicate a less favourable relative position in this dimension. Component B2, in turn, is related with educational and labour market indicators and, in this case, positive scores are associated with less favourable conditions, especially low educational attainment and higher unemployment. Accordingly, upward movements along the B2 axis suggest a deterioration in the conditions captured by this component, whereas downward movements indicate an improvement.

For most of the period, Norte recorded negative scores on B1, reflecting a relatively weak performance in the economic-productivity dimension. This is consistent with lower values in the indicators most strongly represented in this component, including human resources employed in science and technology, GDP per capita, employment rate (excluding agriculture), and labour productivity.

Nevertheless, over the twenty-year period, the region followed a generally positive movement along the B1 axis. Its score increased from -4.05 in 2000 to 0.600 in 2019, indicating an improvement in its relative position on this component. However, this evolution was not linear. Slight backward movements along B1 can be observed in 2001, in 2008 and 2009, and again in 2011. These changes suggest periods of economic contraction and loss of competitiveness.

This pattern is consistent with a broader macroeconomic context in Portugal during the period under analysis. The country was affected by three major recessions, contributing to the interruption of economic growth: the 2002-2003 recession, the international financial crisis of 2008-2009, and the sovereign debt crisis of 2010-2013 (Aguiar-Conraria et al. (2023)).

The first episode corresponded to the first recession of Portugal after joining the single

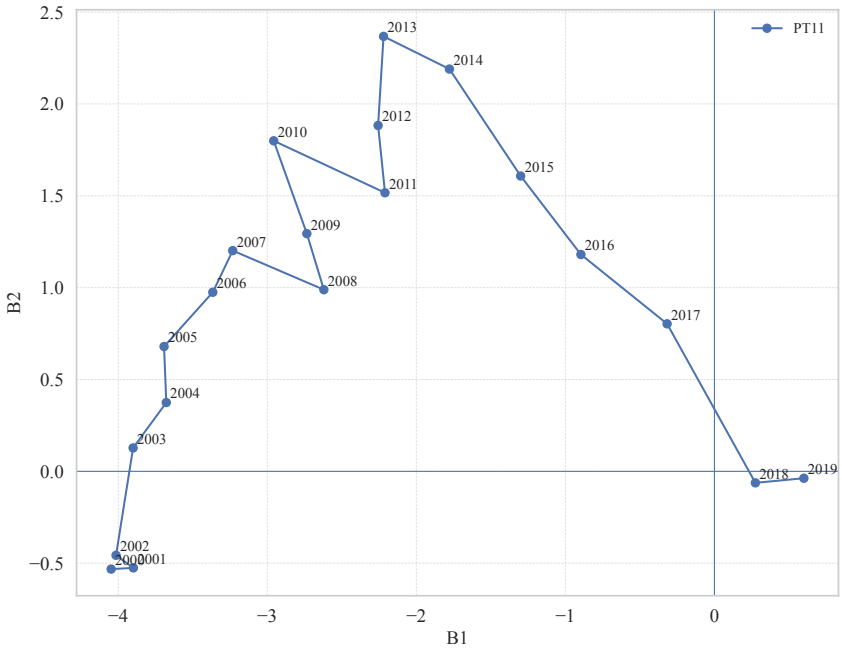


Figure 6.22: Trajectory of the Norte Region of Portugal (PT11) in the B1-B2 component space. The line connects consecutive years over the period under analysis.

currency and was largely associated with domestic economic weaknesses, declining confidence and a general climate of uncertainty. These conditions contributed to the interruption of economic growth and to a significant increase in unemployment, which remain high in the following years.

The second recession was linked to the international financial crisis from the United States which rapidly affected european economies. In Portugal, the decline in external demand had important effects on trade, production and the labour market. The fall in exports and the subsequent slowdown in economic activity contributed to a rise in the unemployment rate.

The third recession, associated with the sovereign debt crisis in the euro area, was particularly severe in Portugal. It was one of the most protracted crisis affecting the Portuguese economy in recent decades and had strong economic and social consequences. These included a sharp fall in GDP per capita and a significant increase in unemployment.

The trajectory of Norte shows that backward movements along B1 were accompanied by upward movements along B2. Given the interpretation of B2, this indicates a worsening of the social and labour market conditions captured by this component, particularly those related to low educational attainment and unemployment. In other words, during these periods, the region not only experienced interruptions in its economic growth but also moved towards a less favourable position in the educational and labour market dimension.

From 2013 onwards, the trajectory of Norte moved downwards along the B2 axis. This suggests an improvement in the conditions represented by this component. This change coincided with the period of economic and social recovery after the sovereign debt crisis, during which several indicators of economic activity and labour market performance began to reverse the negative trends observed during the recession.

In the final two years of the analysis, 2018 and 2019, Norte showed relative stability along the B2 axis while continuing to move positively along B1. This suggests that the region main-

tained the improvements observed after 2013 in the educational and labour market dimension, while continuing to strengthen its relative position in terms of economic performance, competitiveness and productivity. This pattern can also be observed in the original z-score values of the indicators most strongly associated with components B1 and B2, presented in figure 6.23 and figure 6.24.

Indicator	Loading	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
HRST	0.271	-2.52	-2.48	-2.52	-2.49	-2.3	-2.29	-2.19	-2.11	-2.01	-1.92	-1.87	-1.41	-1.3	-1.25	-0.95	-0.84	-0.68	-0.56	-0.43	-0.34
GDP	0.263	-1.11	-1.05	-1.02	-1.01	-0.99	-0.89	-0.81	-0.74	-0.68	-0.75	-0.68	-0.74	-0.75	-0.67	-0.61	-0.54	-0.47	-0.41	-0.3	-0.22
Employm_exclA	0.261	0.14	0.24	0.28	0.1	0.0	-0.04	0.03	0.02	0.06	-0.15	-0.21	-0.19	-0.43	-0.57	-0.31	-0.16	-0.0	0.35	0.57	0.63
Employm_K-N	0.248	-1.49	-1.43	-1.46	-1.45	-1.24	-1.19	-1.23	-1.02	-0.86	-0.75	-0.85	-0.7	-0.87	-0.59	-0.37	-0.49	-0.32	-0.24	-0.41	-0.32
Productivity	0.247	-1.21	-1.23	-1.24	-1.23	-1.25	-1.19	-1.16	-1.16	-1.13	-1.12	-1.1	-1.17	-1.14	-1.09	-1.1	-1.13	-1.12	-1.17	-1.17	-1.16
Income	0.237	-0.59	-0.64	-0.73	-0.71	-0.73	-0.65	-0.69	-0.74	-0.75	-0.72	-0.7	-0.82	-0.82	-0.78	-0.81	-0.75	-0.75	-0.8	-0.77	-0.74

Figure 6.23: Standardized values for the Norte Region (PT11) of the indicators with the highest loadings on component B1. The table shows the B1 loading of each indicator and its annual standardized values from 2000 to 2019.

Indicator	Loading	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Low_edu	0.334	3.58	3.53	3.55	3.48	3.36	3.29	3.17	3.2	3.11	3.02	2.9	2.66	2.58	2.44	2.2	2.12	1.98	1.9	1.74	1.6
Life_exp	0.33	-0.73	-0.7	-0.57	-0.53	-0.24	-0.31	-0.05	0.05	0.18	0.25	0.34	0.51	0.47	0.6	0.73	0.73	0.73	0.83	0.83	0.96
Y_Unemploym	0.316	-1.13	-1.21	-1.06	-0.72	-0.56	-0.41	-0.34	-0.35	-0.38	0.08	0.17	0.63	0.97	1.19	1.21	0.97	0.54	0.38	-0.16	-0.36
Unemployment	0.285	-0.96	-0.99	-0.91	-0.46	-0.32	-0.04	-0.03	0.05	-0.08	0.36	0.67	0.75	1.29	1.52	1.06	0.85	0.55	0.12	-0.33	-0.45
Gender_unemp	0.275	-0.38	-0.13	-0.32	-0.07	-0.26	0.19	0.48	0.89	0.05	0.01	0.62	0.11	-0.35	-0.29	-0.0	-0.47	-0.53	-0.25	-0.52	-0.29
Long-term_unemp	0.247	-0.72	-0.72	-0.72	-0.61	-0.21	0.1	0.18	0.18	0.01	0.24	0.75	0.66	1.17	1.68	1.48	1.17	0.83	0.32	-0.27	-0.35

Figure 6.24: Standardized values for the Norte Region (PT11) of the indicators with the highest loadings on component B2. The table shows the B2 loading of each indicator and its annual standardized values from 2000 to 2019.

The recessions identified above impacted the Portuguese economy as a whole and were naturally reflected in the regional economies. Figure 6.25 presents the trajectories of the other two Portuguese regions included in this study. Overall, their paths show a similar shape to Norte, indicating that the economic and social evolution of Portuguese regions was influenced by the same national economic shocks. However, the regions differ in their initial positions, in the amplitude of their trajectories and in the timing of their turning points.

In 2000, the three Portuguese regions began their path in the third quadrant, although at clearly different positions. Along the B1 axis, Norte was the region located furthest to the left, followed by Centro, while Área Metropolitana de Lisboa (AML) was closer to the vertical axis. In the following years, Centro remained in the third quadrant for a longer period, whereas AML moved more quickly towards the first quadrant, where it ended the period in 2019. By contrast, Norte and Centro finished the period in the fourth quadrant, although Centro was positioned further away from the horizontal axis than Norte.

These differences indicate that, although Portuguese regions were exposed to common national economic shocks, their trajectories were not identical. AML followed a more favorable path along B1, consistent with its stronger economic profile. Norte and Centro also improved over time, but their trajectories suggest a more irregular adjustment.

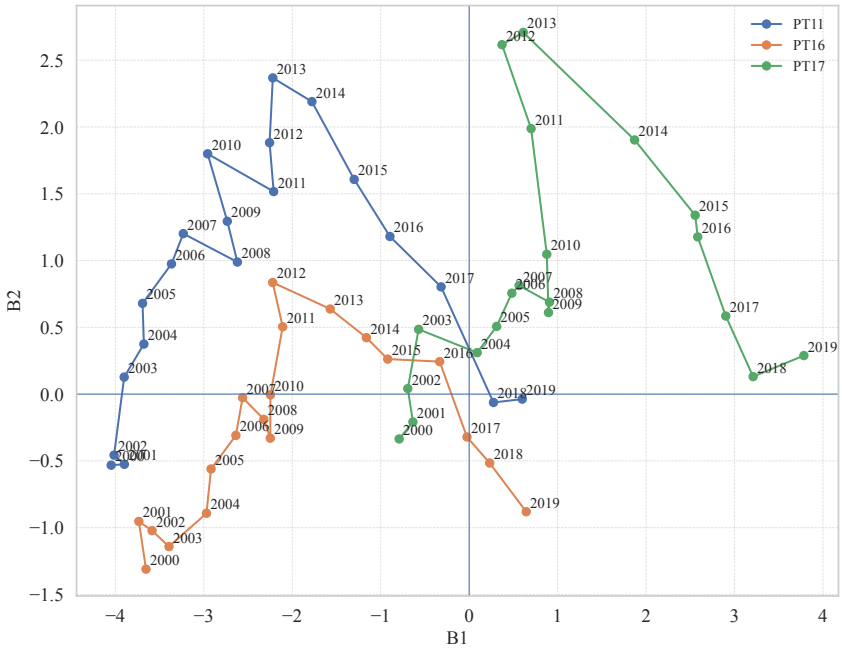


Figure 6.25: Trajectories of the Portuguese NUTS 2 regions PT11 (Norte), PT16 (Centro), and PT17 (Área Metropolitana de Lisboa) in the B1-B2 component space. Each line connects consecutive years over the period under analysis.

Chapter 7

Conclusion

Monitoring regional dynamics from a multidimensional perspective plays a crucial role in providing policymakers and stakeholders with valuable insights to support decision making and steer public policies. In this context, Tucker decomposition has shown to be a useful analytical tool for addressing the research problem. By structuring regional information into a three-mode tensor, this methodology allows the identification of latent patterns and interactions among regions, socioeconomic indicators, and time. It contributes to a deeper understanding of regional development processes and the key factors influencing socioeconomic trends across European Union. Additionally, the detailed examination of individual regional trajectories over time offers further insights into the dynamics of regional transformations. This approach can contribute to a more comprehensive understanding of regional shifts, facilitating more targeted and informed policy interventions.

The analysis of trajectories shows that regional development is highly heterogeneous. The regions did not evolve in the same way over time, nor did they share the same initial position, confirming the existence of differences in their economic and social profiles at the beginning of the period under analysis. At the same time, their relative positions and subsequent evolution suggest that regions with similar structural characteristics tend to follow comparable patterns. This is particularly visible among regions sharing similar institutional or historical contexts, as well as among regions belonging to broader geographical areas with common socioeconomic features. This suggest that, although each region follows its own specific path, regional trajectories are also shaped by common structural conditions.

Finally, the analysis of individual trajectories also shows that the effects of external factors may be asymmetric across regions, as their impact depends on the initial position, structural characteristics and adjustments capacity of each region. This finding reinforces the importance of designing public policies that take regional specificities into account, in order to ensure that policy interventions are effectively adapted to the challenges and strengths of each territory.

Although this study provides relevant insights into regional development dynamics, some limitations should be acknowledged. The selection of indicators was constrained by the availability of consistent and comparable data. The twenty-year period covered by the analysis, together with changes in the NUTS classification over time, limited the inclusion of certain indicators and required careful data harmonisation. As a result, some potentially relevant dimensions of regional development could not be fully represented in the analysis. This was the case, for example, with environmental sustainability, which could not be incorporated due to

the lack of comparable information for all regions and years. Future research could address this limitation by expanding the set of indicators, providing that consistent and comparable data can be collected. This would make it possible to include additional socioeconomic dimensions. In addition, extending the study to other regions outside the European Union would provide a wider comparative perspective on regional development trends.

Despite these limitations, the results of this study are broadly consistent with the main conclusions of existing reports on the performance of European regions. The analysis confirms the persistence of significant territorial disparities across Europe and the existence of different development paths. These findings reinforce the idea that regional development is not a uniform process, but a differentiated one, shaped by economic, social and institutional factors. In this sense, the study highlights the importance of public policies that recognize territorial diversity and are adapted to the specific needs and structural imbalances of each region.

Bibliography

Acar, E., & Yener, B. (2008). Unsupervised multiway data analysis: A literature survey. *IEEE transactions on knowledge and data engineering*, *21*(1), 6–20.

Aguiar-Conraria, L., Bação, P., Correia, I. H., Ferreira, J. A., Reis, R., Valério, N., & Varejão, J. (2023). *Crises na economia portuguesa de 1910 a 2022*.

Bahadori, M. T., Yu, Q. R., & Liu, Y. (2014). Fast multivariate spatio-temporal analysis via low rank tensor learning. *Advances in neural information processing systems*, *27*.

Ballard, G., & Kolda, T. G. (2025). *Tensor decompositions for data science*. Cambridge University Press. Retrieved from https://tensortextbook.com/

Barca, F., McCann, P., & Rodríguez-Pose, A. (2012). The case for regional development intervention: place-based versus place-neutral approaches. *Journal of regional science*, *52*(1), 134–152.

Commission, E. E., et al. (2024). *Regions in the european union. nomenclature of territorial units for statistics*. Publications offices of the European Union Luxembourg.

Correa, F., Oliveira, M. D., Gama, J., Corrêa, P. L. P., & Rady, J. (2016). Analyzing the behavior dynamics of grain price indexes using tucker tensor decomposition and spatio-temporal trajectories. *Computers and Electronics in Agriculture*, *120*, 72–78.

De Dominicis, L., Cabeza Martinez, B., Kovacic, M., & Papadimitriou, E. (2024). *The eu regional social progress index 2.0: 2024 edition* (Report). Luxembourg: Publications Office of the European Union.

De Lathauwer, L., De Moor, B., & Vandewalle, J. (2000). A multilinear singular value decomposition. *SIAM journal on Matrix Analysis and Applications*, *21*(4), 1253–1278.

Dijkstra, L., Papadimitriou, E., Cabeza Martinez, B., De Dominicis, L., & Kovacic, M. (2023). Eu regional competitiveness index 2.0. *European Commission*.

European Commission. (2023, June). *Regional trends for growth and convergence in the european union* (Tech. Rep. No. SWD(2023) 173 final). Brussels: European Commission.

European Commission, Directorate-General for Regional and Urban Policy. (2022). *Eighth report on economic, social and territorial cohesion*. Luxembourg: Publications Office of the European Union.

European Union. (2021, June). *Regulation (eu) 2021/1060 of the european parliament and of the council of 24 june 2021 laying down common provisions on the european regional development fund, the european social fund plus, the cohesion fund, the just transition fund and the european maritime, fisheries and aquaculture fund and financial rules for those and for the asylum, migration and integration fund, the internal security fund and the instrument for financial support for border management and visa policy* (Tech. Rep. No. EU 2021/1060). European Parliament and Council.

European Commission, D.-G. f. R., & Policy, U. (2024). *Ninth report on economic, social and territorial cohesion* (Report). Brussels, Belgium: European Commission.

Gonzalez, K., Gildin, E., & Gibson Jr, R. L. (2021). Improving microseismic denoising using

4d (temporal) tensors and high-order singular value decomposition. In *Spe/aapg/seg unconventional resources technology conference* (p. D011S023R001).

Guarascio, D., Reljic, J., & Stöllinger, R. (2025). Diverging paths: Ai exposure and employment across european regions. *Structural Change and Economic Dynamics*, *73*, 11–24.

Hollanders, H., & Es-Sadki, N. (2023). *Regional innovation scoreboard 2023* (Report). Luxembourg: Publications Office of the European Union.

Jean-Paul, F., Martine, D., et al. (2018). *Beyond gdp measuring what counts for economic and social performance: measuring what counts for economic and social performance*. OECD Publishing.

Kiers, H. A. (2000). Towards a standardized notation and terminology in multiway analysis. *Journal of Chemometrics: A Journal of the Chemometrics Society*, *14*(3), 105–122.

Kolda, T. G., & Bader, B. W. (2009). Tensor decompositions and applications. *SIAM review*, *51*(3), 455–500.

Kolda, T. G., & Sun, J. (2008). Scalable tensor decompositions for multi-aspect data mining. In *2008 eighth ieee international conference on data mining* (pp. 363–372).

Kossaifi, J., Panagakis, Y., Anandkumar, A., & Pantic, M. (2019). Tensorly: Tensor learning in python. *Journal of Machine Learning Research*, *20*(26), 1–6.

Liu, Y., Liu, J., Long, Z., & Zhu, C. (2022). *Tensor computation for data analysis*. Springer.

OECD. (2024). *How's life? 2024: Well-being and resilience in times of crisis*. Paris: OECD Publishing. Retrieved from https://doi.org/10.1787/90ba854a-en doi: 10.1787/90ba854a-en

OECD. (2024). *Oecd regions and cities at a glance 2024* (Report). Paris, France: OECD Publishing.

Oliveira, M., & Gama, J. (2012). A framework to monitor clusters evolution applied to economy and finance problems. *Intelligent Data Analysis*, *16*(1), 93–111.

Oliveira, M., & Gama, J. (2013). Visualization of evolving social networks using actor-level and community-level trajectories. *Expert Systems*, *30*(4), 306–319.

Oliveira, M. D. B., & Gama, J. (2011). *How we got here? a methodology to study the evolution of economies* (Tech. Rep.). Universidade do Porto, Faculdade de Economia do Porto.

Rodríguez-Pose, A., & Crescenzi, R. (2008). Research and development, spillovers, innovation systems, and the genesis of regional growth in europe. *Regional studies*, *42*(1), 51–67.

Sangveraphunsiri, T., Fukushige, T., Jongwiriyanurak, N., Tanaksaranond, G., & Jarumaneeroj, P. (2022). Impacts of the covid-19 pandemic on the spatio-temporal characteristics of a bicycle-sharing system: A case study of pun pun, bangkok, thailand. *PloS one*, *17*(8), e0272537.

Savas, B., & Eldén, L. (2007). Handwritten digit classification using higher order singular value decomposition. *Pattern recognition*, *40*(3), 993–1003.

Siddiqui, Z. F., Oliveira, M., Gama, J., & Spiliopoulou, M. (2012). Where are we going? predicting the evolution of individuals. In *Advances in intelligent data analysis xi: 11th international symposium, ida 2012, helsinki, finland, october 25-27, 2012. proceedings 11* (pp. 357–368).

Symeonidis, P. (2015). Clusthosvd: Item recommendation by combining semantically enhanced tag clustering with tensor hosvd. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *46*(9), 1240–1251.

Tucker, L. R. (1963). Implications of factor analysis of three-way matrices for measurement of change. *Problems in measuring change*, *15*(122-137), 3.

Tucker, L. R. (1966). Some mathematical notes on three-mode factor analysis. *Psychometrika*, *31*(3), 279–311.

Wang, X., Wang, W., Yang, L. T., Liao, S., Yin, D., & Deen, M. J. (2018). A distributed hosvd

method with its incremental computation for big data in cyber-physical-social systems. *IEEE Transactions on Computational Social Systems*, *5*(2), 481–492.

Xu, Y., Wu, Z., Chanussot, J., & Wei, Z. (2020). Hyperspectral computational imaging via collaborative tucker3 tensor decomposition. *IEEE Transactions on Circuits and Systems for Video Technology*, *31*(1), 98–111.

Appendix A

Regional Competitiveness Index 2.0, 2022 edition: List of indicators

Sub-indices	Pillar name	Indicator name
Basic	**Institutions**	Corruption
		Quality and accountability
		Impartiality
		Individuals who used the internet for interaction with public authorities
		Presence of corruption in the national public institutions in the country
		Presence of corruption in the local or regional public institutions in the country
		Ease of doing business
		Property rights
		Intellectual property protection
		Efficiency of legal framework in settling disputes
		Efficiency of legal framework in challenging regulations
		Organised crime
		Reliability of police services
		Judicial independence
	Macroeconomic stability	General government deficit/surplus
		National savings
		Government bond yields
		Government debt
		Net international investment position
	Infrastructure	Road transport performance
		Rail transport performance
		Accessibility to passenger flights
	Health	Road fatalities
		Healthy life expectancy
		Infant mortality
		Cancer disease death rate
		Heart disease death rate
		Suicide death rate
	Basic education	Low achievement in reading (15-year-olds)
		Low achievement in maths (15-year-olds)
		Low achievement in science (15-year-olds)
Efficiency	**Higher education and lifelong learning**	Higher educational attainment
		Lifelong learning
		Early school leavers
		University accessibility
		Lower-secondary completion only
	Labour market efficiency	Employment rate (excluding agriculture)
		Long-term unemployment
		Unemployment rate
		Labour productivity
		Gender balance unemployment
		Gender balance employment
		NEET
		Labour market slack
		Temporary employment
	Market size	Disposable income per capita
		Potential market size expressed in GDP
		Potential market size expressed in population
Innovation	**Technological readiness**	Households with broadband access
		Individuals buying over internet the last year
		Access to high-speed broadband
		Individuals with above-basic overall digital skills
		Enterprises having received orders online (at least 1 %)
		Enterprises with fixed broadband access.
	Business sophistication	Employment (K-N sectors)
		Gross value added (GVA) (K-N sectors)
		Innovative SMEs collaborating with others
		Marketing or organisational innovators
	Innovation	Total patent applications
		Core creative class employment
		Knowledge workers
		Scientific publications
		Total intramural research and development expenditure
		Human Resources in Science and Technology
		Employment in technology and knowledge-intensive sectors
		Trademark applications
		Design applications
		Sales of new-to-market and new-to-firms innovation

Appendix B

Regional Innovation Scoreboard, 2023 edition: List of indicators

Activities	Dimension	Indicator name
Framework Conditions	**Human Resources**	Population with tertiary education
		Population involved in lifelong learning
	Attractive research systems	International scientific co-publications
		Scientific publications among the top 10% most cited
	Digitalisation	Individuals with above basic overall digital skills
Investments	**Finance and support**	R&D expenditure in the public sector
	Firm investments	R&D expenditure in the business sector
		Non-R&D innovation expenditures
		Innovation expenditures per person employed
	Use of information technologies	Employed ICT specialists
Innovation activities	**Innovators**	SMEs introducing product innovations
		SMEs introducing business process innovations
	Linkages	Innovative SMEs collaborating with others
		Public-private co-publications
	Intellectual assets	PCT patent applications
		Trademark applications
		Design applications
Impacts	**Employment impacts**	Employment in knowledge-intensive activities
		Employment in innovative enterprises
	Sales impacts	Sales of new-to-market and new-to-firm innovations
	Environmental sustainability	Air emissions by fine particulates

Appendix C

European Regional Social Progress Index 2.0, 2024 edition: List of indicators

Dimensions	Components	Indicator name
Basic needs	**Nutrition and medical care**	Infant mortality
		Unmet dental needs
		Unmet medical needs
		Insufficient food
	Water and Sanitation	Satisfaction with water quality
		Lack of toilet in dwelling
		Uncollected sewage
		Sewage treatment
	Housing	Burdensome cost of housing
		Housing quality - dampness
		Overcrowding
		Lack of adequate heating
	Safety	Traffic deaths
		Safety at night
		Money stolen
		Assaulted/Mugged
Foundations of wellbeing	**Basic education**	Share of low-achieving 15-year-old in reading (level 1a or lower)
		Share of low-achieving 15-year-old in maths (level 2 or lower)
		Lower-secondary completion only
		Early school leavers
	Information and communications	High-speed broadband
		Digital skills above the basic level
		Online interaction with public authorities
		Freedom of media
		Internet access
	Health	Years of life lost caused by PM2.5, NO_2 and ozone (SOMO35)
		Subjective health status
		Standardised cancer death rate
		Standardised heart disease death rate
		Positive feelings
	Environmental quality	NO_2 air pollution
		Ozone (SOMO35) air pollution
		PM2.5 air pollution
		Bathing water quality
Opportunity	**Trust and governance**	Trust in the national government
		Trust in the judicial system
		Trust in the police
		Voiced your opinion to a public official
		Female participation in regional assemblies
		Institution quality index
	Freedom and choice	Freedom over life choices
		Job opportunities
		Teenage pregnancy
		Young people not in education, employment or training (NEET)
		Institutions corruption index
	Inclusive society	Institution impartiality index
		Tolerance towards immigrants
		Tolerance towards minorities
		Tolerance towards gay/ lesbian
		Women treated with respect
	Advanced education	Tertiary education attainment
		Lifelong learning
		Citations

Appendix D

Regional coverage of the study (based on the NUTS 2016 classification)

Country	NUTS2 Regions included		NUTS2 Regions not included	
AT (Austria)	AT12 (Niederösterreich) AT22 (Steiermark)	AT13 (Wien) AT31 (Oberösterreich)	AT11 (Burgenland) AT32 (Salzburg) AT34 (Vorarlberg)	AT21 (Kärnten) AT33 (Tirol)
BE (Belgium)	BE21 (Prov. Antwerpen) BE23 (Prov. Oost-Vlaanderen) BE25 (Prov. West-Vlaanderen) BE33 (Prov. Liège)	BE22 (Prov. Limburg (BE)) BE24 (Prov. Vlaams-Brabant) BE32 (Prov. Hainaut) BE35 (Prov. Namur)	BE10 (Région de Bruxelles-Capitale/Brussels Hoofdstedelijk Gewest) BE31 (Prov. Brabant wallon)	 BE34 (Prov. Luxembourg (BE))
BG (Bulgaria)	BG32 (Severen tsentralen) BG34 (Yugoiztochen) BG42 (Yuzhen tsentralen)	BG33 (Severoiztochen) BG41 (Yugozapaden)	BG31 (Severozapaden)	
CY (Cyprus)	CY00 (Kýpros)			
CZ (Czechia)	CZ01 (Praha) CZ03 (Jihozápad) CZ05 (Severovýchod) CZ07 (Střední Morava)	CZ02 (Střední Čechy) CZ04 (Severozápad) CZ06 (Jihovýchod) CZ08 (Moravskoslezsko)		
DE (Germany)	DE11 (Stuttgart) DE13 (Freiburg) DE21 (Oberbayern) DE27 (Schwaben) DE71 (Darmstadt) DE80 (Mecklenburg-Vorpommern) DE92 (Hannover) DE94 (Weser-Ems) DEA2 (Köln) DEA4 (Detmold) DEB1 (Koblenz) DED2 (Dresden) DEF0 (Schleswig-Holstein)	DE12 (Karlsruhe) DE14 (Tübingen) DE25 (Mittelfranken) DE40 (Brandenburg) DE72 (Gießen) DE91 (Braunschweig) DE93 (Lüneburg) DEA1 (Düsseldorf) DEA3 (Münster) DEA5 (Arnsberg) DEB3 (Rheinhessen-Pfalz) DEE0 (Sachsen-Anhalt) DEG0 (Thüringen)	DE22 (Niederbayern) DE24 (Oberfranken) DE30 (Berlin) DE60 (Hamburg) DEB2 (Trier) DED4 (Chemnitz)	DE23 (Oberpfalz) DE26 (Unterfranken) DE50 (Bremen) DE73 (Kassel) DEC0 (Saarland) DED5 (Leipzig)
DK (Denmark)			DK01 (Hovedstaden) DK03 (Syddanmark) DK05 (Nordjylland)	DK02 (Sjælland) DK04 (Midtjylland)
EE (Estonia)	EE00 (Eesti)			
EL (Greece)	EL30 (Attiki) EL51 (Anatoliki Makedonia, Thraki) EL52 (Kentriki Makedonia) EL63 (Dytiki Elláda) EL65 (Peloponnisos)	EL43 (Kriti) EL61 (Thessalia) EL64 (Sterea Elláda)	EL41 (Voreio Aigaio) EL53 (Dytiki Makedonia) EL62 (Ionia Nisia)	EL42 (Notio Aigaio) EL54 (Ipeiros)
ES (Spain)	ES11 (Galicia) ES13 (Cantabria) ES22 (Comunidad Foral de Navarra) ES23 (La Rioja) ES30 (Comunidad de Madrid) ES42 (Castilla-La Mancha) ES51 (Cataluña) ES53 (Illes Balears) ES62 (Región de Murcia)	ES12 (Principado de Asturias) ES21 (País Vasco) ES24 (Aragón) ES41 (Castilla y León) ES43 (Extremadura) ES52 (Comunitat Valenciana) ES61 (Andalucía) ES70 (Canarias)	ES63 (Ciudad de Ceuta)	ES64 (Ciudad de Melilla)
FI (Finland)	FI19 (Länsi-Suomi)		FI1B (Helsinki-Uusimaa) FI1D (Pohjois- ja Itä-Suomi)	FI1C (Etelä-Suomi) FI20 (Åland)
FR (France)	FR10 (Ile de France) FRC1 (Bourgogne) FRD2 (Haute-Normandie) FRE2 (Picardie) FRF2 (Champagne-Ardenne) FRG0 (Pays de la Loire) FRI1 (Aquitaine) FRJ1 (Languedoc-Roussillon) FRK1 (Auvergne) FRL0 (Provence-Alpes-Côte d'Azur)	FRB0 (Centre — Val de Loire) FRC2 (Franche-Comté) FRE1 (Nord-Pas de Calais) FRF1 (Alsace) FRF3 (Lorraine) FRH0 (Bretagne) FRI3 (Poitou-Charentes) FRJ2 (Midi-Pyrénées) FRK2 (Rhône-Alpes)	FRD1 (Basse-Normandie) FRM0 (Corse) FRY2 (Martinique) FRY4 (La Réunion)	FRI2 (Limousin) FRY1 (Guadeloupe) FRY3 (Guyane) FRY5 (Mayotte)
HR (Croatia)			HR03 (Jadranska Hrvatska)	HR04 (Kontinentalna Hrvatska)
HU (Hungary)	HU21 (Közép-Dunántúl) HU23 (Dél-Dunántúl) HU32 (Észak-Alföld)	HU22 (Nyugat-Dunántúl) HU31 (Észak-Magyarország) HU33 (Dél-Alföld)	HU11 (Budapest)	HU12 (Pest)
IE (Ireland)			IE04 (Northern and Western) IE06 (Eastern and Midland)	IE05 (Southern)
IT (Italy)	ITC1 (Piemonte) ITC4 (Lombardia) ITF3 (Campania) ITF5 (Basilicata) ITG1 (Sicilia) ITH3 (Veneto) ITI1 (Toscana) ITI4 (Lazio)	ITC3 (Liguria) ITF1 (Abruzzo) ITF4 (Puglia) ITF6 (Calabria) ITG2 (Sardegna) ITH4 (Friuli-Venezia Giulia) ITI2 (Umbria)	ITC2 (Valle d'Aosta/Vallée d'Aoste) ITF2 (Molise) ITH1 (Provincia Autonoma di Bolzano/Bozen) ITH2 (Provincia Autonoma di Trento) ITH5 (Emilia-Romagna)	ITI3 (Marche)

Country	NUTS2 Regions included		NUTS2 Regions not included	
LT (Lithuania)			LT01 (Sostinės regionas) LT02 (Vidurio ir vakarų Lietuvos regionas)	
LU (Luxembourg)	LU00 (Luxembourg)			
LV (Latvia)	LV00 (Latvija)			
MT (Malta)	MT00 (Malta)			
NL (Netherlands)	NL11 (Groningen) NL13 (Drenthe) NL22 (Gelderland) NL32 (Noord-Holland) NL41 (Noord-Brabant)	NL12 (Friesland (NL)) NL21 (Overijssel) NL23 (Flevoland) NL34 (Zeeland) NL42 (Limburg (NL))	NL31 (Utrecht (NUTS 2021)) NL33 (Zuid-Holland (NUTS 2021))	
PL (Poland)	PL21 (Małopolskie) PL41 (Wielkopolskie) PL51 (Dolnośląskie) PL62 (Warmińsko-mazurskie)	PL22 (Śląskie) PL42 (Zachodniopomorskie) PL61 (Kujawsko-pomorskie) PL63 (Pomorskie)	PL43 (Lubuskie) PL71 (Łódzkie) PL81 (Lubelskie) PL84 (Podlaskie) PL92 (Mazowiecki regionalny)	PL52 (Opolskie) PL72 (Świętokrzyskie) PL82 (Podkarpackie) PL91 (Warszawski stołeczny)
PT (Portugal)	PT11 (Norte) PT17 (Área Metropolitana de Lisboa (NUTS 2021))	PT16 (Centro (PT) (NUTS 2021))	PT15 (Algarve) PT20 (Região Autónoma dos Açores) PT30 (Região Autónoma da Madeira)	PT18 (Alentejo (NUTS 2021))
RO (Romania)	RO11 (Nord-Vest) RO21 (Nord-Est) RO31 (Sud-Muntenia) RO41 (Sud-Vest Oltenia)	RO12 (Centru) RO22 (Sud-Est) RO32 (Bucureşti-Ilfov) RO42 (Vest)		
SE (Sweden)	SE11 (Stockholm) SE21 (Småland med öarna) SE23 (Västsverige)	SE12 (Östra Mellansverige) SE22 (Sydsverige) SE31 (Norra Mellansverige)	SE32 (Mellersta Norrland)	SE33 (Övre Norrland)
SI (Slovenia)			SI03 (Vzhodna Slovenija)	SI04 (Zahodna Slovenija)
SK (Slovakia)	SK02 (Západné Slovensko) SK04 (Východné Slovensko)	SK03 (Stredné Slovensko)	SK01 (Bratislavský kraj)	

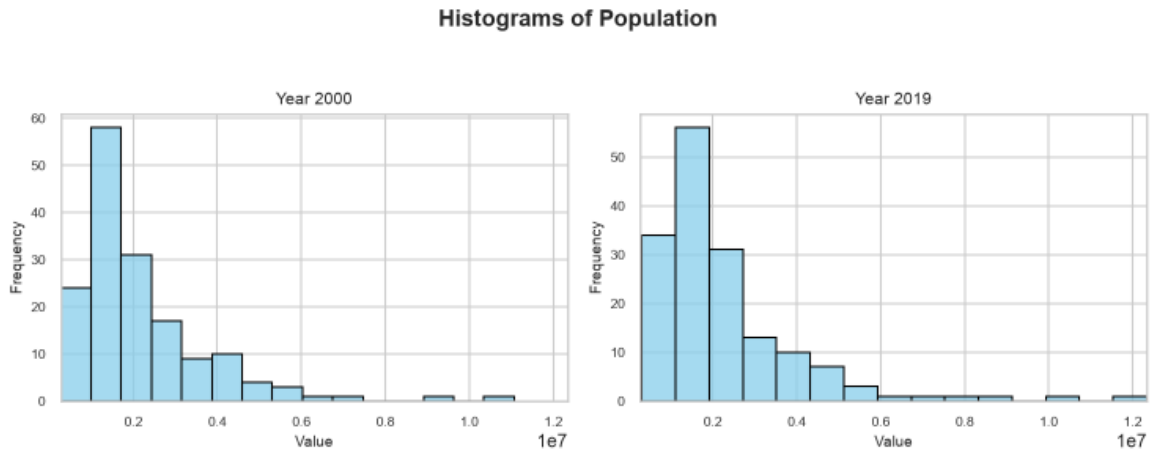
Appendix E

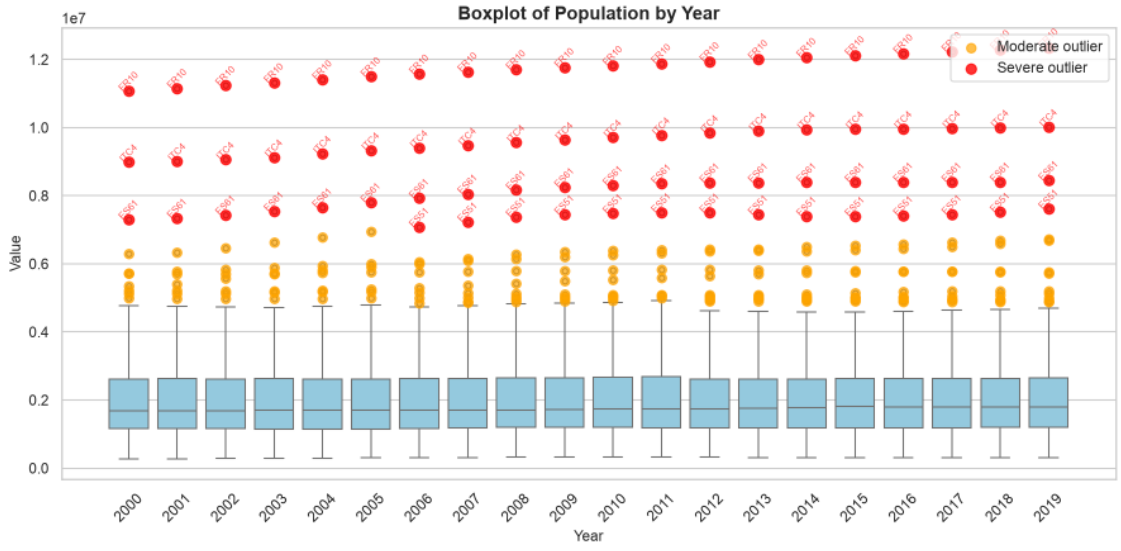
Descriptive statistics of the selected indicators

Indicator name	Population
Reference	Cohesion Policy 2021-2027

Description	Average annual population used to calculate regional GDP data (thousand persons). The population figure is averaged over a year, not just a single point in time, to create a more stable and representative metric that accounts for population changes throughout the year.
Unit of measure	Number
Data source	Eurostat: Average annual population to calculate regional GDP data (thousand persons) by NUTS 3 regions.
Data availability (2000-2019)	100.00 %
Missing data (2000-2019)	0 regions with at least one year missing

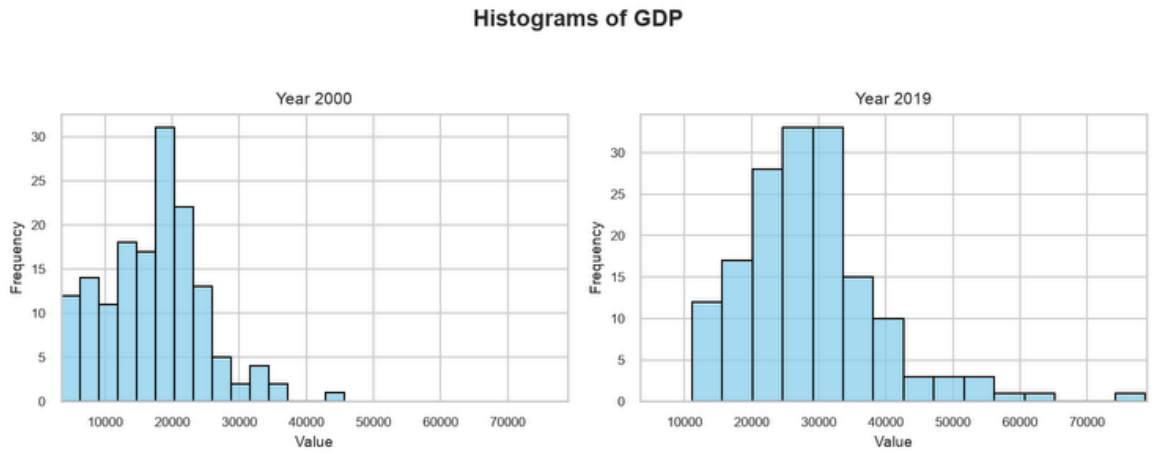
Descriptive statistics	N(valid)	N(missing)	%(missing)	Min.	Max.	Mean	Median	Std.Dev	CV	Skewness	Kurtosis
2000	160	0	0	274500	11066900	2155449	1689095	1594887	0,74	2,24	7,62
2019	160	0	0	314400	12336340	2256346	1800265	1774078	0,79	2,5	8,83

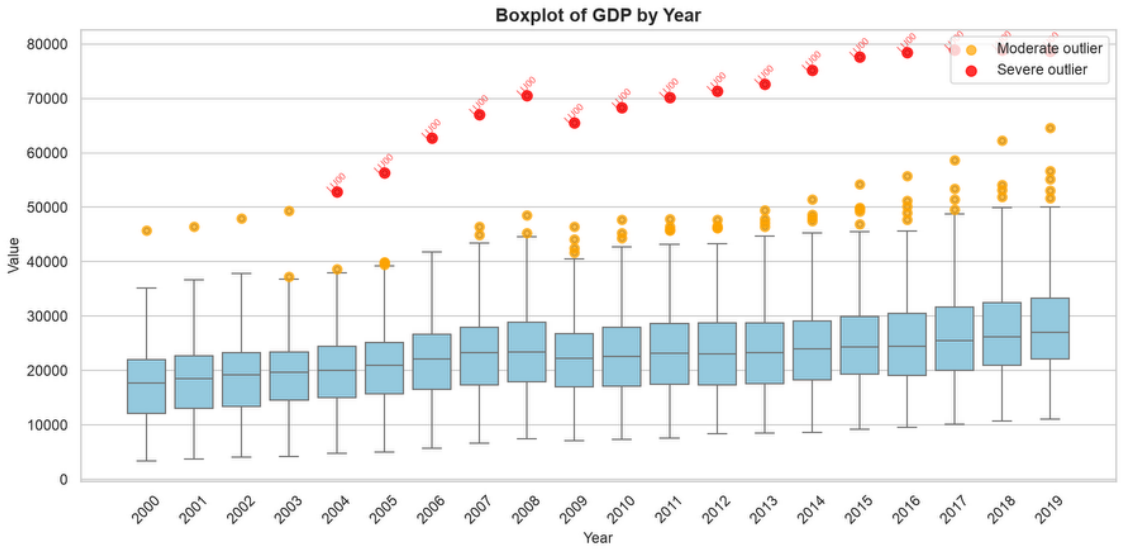




Indicator name	GDP
Reference	Cohesion Policy 2021-2027
Description	Gross domestic product (GDP) at current market prices, in purchasing power standard (PPS, EU27 from 2020), per inhabitant.
Unit of measure	Purchasing power standard (PPS, EU27 from 2020), per inhabitant
Data source	Eurostat: Gross domestic product (GDP) at current market prices by NUTS 2 region.
Data availability (2000-2019)	99.25 %
Missing data (2000-2019)	8 regions with at least one year missing

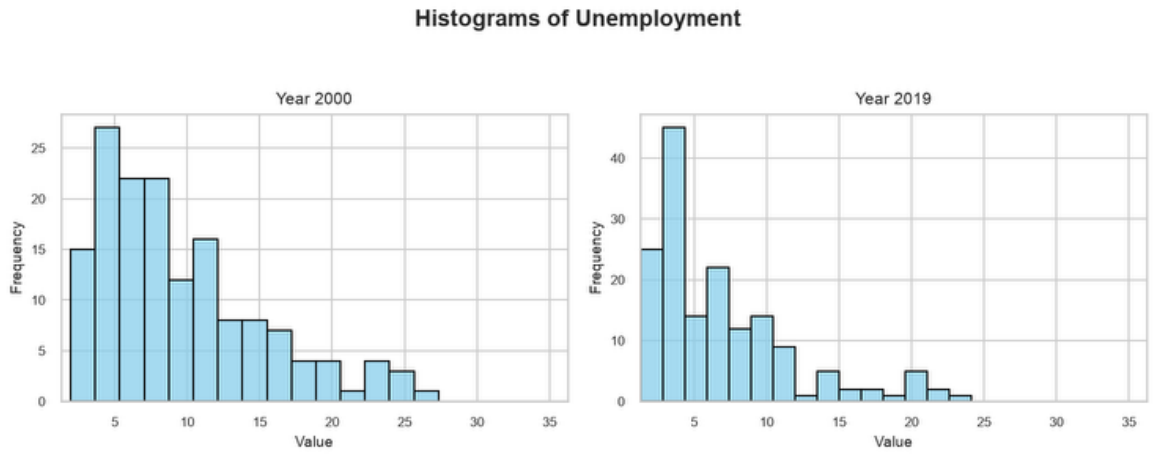
Descriptive statistics	N(valid)	N(missing)	%(missing)	Min.	Max.	Mean	Median	Std.Dev	CV	Skewness	Kurtosis
2000	152	8	5	3400	45700	17238,16	17700	7569,1	0,44	0,4	0,63
2019	160	0	0	11100	78700	28726,25	27050	10288,79	0,36	1,33	3,65

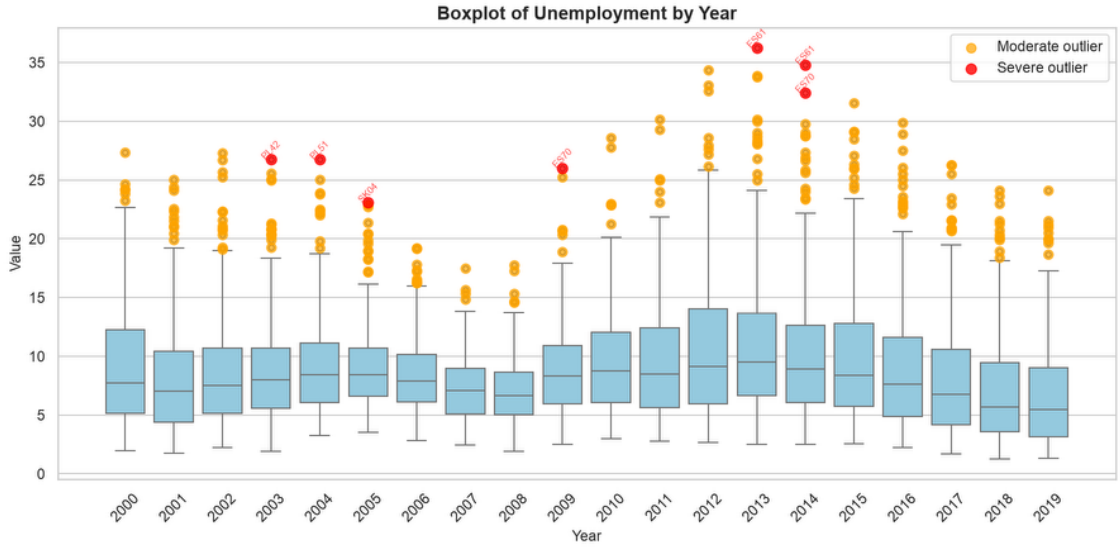




Indicator name	Unemployment
Reference	Cohesion Policy 2021-2027 RCI 2.0, 2022
Description	Share of unemployed persons aged 15–74 as a percentage of the labour force (given by the total number of people employed and unemployed).
Unit of measure	Percentage of active population
Data source	Eurostat: Unemployment by sex, age, educational attainment level and NUTS 2 region (1 000); Economically active population by sex, age and NUTS 2 region (1 000).
Data availability (2000-2019)	99.47 %
Missing data (2000-2019)	7 regions with at least one year missing

Descriptive statistics	N(valid)	N(missing)	%(missing)	Min.	Max.	Mean	Median	Std.Dev	CV	Skewness	Kurtosis
2000	154	6	3,75	1,95	27,35	9,52	7,74	5,66	0,6	1,04	0,51
2019	160	0	0	1,31	24,14	6,83	5,45	4,97	0,73	1,44	1,67

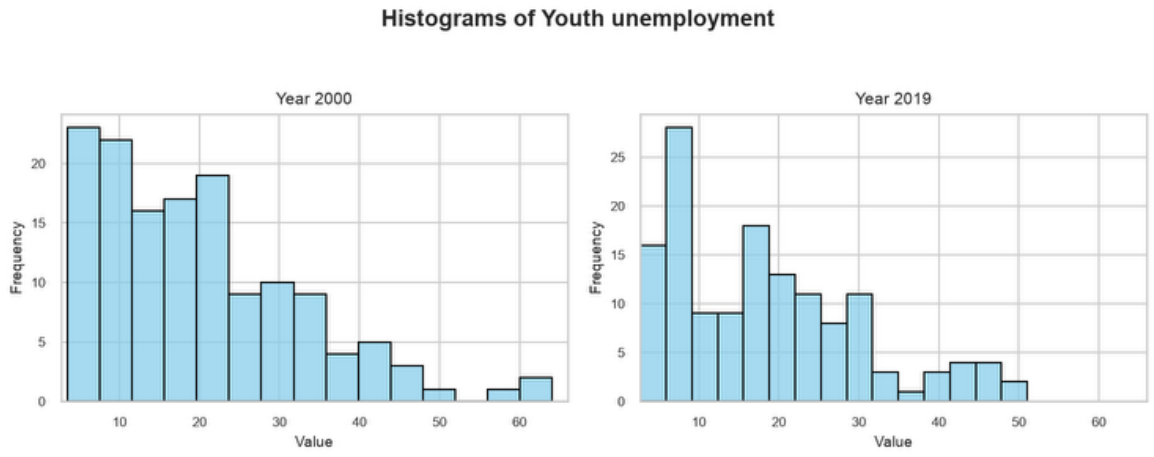


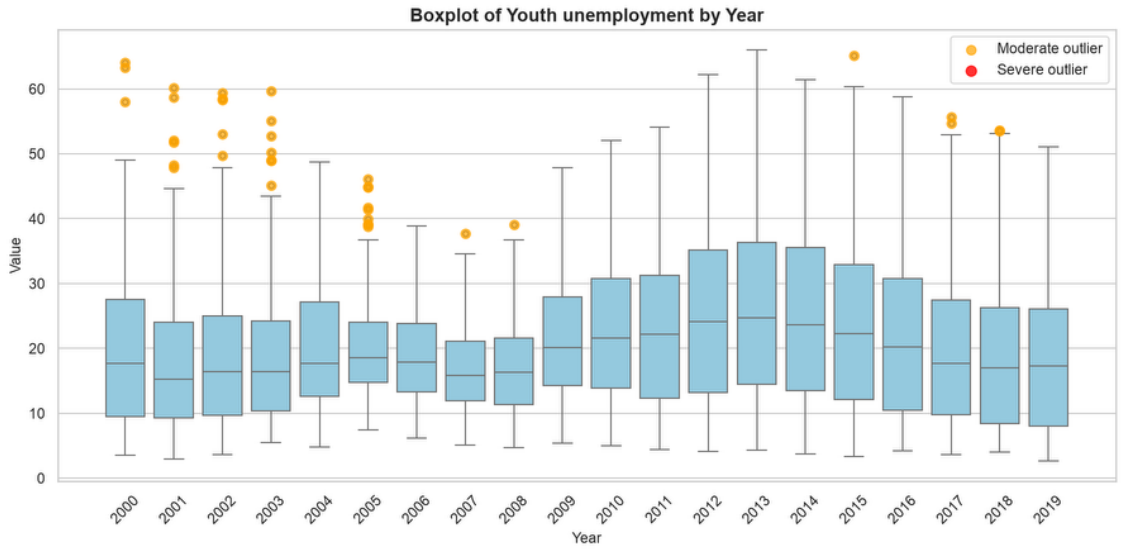


Indicator name	Youth unemployment
Reference	Cohesion Policy 2021-2027

Description	Share of young persons unemployed as a percentage of the economically active population (age group 15-24).
Unit of measure	Percentage
Data source	Eurostat: Unemployment by sex, age, educational attainment level and NUTS 2 region (1 000); Economically active population by sex, age and NUTS 2 region (1 000).
Data availability (2000-2019)	95.59 %
Missing data (2000-2019)	54 regions with at least one year missing

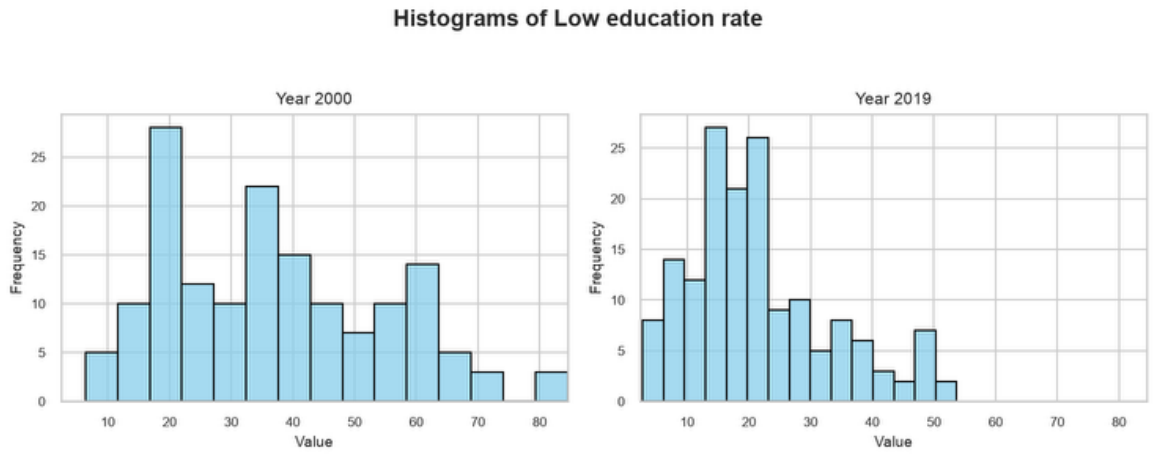
Descriptive statistics	N(valid)	N(missing)	%(missing)	Min.	Max.	Mean	Median	Std.Dev	CV	Skewness	Kurtosis
2000	141	19	11,88	3,5	64,09	20,03	17,67	12,71	0,63	1,07	1,09
2019	140	20	12,5	2,68	51,07	18,56	17,32	11,84	0,64	0,81	-0,01

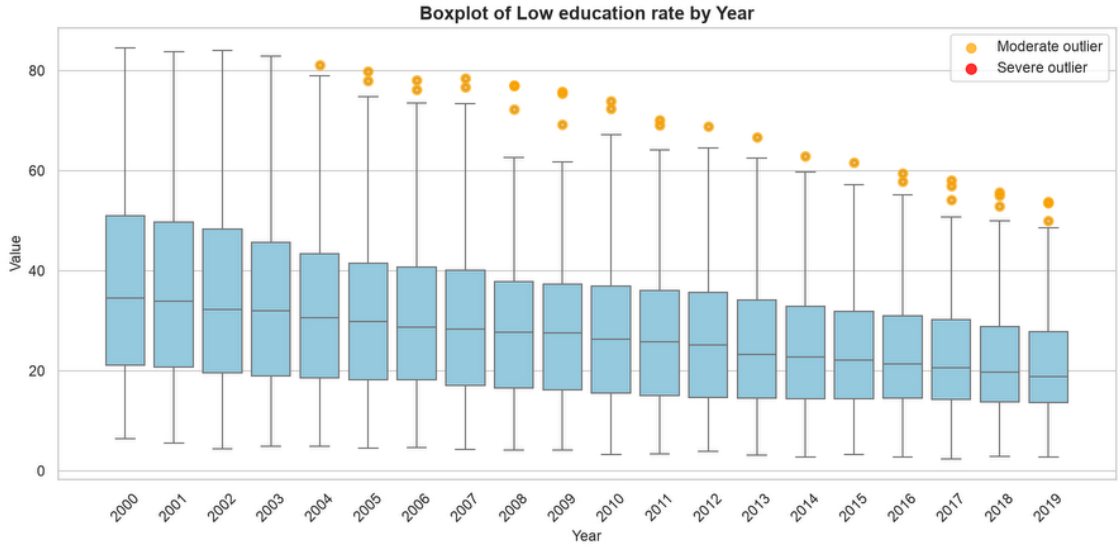




Indicator name	Low education rate
Reference	Cohesion Policy 2021-2027 RCI 2.0, 2022
Description	Percentage of population aged 25-64 with low education (less than primary, primary and lower secondary education)
Unit of measure	Percentage
Data source	Eurostat: Population by educational attainment level, sex and NUTS 2 region (%).
Data availability (2000-2019)	99.50 %
Missing data (2000-2019)	6 regions with at least one year missing

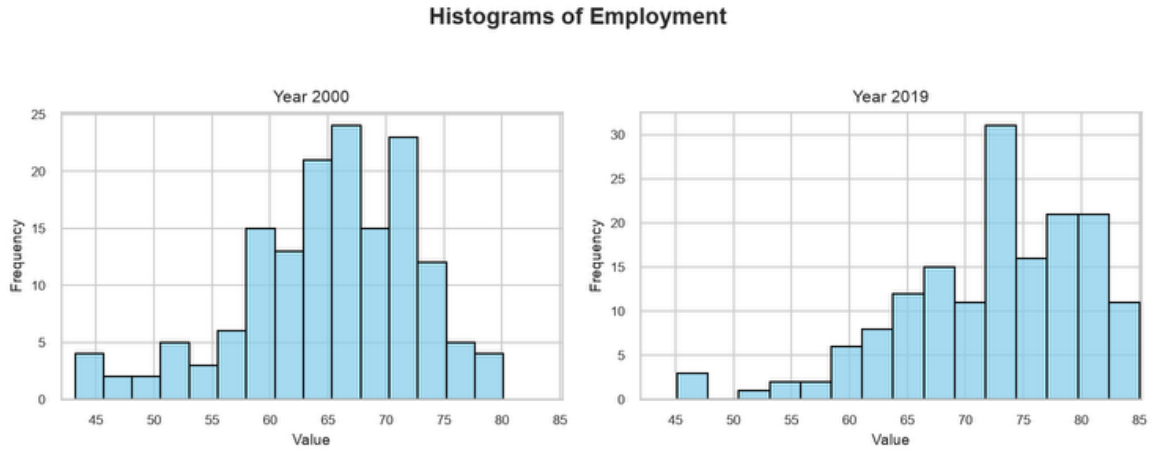
Descriptive statistics	N(valid)	N(missing)	%(missing)	Min.	Max.	Mean	Median	Std.Dev	CV	Skewness	Kurtosis
2000	154	6	3,75	6,4	84,5	36,92	34,55	17,89	0,48	0,49	-0,55
2019	160	0	0	2,8	53,7	21,52	18,8	11,69	0,54	0,86	0,14

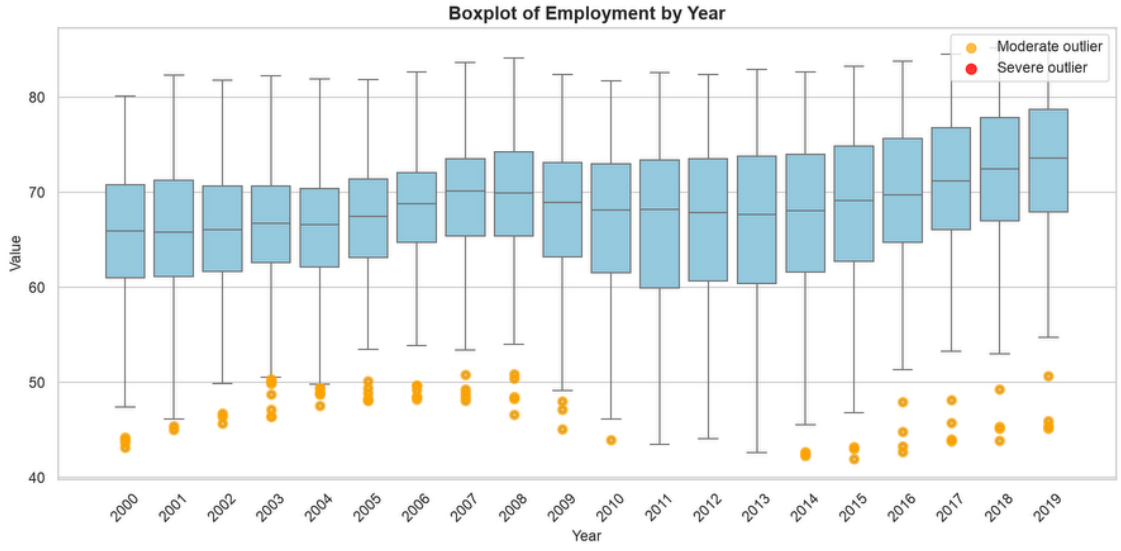




Indicator name	Employment
Reference	Cohesion Policy 2021-2027
Description	Percentage of people aged 20–64 that are currently employed.
Unit of measure	Percentage
Data source	Eurostat: Employment by sex, age and NUTS 2 regions (1 000); Population on 1 January by age group, sex and NUTS 2 region
Data availability (2000-2019)	99.50 %
Missing data (2000-2019)	6 regions with at least one year missing

Descriptive statistics	N(valid)	N(missing)	%(missing)	Min.	Max.	Mean	Median	Std.Dev	CV	Skewness	Kurtosis
2000	154	6	3,75	43,18	80,14	65,12	65,96	7,64	0,12	-0,69	0,44
2019	160	0	0	45,16	85,02	72,42	73,63	8,02	0,11	-0,99	1,16

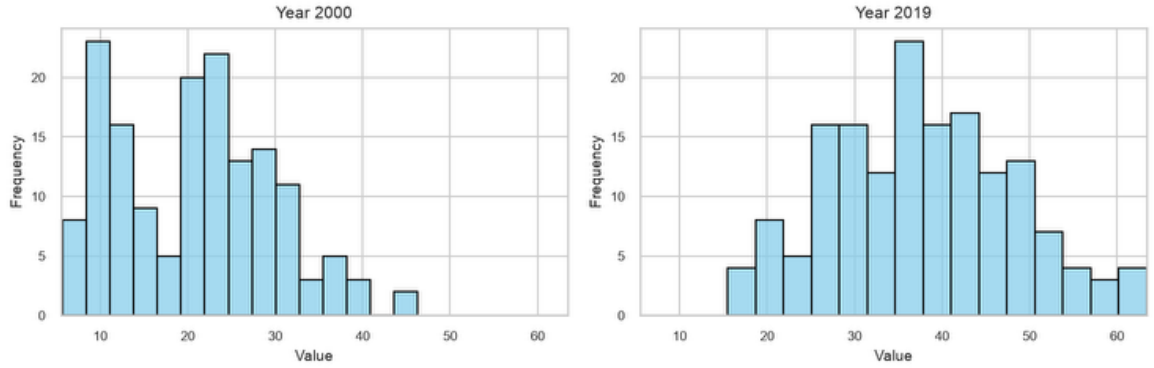




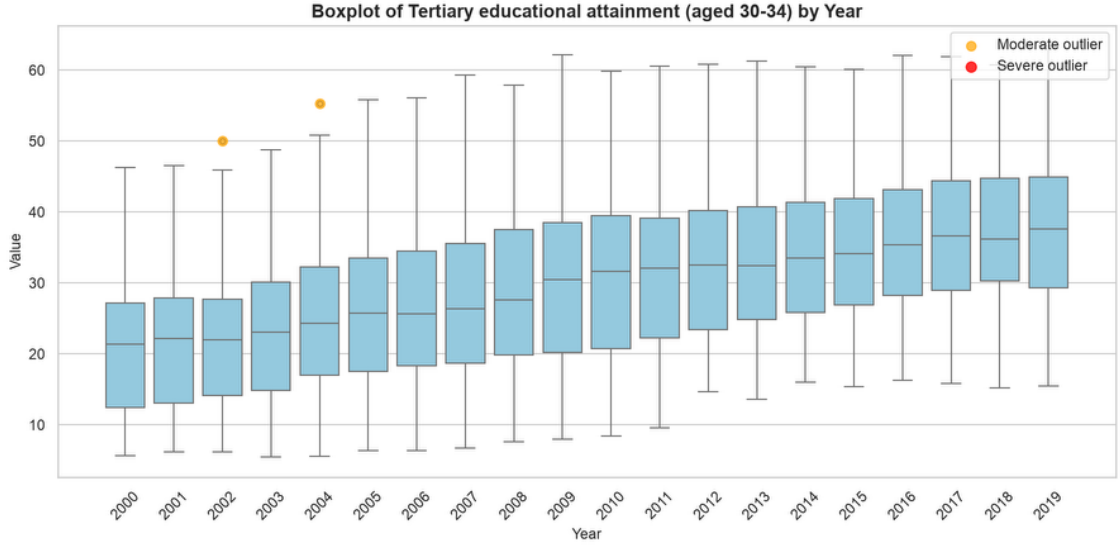
Indicator name	Tertiary educational attainment (aged 30-34)
Reference	Cohesion Policy 2021-2027 RCI 2.0, 2022 (1) RIS, 2023 (1)
Description	Percentage of population aged 30-34 with tertiary education (ISCED 5-8) attainment. ((1) In these documents the age group is 25–34)
Unit of measure	Percentage
Data source	Eurostat: Population by educational attainment level, sex and NUTS 2 regions (%).
Data availability (2000-2019)	99.50 %
Missing data (2000-2019)	6 regions with at least one year missing

Descriptive statistics	N(valid)	N(missing)	%(missing)	Min.	Max.	Mean	Median	Std.Dev	CV	Skewness	Kurtosis
2000	154	6	3,75	5,7	46,3	20,97	21,4	9,07	0,43	0,32	-0,51
2019	160	0	0	15,5	63,4	37,83	37,6	10,61	0,28	0,16	-0,46

Histograms of Tertiary educational attainment (aged 30-34)

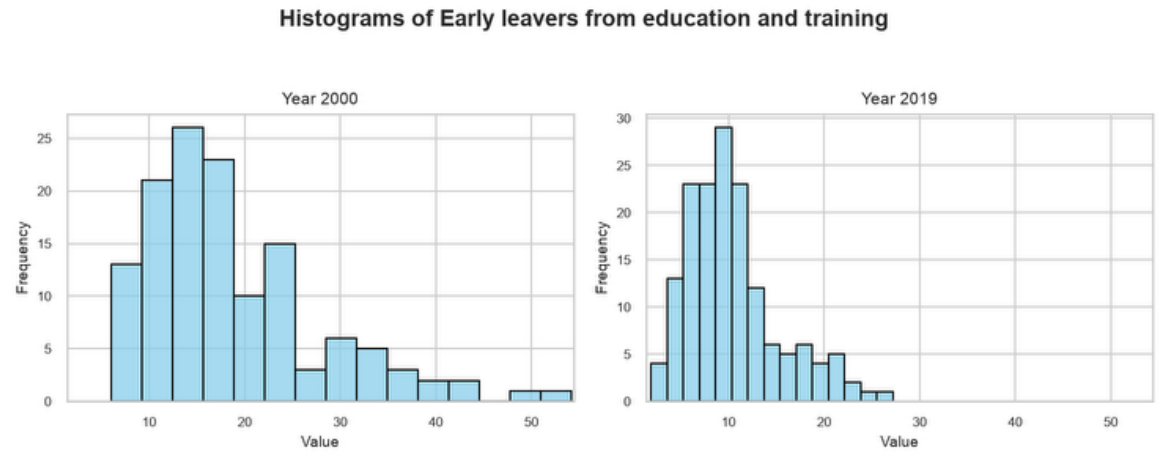


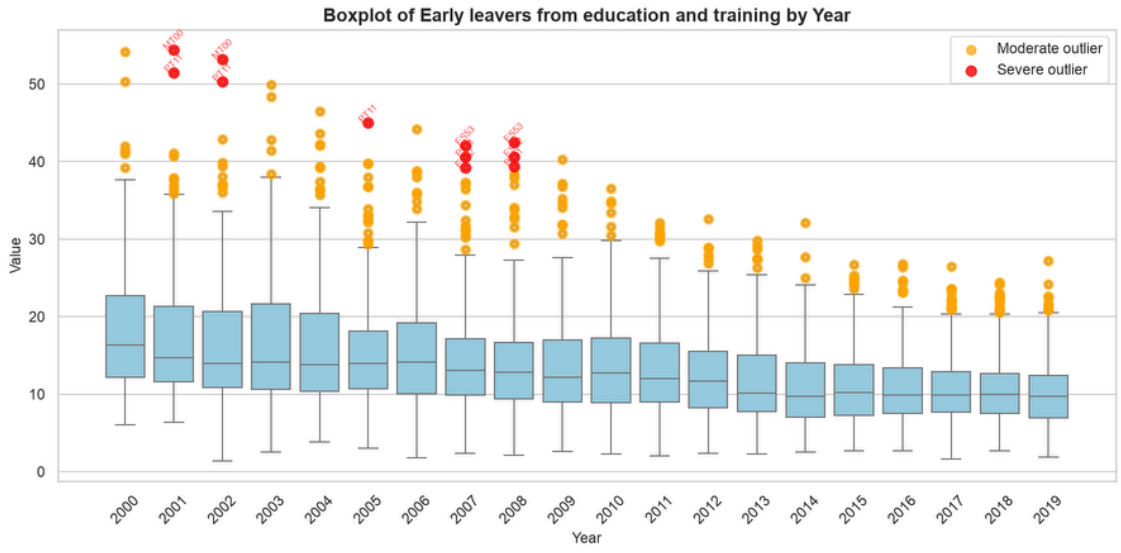
Boxplot of Tertiary educational attainment (aged 30-34) by Year



Indicator name	Early leavers from education and training
Reference	Cohesion Policy 2021-2027 RCI 2.0, 2022
Description	Percentage of the population aged 18-24 having attained at most lower secondary education and not being involved in further education or training.
Unit of measure	Percentage
Data source	Eurostat: Early leavers from education and training by sex and NUTS 2 regions.
Data availability (2000-2019)	98.03 %
Missing data (2000-2019)	33 regions with at least one year missing

Descriptive statistics	N(valid)	N(missing)	%(missing)	Min.	Max.	Mean	Median	Std.Dev	CV	Skewness	Kurtosis
2000	131	29	18,12	6	54,2	18,76	16,3	9,14	0,49	1,35	2,05
2019	157	3	1,88	1,9	27,2	10,42	9,7	4,79	0,46	1,02	0,93





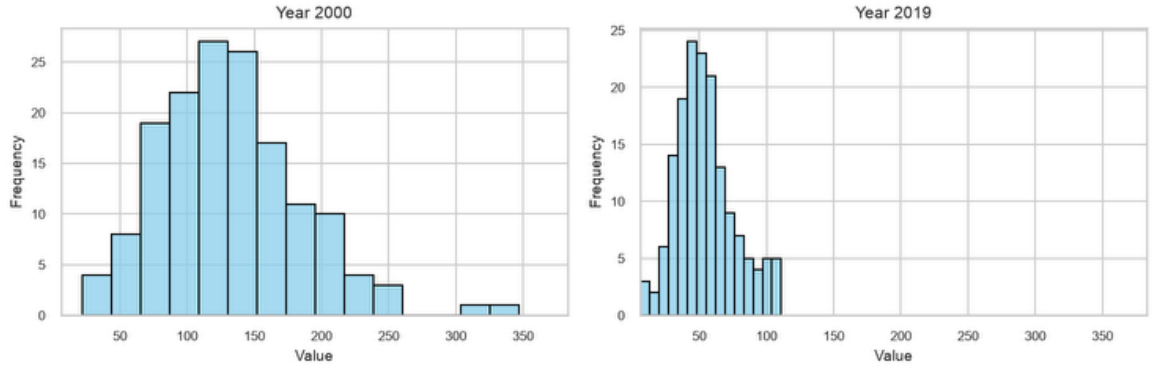
Indicator name	Road fatalities
Reference	RCI 2.0, 2022

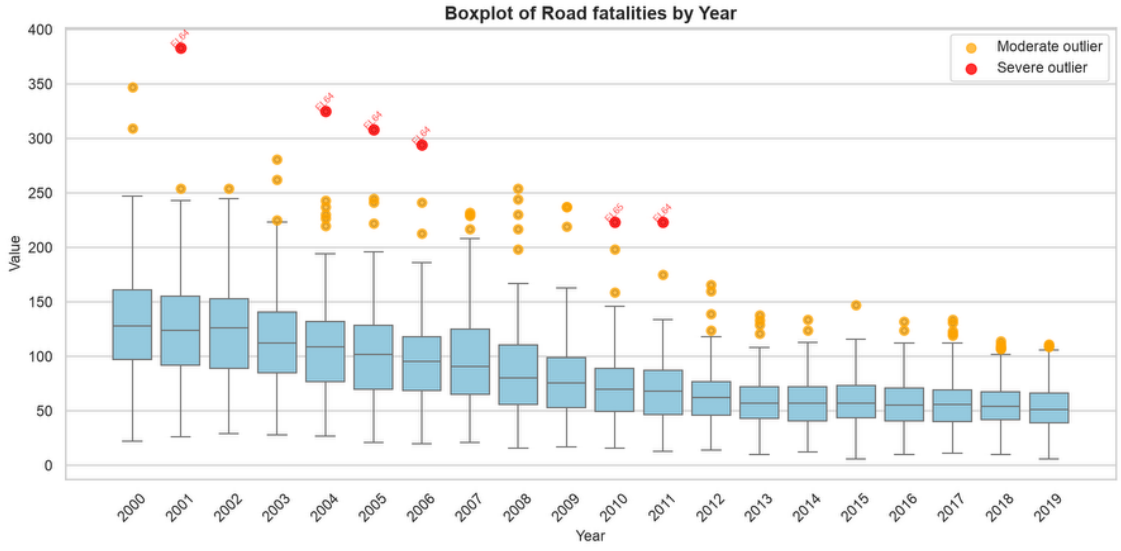
Description	Number of deaths in road accidents per million inhabitants.
Unit of measure	Per million inhabitants
Data source	Eurostat: Victims in road accidents by NUTS 2 region.

Data availability (2000-2019)	99.19 %		Missing data (2000-2019)	7 regions with at least one year missing	

Descriptive statistics	N(valid)	N(missing)	%(missing)	Min.	Max.	Mean	Median	Std.Dev	CV	Skewness	Kurtosis
2000	153	7	4,38	22	347	132,69	128	52,77	0,4	0,83	1,46
2019	160	0	0	6	111	54,21	51,5	21,78	0,4	0,58	0,14

Histograms of Road fatalities



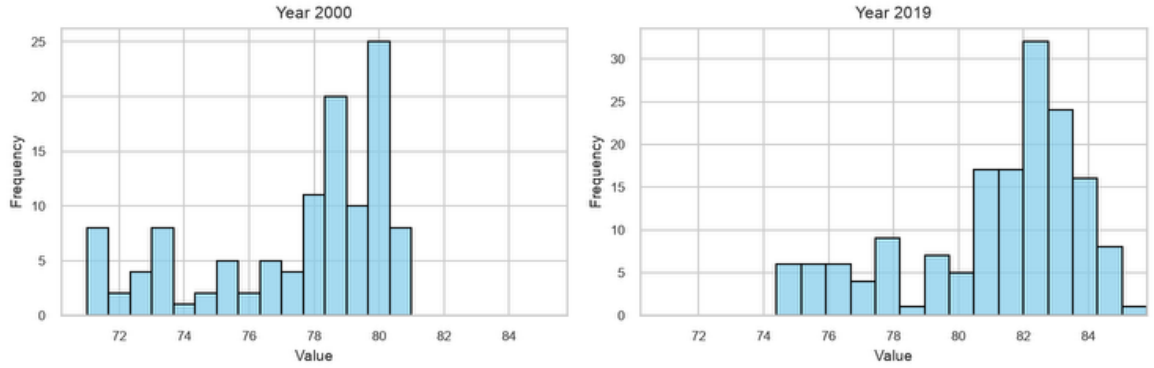


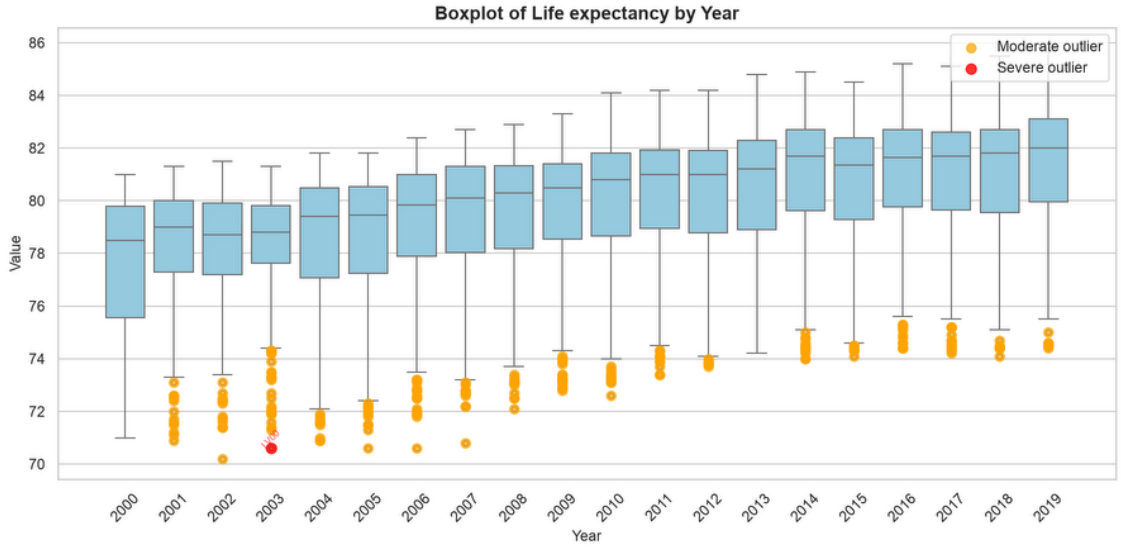
Indicator name	Life expectancy
Reference	RCI 2.0, 2022

Description	Number of years of life expected. (The indicator included in the RCI is "Healthy life expectancy," but this indicator is only available at the country level. Therefore, in this study "Life expectancy" was used).
Unit of measure	Year
Data source	Eurostat: Life expectancy by age, sex and NUTS 2 region.
Data availability (2000-2019)	96.62 %
Missing data (2000-2019)	54 regions with at least one year missing

Descriptive statistics	N(valid)	N(missing)	%(missing)	Min.	Max.	Mean	Median	Std.Dev	CV	Skewness	Kurtosis
2000	115	45	28,12	71	81	77,43	78,5	2,9	0,04	-0,93	-0,42
2019	159	1	0,62	74,4	85,8	81,13	82	2,74	0,03	-0,96	-0,03

Histograms of Life expectancy





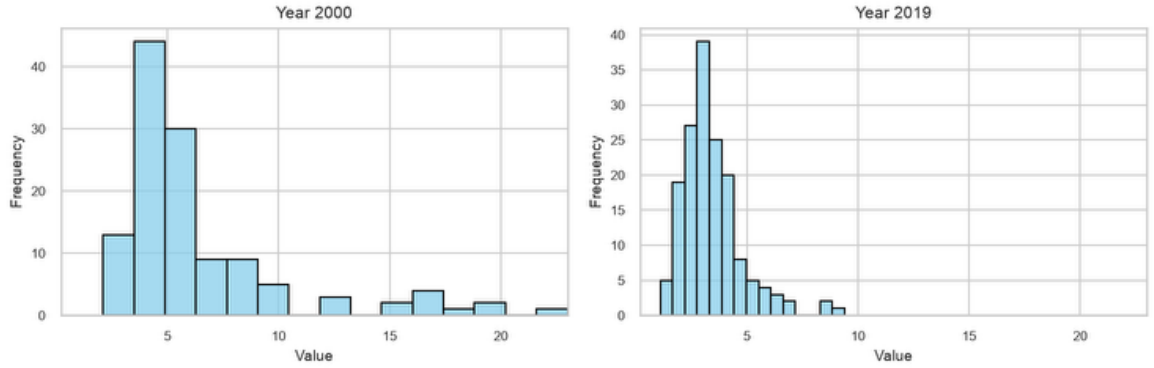
Indicator name	Infant mortality
Reference	RCI 2.0, 2022

Description	Number of deaths of children under 1 year of age during the year to the number of live births in that year (per 1 000 live births).
Unit of measure	Rate
Data source	Eurostat: Infant mortality rates by NUTS 2 region.

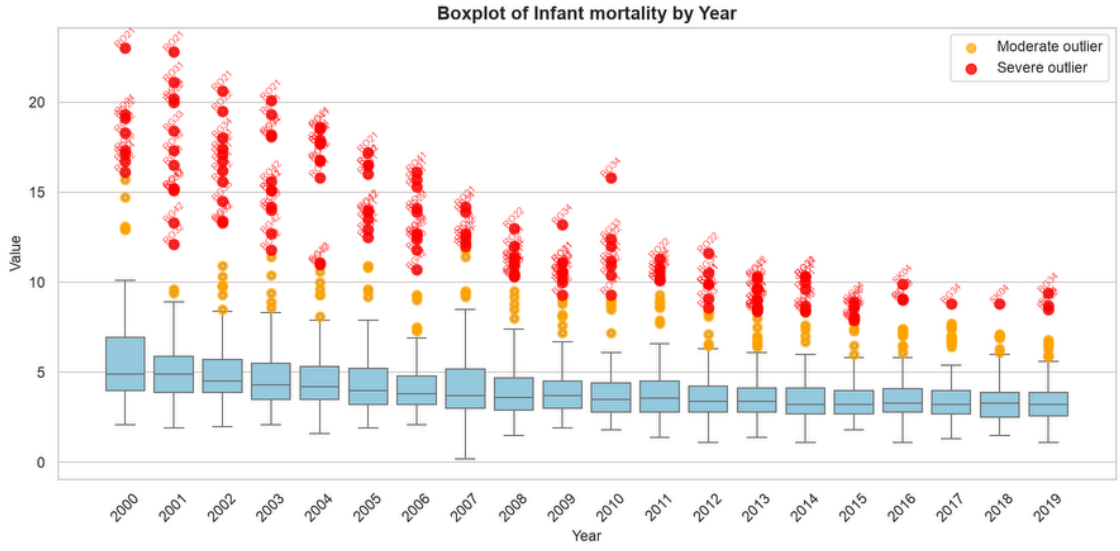
Data availability (2000-2019)	97.75 %	Missing data (2000-2019)	45 regions with at least one year missing	

Descriptive statistics	N(valid)	N(missing)	%(missing)	Min.	Max.	Mean	Median	Std.Dev	CV	Skewness	Kurtosis
2000	123	37	23,12	2,1	23	6,37	4,9	4,04	0,63	2,08	4,05
2019	160	0	0	1,1	9,4	3,44	3,2	1,35	0,39	1,62	4,08

Histograms of Infant mortality

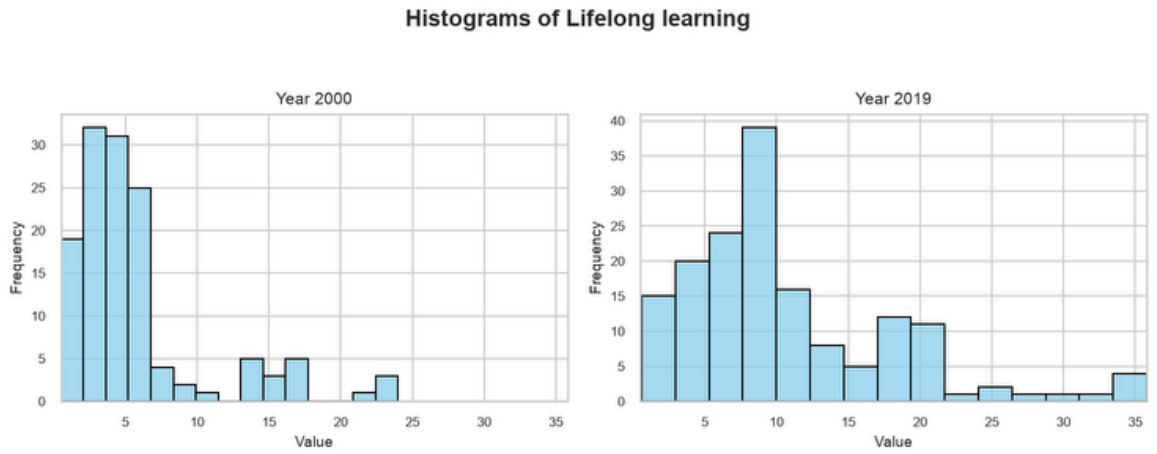


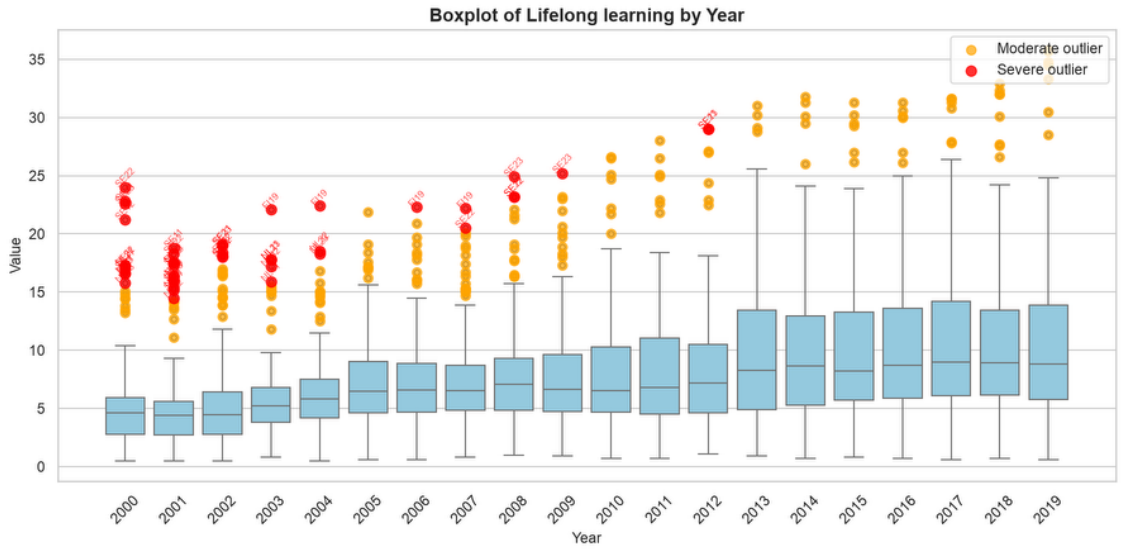
Boxplot of Infant mortality by Year



Indicator name	Lifelong learning
Reference	RCI 2.0, 2022 RIS, 2023 EU-SPI 2.0, 2024
Description	Adult population participation (% of population aged 25–64) in lifelong learning (i.e. received education or training in the 4 weeks preceding the survey).
Unit of measure	Percentage
Data source	Eurostat: Participation rate in education and training (last 4 weeks) by NUTS 2 region.
Data availability (2000-2019)	97.94 %
Missing data (2000-2019)	37 regions with at least one year missing

Descriptive statistics	N(valid)	N(missing)	%(missing)	Min.	Max.	Mean	Median	Std.Dev	CV	Skewness	Kurtosis
2000	131	29	18,12	0,5	24	5,71	4,6	4,93	0,86	1,94	3,44
2019	160	0	0	0,6	35,8	10,68	8,8	7,53	0,71	1,3	1,79

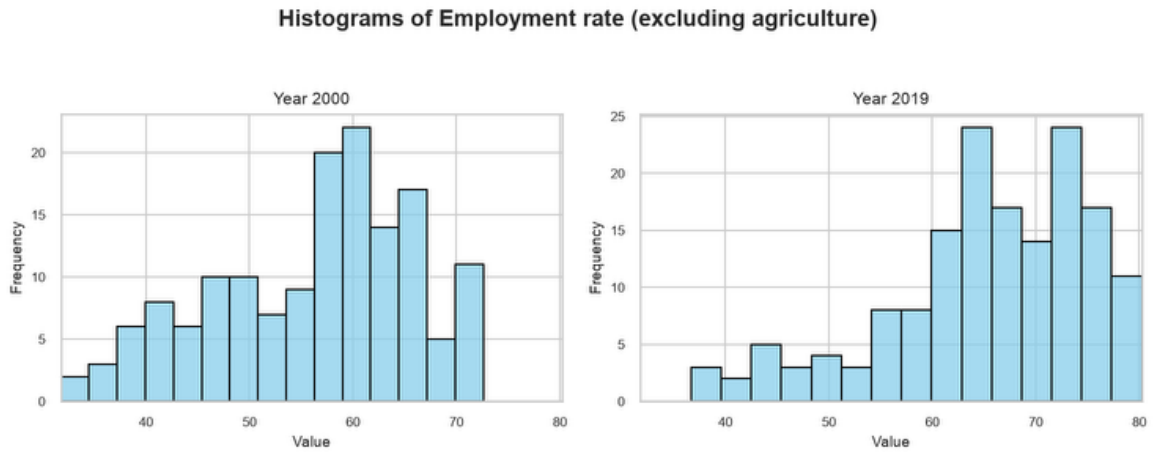


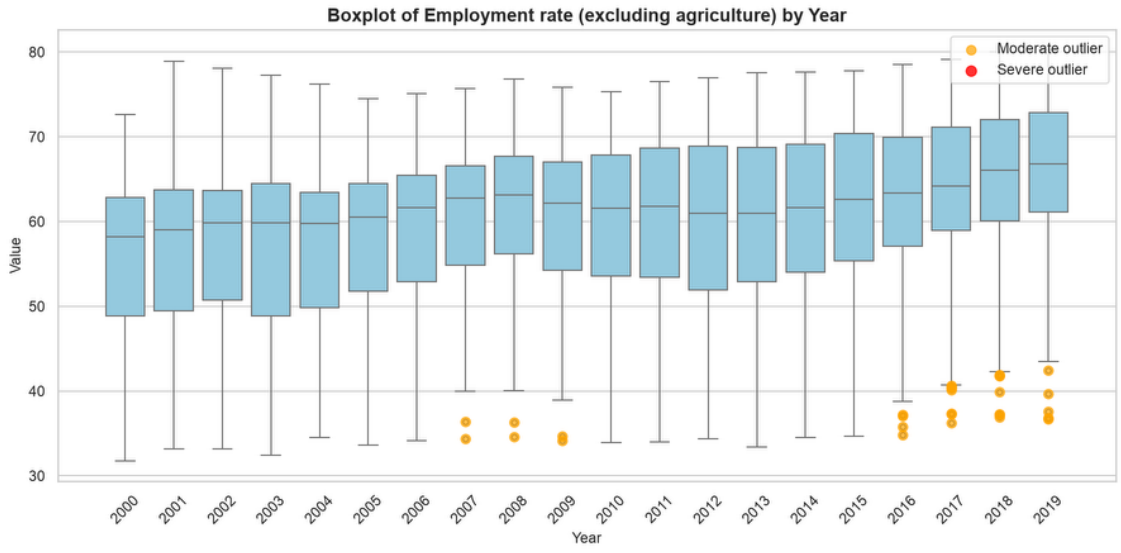


Indicator name	Employment rate (excluding agriculture)
Reference	RCI 2.0, 2022

Description	Percentage of people aged 15–64 that are currently employed in all economic sectors excluding agriculture
Unit of measure	Percentage
Data source	Eurostat: Employment by sex, age, economic activity and NUTS 2 region (NACE Rev. 2) (1 000); Employment by sex, age, economic activity and NUTS 2 region (1999-2008, NACE Rev. 1.1) (1 000); Population by sex, age, educational attainment level and NUTS 2 region (1 000).
Data availability (2000-2019)	98.12 %
Missing data (2000-2019)	24 regions with at least one year missing

Descriptive statistics	N(valid)	N(missing)	%(missing)	Min.	Max.	Mean	Median	Std.Dev	CV	Skewness	Kurtosis
2000	150	10	6,25	31,77	72,59	56,15	58,22	9,83	0,18	-0,51	-0,58
2019	158	2	1,25	36,7	80,24	65,37	66,81	9,93	0,15	-0,89	0,39





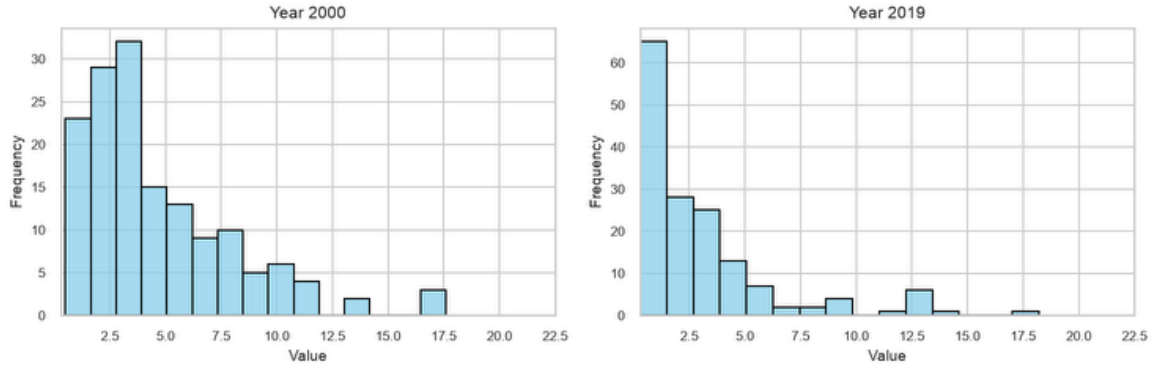
Indicator name	Long-term unemployment
Reference	RCI 2.0, 2022

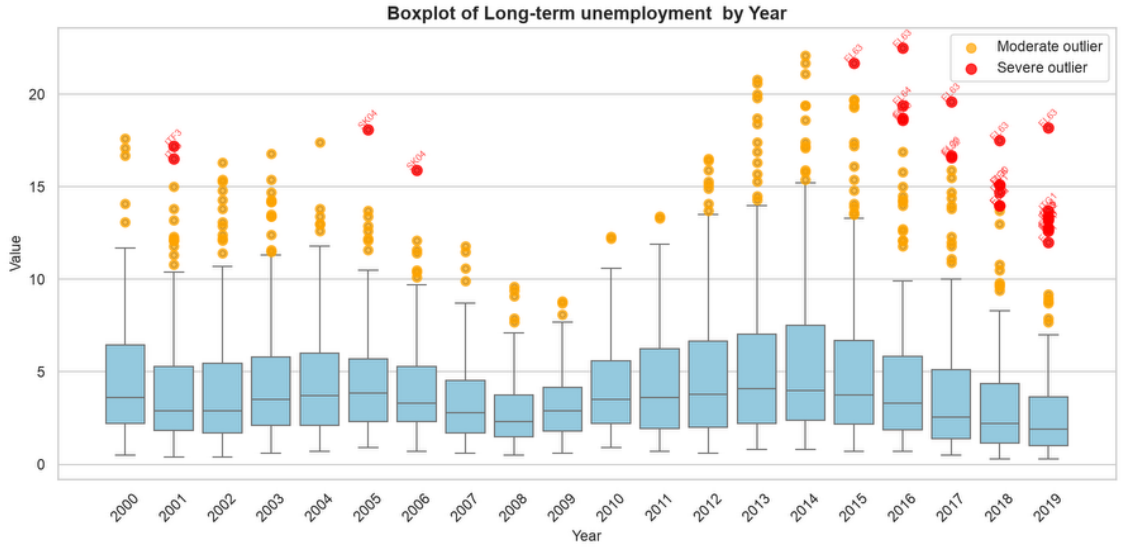
Description	Percentage of unemployed people actively looking for a job (in the last 12 months or more).
Unit of measure	Percentage of population in the labour force
Data source	Eurostat: Long-term unemployment (12 months and more) by sex, age, educational attainment level and NUTS 2 region (%).

Data availability (2000-2019)	97.44 %			Missing data (2000-2019)	38 regions with at least one year missing

Descriptive statistics	N(valid)	N(missing)	%(missing)	Min.	Max.	Mean	Median	Std.Dev	CV	Skewness	Kurtosis
2000	151	9	5,62	0,5	17,6	4,71	3,6	3,43	0,73	1,44	2,25
2019	155	5	3,12	0,3	18,2	3,07	1,9	3,26	1,06	2,24	5,21

Histograms of Long-term unemployment



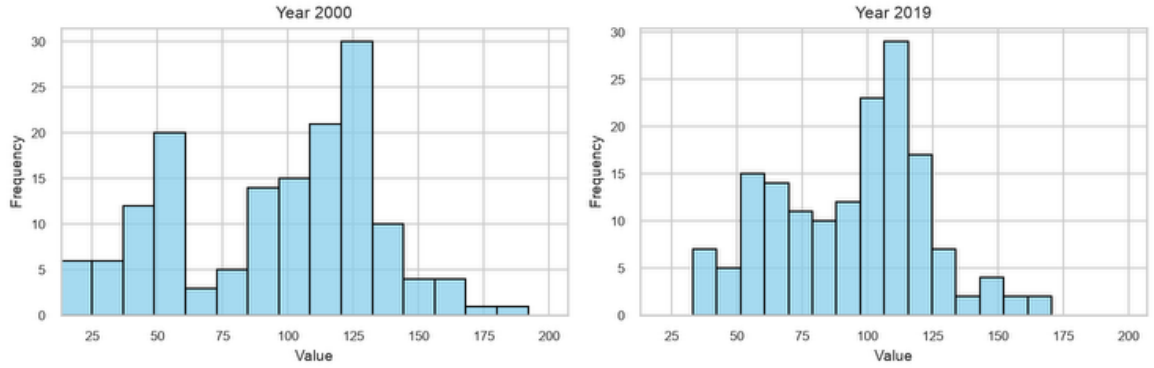


Indicator name	Labour productivity
Reference	RCI 2.0, 2022

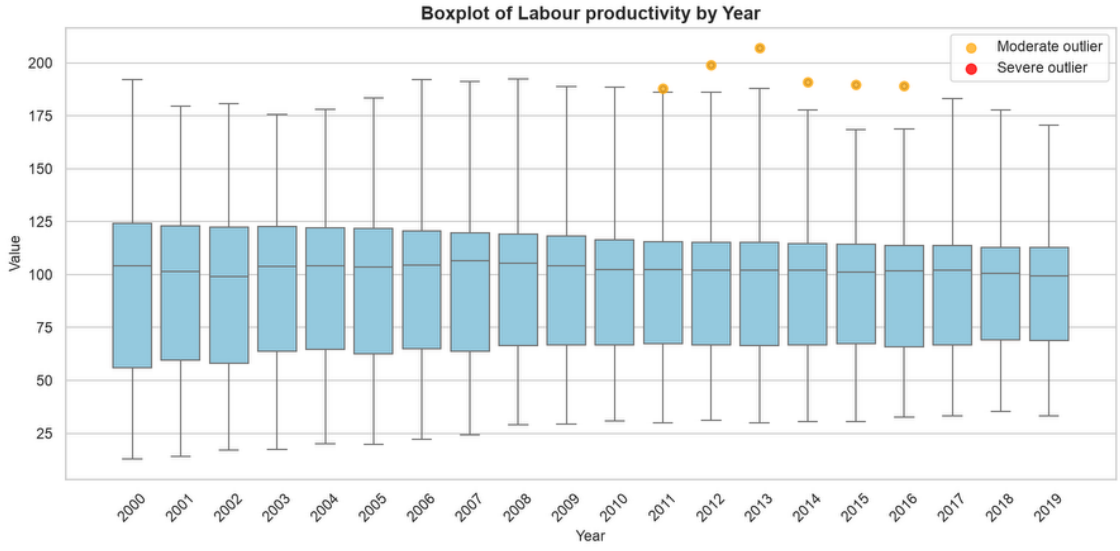
Description	Gross domestic product (in terms of PPS - purchasing power standards) relative to the number of hours worked.
Unit of measure	Index (PPS) EU-27=100
Data source	Eurostat: Gross domestic product (GDP) at current market prices by NUTS 2 region; Employment (thousand hours worked) by NUTS 2 region
Data availability (2000-2019)	99.25 %
Missing data (2000-2019)	8 regions with at least one year missing

Descriptive statistics	N(valid)	N(missing)	%(missing)	Min.	Max.	Mean	Median	Std.Dev	CV	Skewness	Kurtosis
2000	152	8	5	12,99	191,95	95,34	104,15	39,22	0,41	-0,27	-0,79
2019	160	0	0	33,12	170,55	93,86	99,38	28,91	0,31	-0,01	-0,41

Histograms of Labour productivity



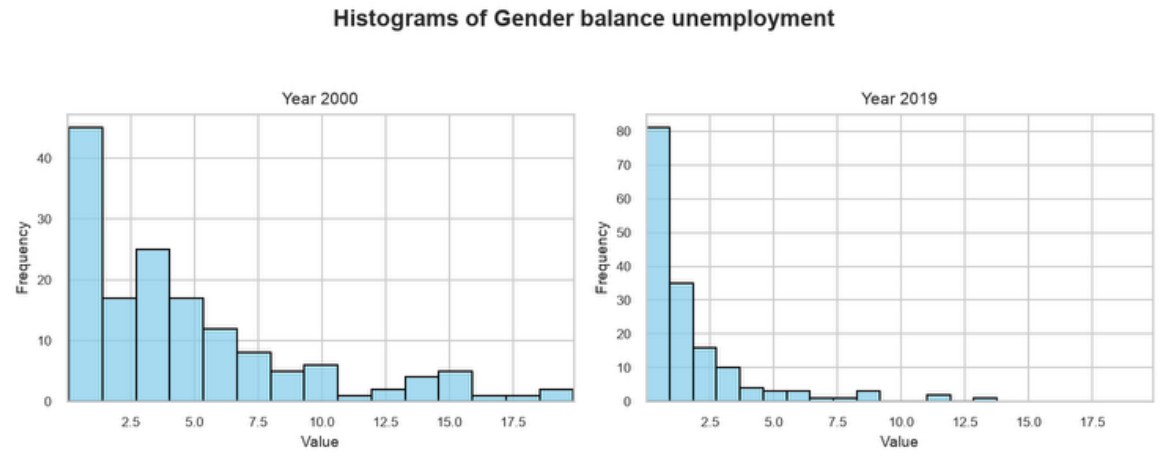
Boxplot of Labour productivity by Year

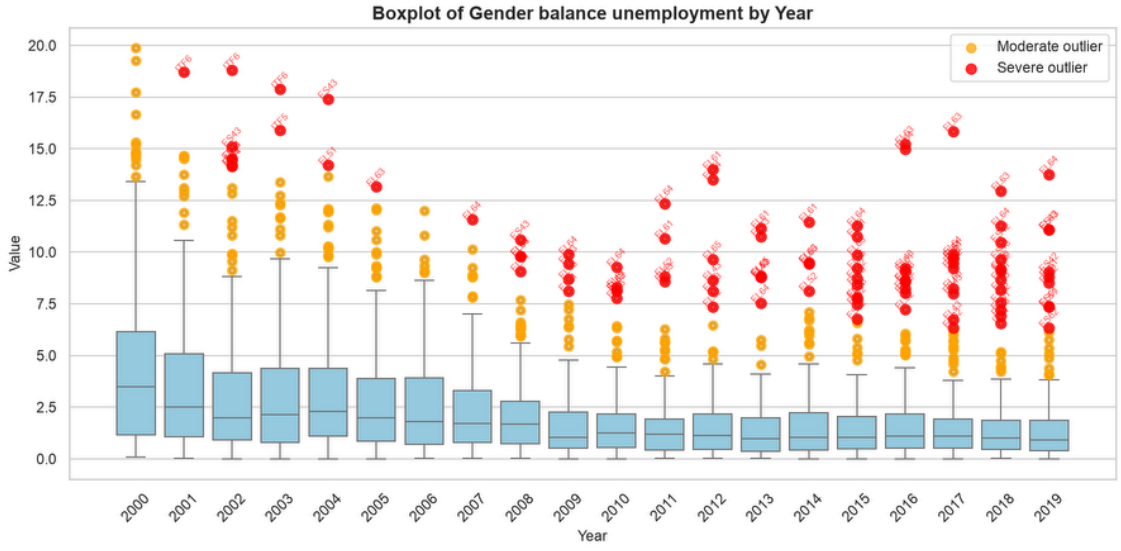


Indicator name	Gender balance unemployment
Reference	RCI 2.0, 2022

Description	Difference between female and male unemployment rates (in absolute value) as an indicator of the distance from gender parity (age group 15-74).
Unit of measure	Rate difference
Data source	Eurostat: Unemployment by sex, age, educational attainment level and NUTS 2 region (1 000); Economically active population by sex, age and NUTS 2 region (1 000).
Data availability (2000-2019)	98.72 %
Missing data (2000-2019)	21 regions with at least one year missing

Descriptive statistics	N(valid)	N(missing)	%(missing)	Min.	Max.	Mean	Median	Std.Dev	CV	Skewness	Kurtosis
2000	151	9	5,62	0,08	19,87	4,63	3,48	4,5	0,97	1,41	1,49
2019	160	0	0	0	13,76	1,7	0,91	2,27	1,34	2,78	8,83



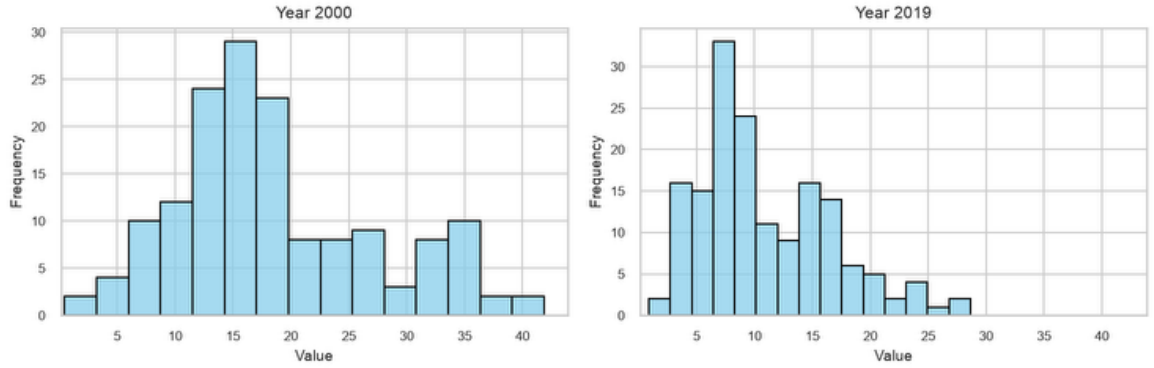


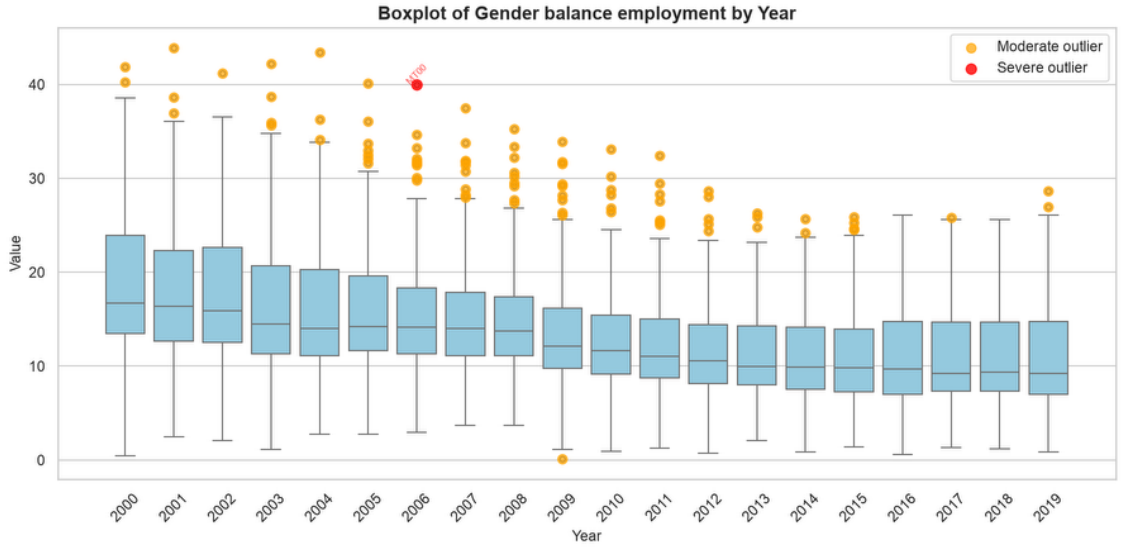
Indicator name	Gender balance employment
Reference	RCI 2.0, 2022

Description	Difference between female and male employment rates (in absolute value) as an indicator of the distance from gender parity (age group 15-64).
Unit of measure	Rate difference
Data source	Eurostat: Employment by sex, age and NUTS 2 region (1 000); Population by sex, age, educational attainment level and NUTS 2 region (1 000).
Data availability (2000-2019)	99.50 %
Missing data (2000-2019)	6 regions with at least one year missing

Descriptive statistics	N(valid)	N(missing)	%(missing)	Min.	Max.	Mean	Median	Std.Dev	CV	Skewness	Kurtosis
2000	154	6	3,75	0,46	41,87	18,67	16,71	8,53	0,46	0,62	-0,13
2019	160	0	0	0,89	28,66	10,96	9,24	5,65	0,52	0,8	0,21

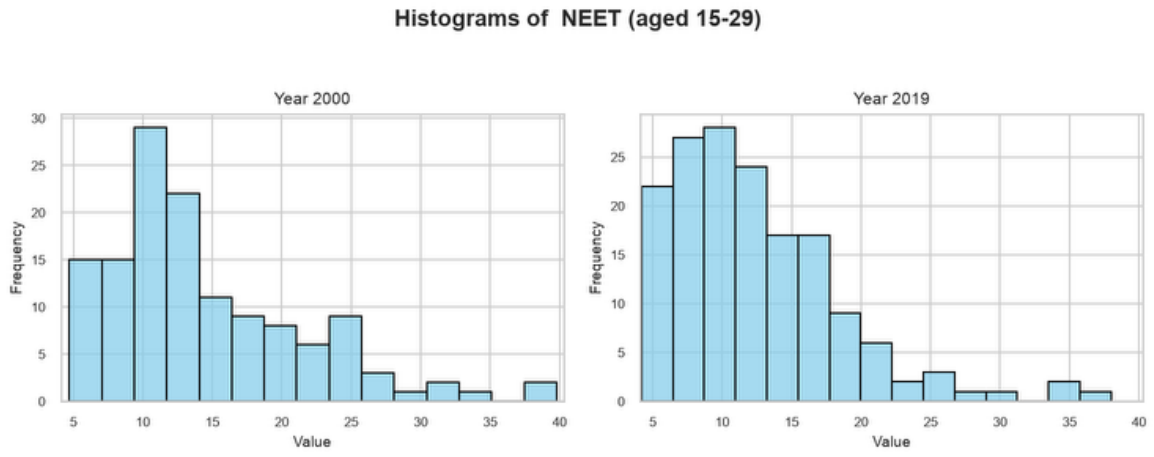
Histograms of Gender balance employment

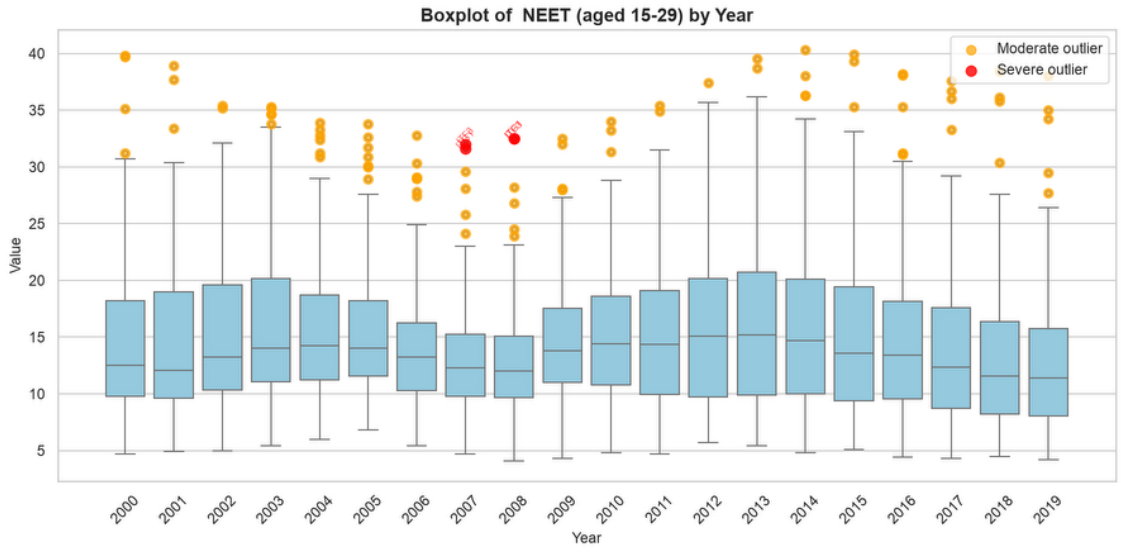




Indicator name	NEET (aged 15-29)
Reference	RCI 2.0, 2022 EU-SPI 2.0, 2024 (2)
Description	Young people not in employment or education and training (percentage of population aged 15–29). ((2) In this document the age group is 15-24)
Unit of measure	Percentage
Data source	Eurostat: Young people neither in employment nor in education and training by sex and NUTS 2 region (NEET rates).
Data availability (2000-2019)	98.47 %
Missing data (2000-2019)	27 regions with at least one year missing

Descriptive statistics	N(valid)	N(missing)	%(missing)	Min.	Max.	Mean	Median	Std.Dev	CV	Skewness	Kurtosis
2000	133	27	16,88	4,7	39,8	14,52	12,5	7,19	0,5	1,18	1,42
2019	160	0	0	4,2	38	12,53	11,4	6,16	0,49	1,41	2,71



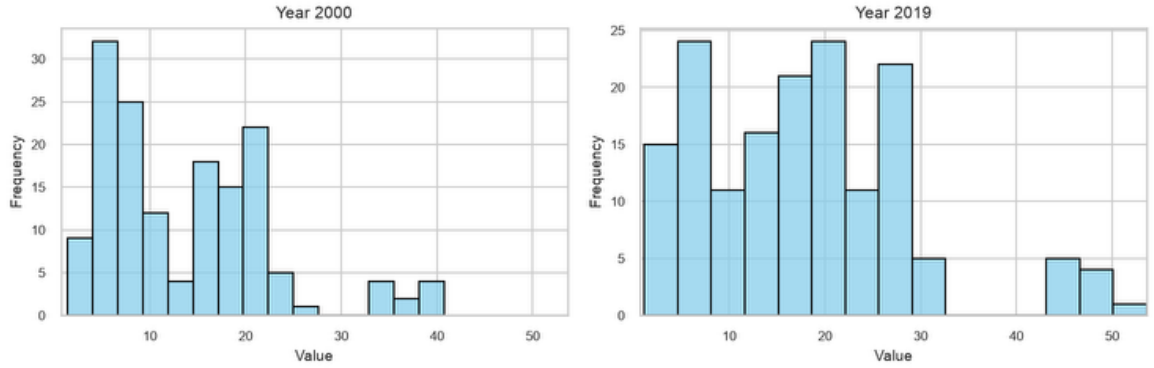


Indicator name	Temporary employment
Reference	RCI 2.0, 2022

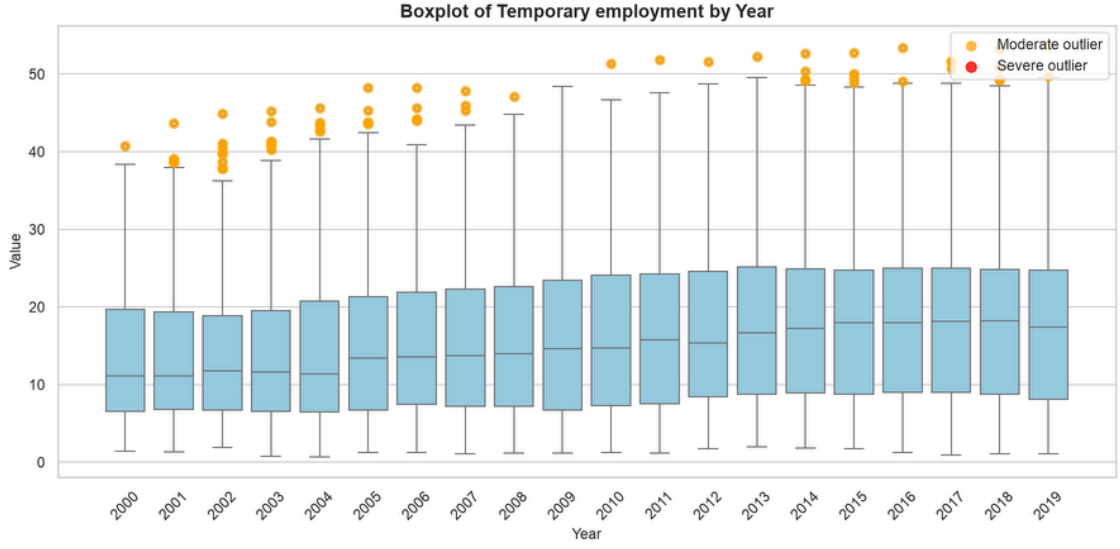
Description	Temporary employees as a percentage of the total number of employees aged 20–64.
Unit of measure	Share of employed people aged 20–64
Data source	Eurostat: Employment by sex, age, full-time/part-time, professional status and NUTS 2 region (1 000).

Data availability (2000-2019)	99.19 %					Missing data (2000-2019)		10 regions with at least one year missing			
Descriptive statistics	N(valid)	N(missing)	%(missing)	Min.	Max.	Mean	Median	Std.Dev	CV	Skewness	Kurtosis
2000	153	7	4,38	1,39	40,75	13,74	11,16	8,75	0,64	1,02	0,86
2019	159	1	0,62	1,12	53,62	17,91	17,43	11,26	0,63	0,9	0,98

Histograms of Temporary employment



Boxplot of Temporary employment by Year



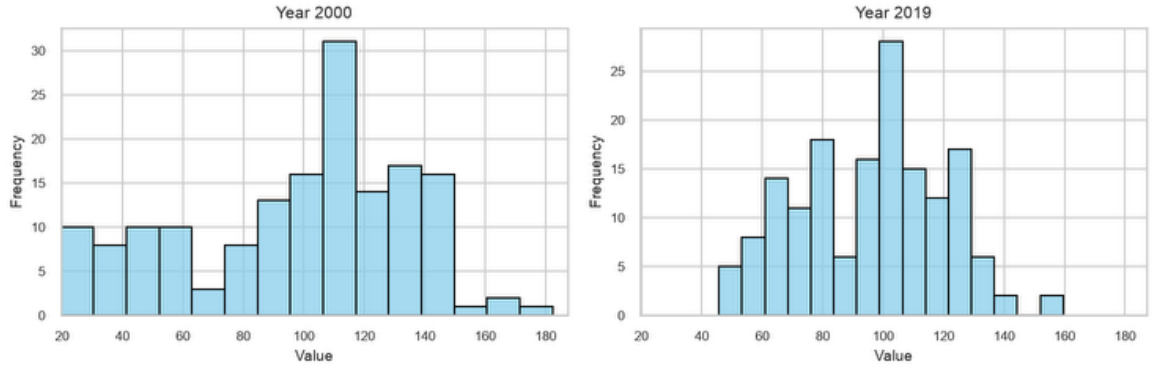
Indicator name	Disposable income per capita
Reference	RCI 2.0, 2022

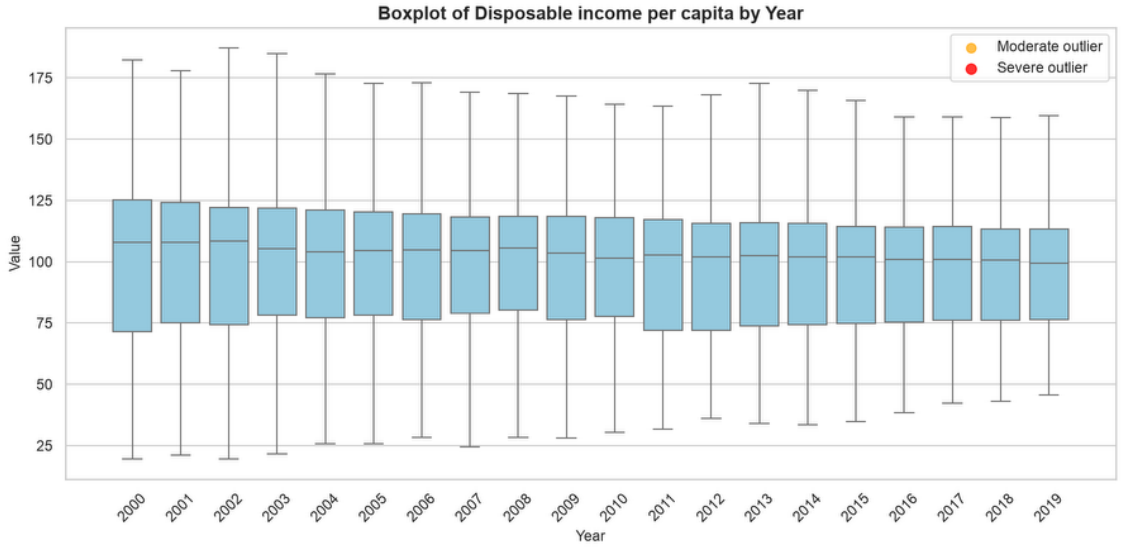
Description	Net adjusted disposable household income in purchasing power consumption standards (PPCS) per capita
Unit of measure	Index (PPCS) EU-27=100
Data source	Eurostat: Income of households by NUTS 2 region.

Data availability (2000-2019)	100.00 %			Missing data (2000-2019)	0 regions with at least one year missing

Descriptive statistics	N(valid)	N(missing)	%(missing)	Min.	Max.	Mean	Median	Std.Dev	CV	Skewness	Kurtosis
2000	160	0	0	19,63	182,24	97,57	107,94	37,44	0,38	-0,46	-0,67
2019	160	0	0	45,66	159,54	95,99	99,42	24,22	0,25	-0,08	-0,63

Histograms of Disposable income per capita

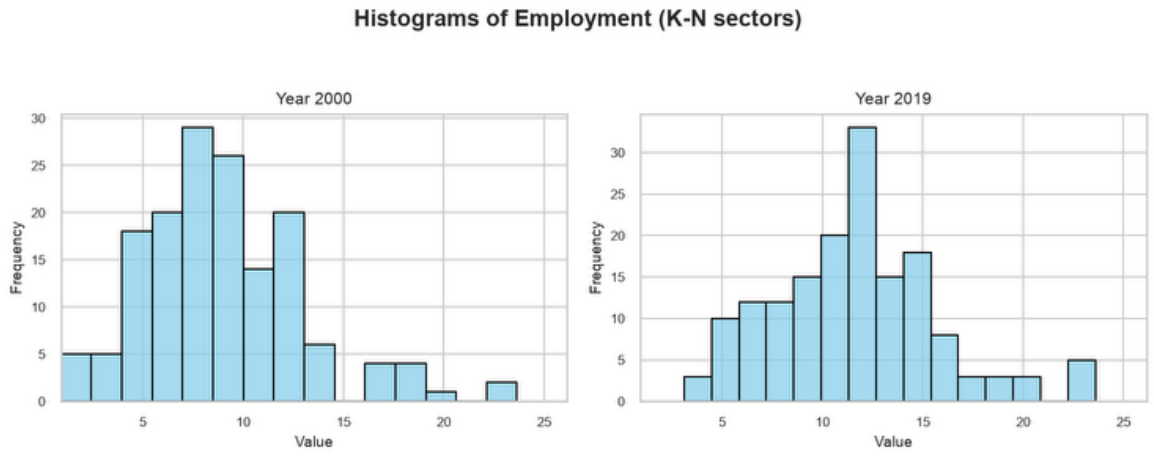


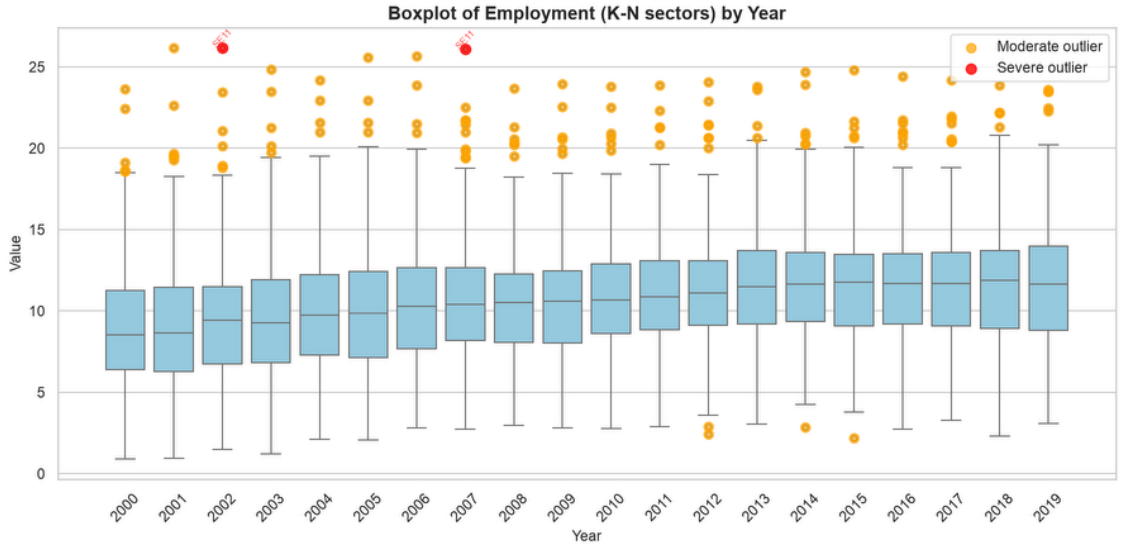


Indicator name	Employment (K-N sectors)
Reference	RCI 2.0, 2022

Description	Employment in the 'Financial and insurance activities; real estate activities; professional, scientific and technical activities; administrative and support service activities' sectors (K-N) as % of total employment (age group 15-64).
Unit of measure	Percentage of total employment (15-64)
Data source	Eurostat: Employment by sex, age, economic activity and NUTS 2 region (NACE Rev. 2) (1 000).

Data availability (2000-2019)	99.41 %					Missing data (2000-2019)		8 regions with at least one year missing			
Descriptive statistics	N(valid)	N(missing)	%(missing)	Min.	Max.	Mean	Median	Std.Dev	CV	Skewness	Kurtosis
2000	154	6	3,75	0,91	23,65	8,98	8,52	4,03	0,45	0,89	1,4
2019	160	0	0	3,1	23,6	11,62	11,66	4,12	0,35	0,5	0,53



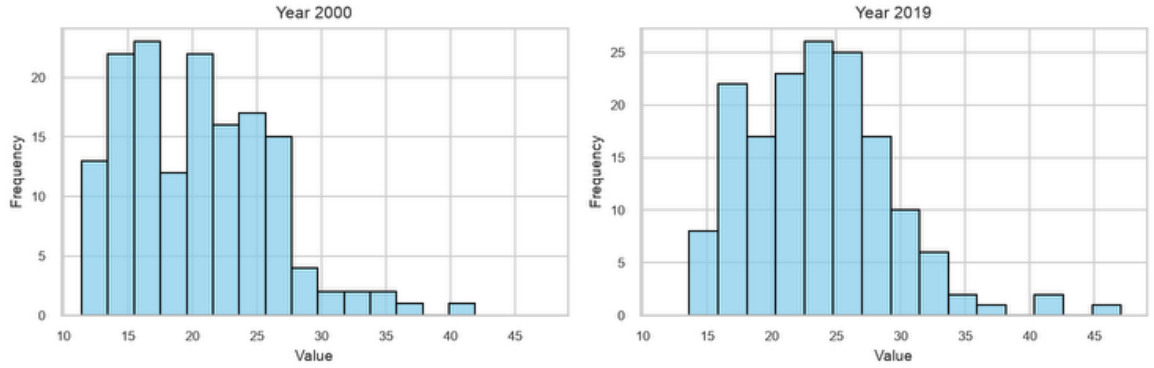


Indicator name	Gross value added (K-N sectors)
Reference	RCI 2.0, 2022

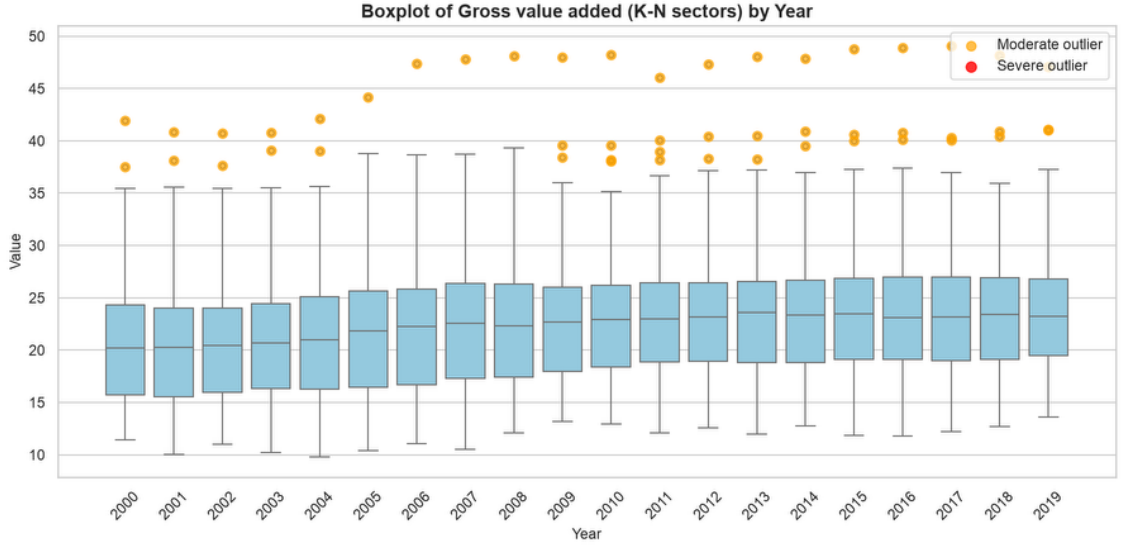
Description	Gross value added (GVA) in the 'Financial and insurance activities; real estate activities; professional, scientific and technical activities; administrative and support service activities' sectors (K-N) as % of total GVA.
Unit of measure	Percentage of total GVA
Data source	Eurostat: Gross value added at basic prices and previous year prices by NUTS region.

Data availability (2000-2019)	99.25 %					Missing data (2000-2019)	8 regions with at least one year missing				
Descriptive statistics	N(valid)	N(missing)	%(missing)	Min.	Max.	Mean	Median	Std.Dev	CV	Skewness	Kurtosis
2000	152	8	5	11,42	41,91	20,32	20,22	5,81	0,29	0,75	0,71
2019	160	0	0	13,6	47,06	23,57	23,2	5,72	0,24	0,82	1,49

Histograms of Gross value added (K-N sectors)



Boxplot of Gross value added (K-N sectors) by Year

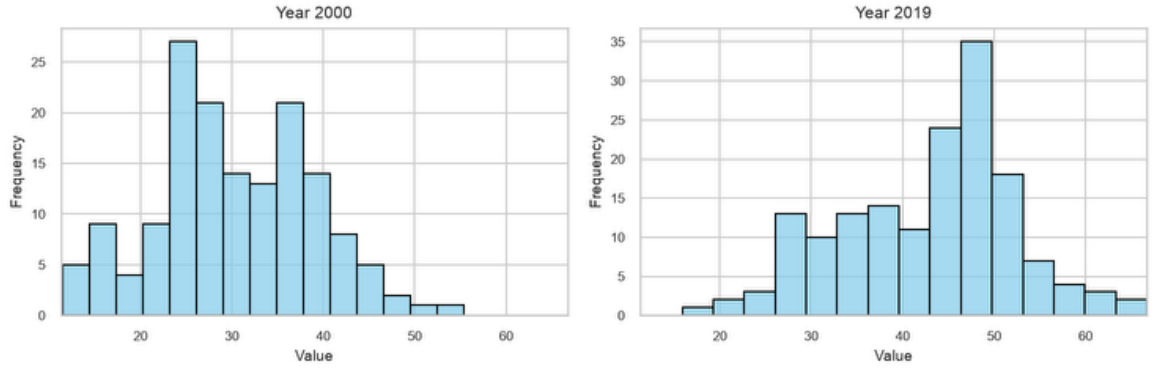


Indicator name	Human Resources in Science and Technology
Reference	RCI 2.0, 2022

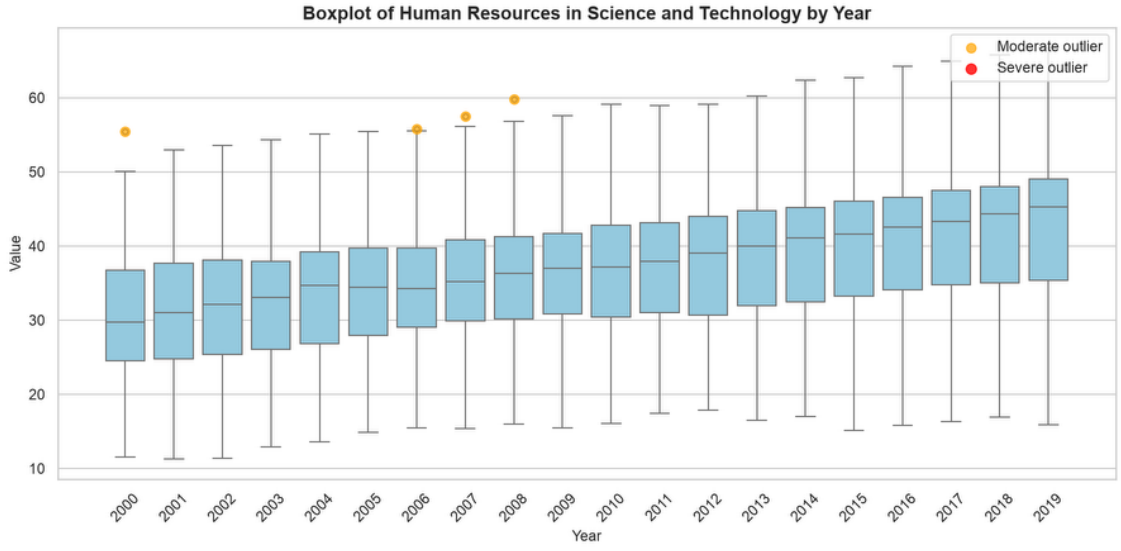
Description	Share of persons with successfully completed tertiary education and/or those without tertiary education but employed in a science and technology occupation where tertiary education normally required.
Unit of measure	Percentage of population in the labour force
Data source	Eurostat: HRST by category and NUTS 2 region.

Data availability (2000-2019)	99.50 %					Missing data (2000-2019)	6 regions with at least one year missing				
Descriptive statistics	N(valid)	N(missing)	%(missing)	Min.	Max.	Mean	Median	Std.Dev	CV	Skewness	Kurtosis
2000	154	6	3,75	11,5	55,4	30,26	29,75	8,61	0,28	0,03	-0,25
2019	160	0	0	15,9	66,7	42,9	45,3	9,58	0,22	-0,31	-0,31

Histograms of Human Resources in Science and Technology



Boxplot of Human Resources in Science and Technology by Year

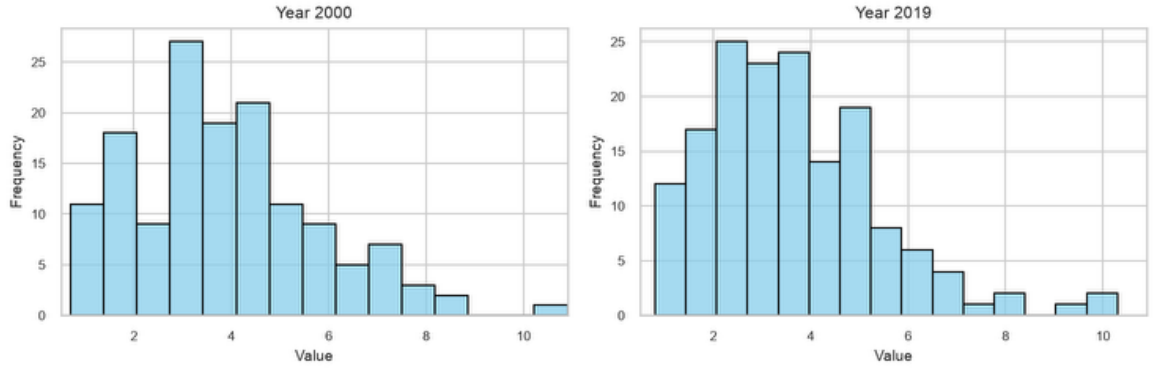


Indicator name	Employment in technology and knowledge-intensive sectors
Reference	RCI 2.0, 2022

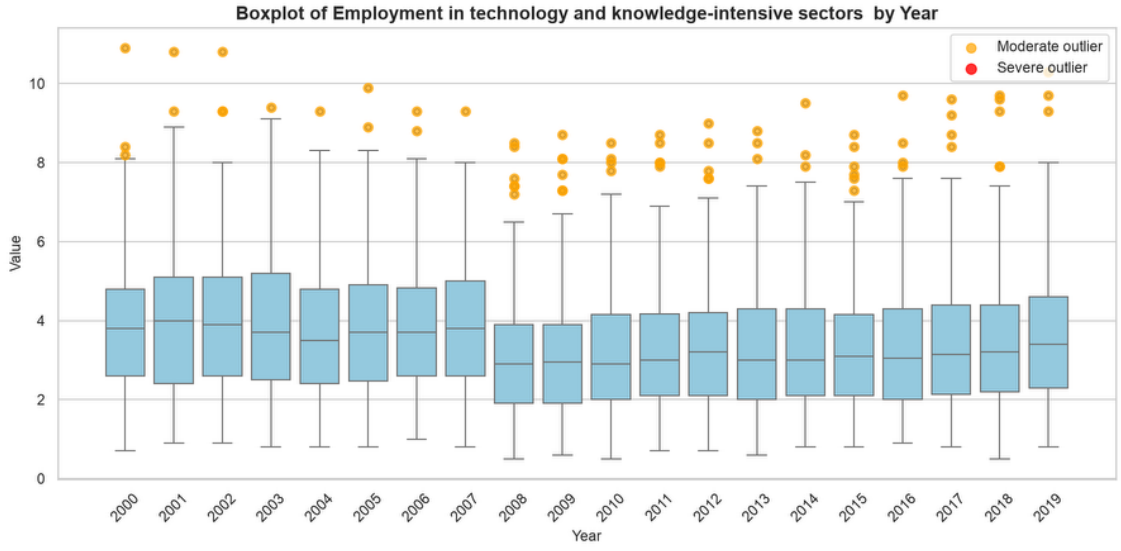
Description	Employment in technology and knowledge-intensive sectors by NUTS 2 regions (% of total employment).
Unit of measure	Percentage of total employment
Data source	Eurostat: Employment in technology and knowledge-intensive sectors by NUTS 2 region and sex (1994-2008, NACE Rev. 1.1); Employment in technology and knowledge-intensive sectors by NUTS 2 region and sex (from 2008 onwards, NACE Rev. 2).
Data availability (2000-2019)	96.97 %
Missing data (2000-2019)	32 regions with at least one year missing

Descriptive statistics	N(valid)	N(missing)	%(missing)	Min.	Max.	Mean	Median	Std.Dev	CV	Skewness	Kurtosis
2000	143	17	10,62	0,7	10,9	3,88	3,8	1,88	0,49	0,72	0,62
2019	158	2	1,25	0,8	10,3	3,61	3,4	1,77	0,49	1,02	1,58

Histograms of Employment in technology and knowledge-intensive sectors



Boxplot of Employment in technology and knowledge-intensive sectors by Year



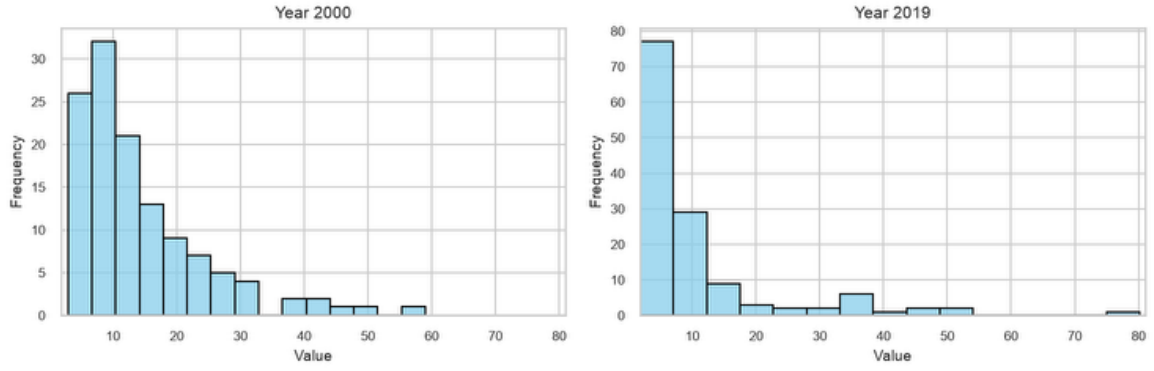
Indicator name	Teenage pregnancy
Reference	EU-SPI 2.0, 2024

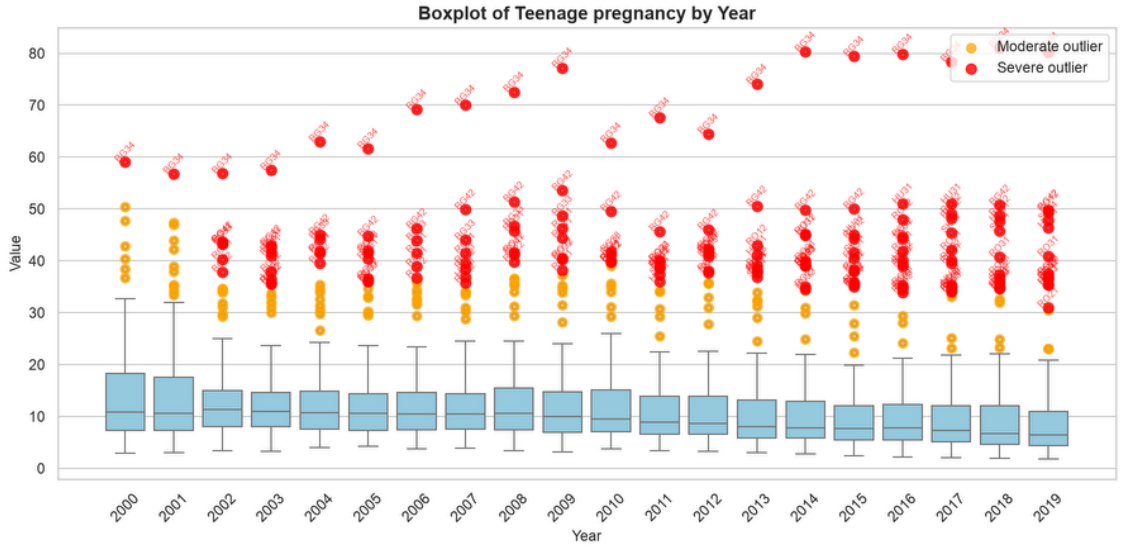
Description	Ratio between births by mothers aged 15-19 years old and the female population of the same age cohort.
Unit of measure	Percentage
Data source	Eurostat: Live births by mother's age and NUTS 2 region; Population on 1 January by age group, sex and NUTS 2 region.

Data availability (2000-2019)	96.44 %			Missing data (2000-2019)	36 regions with at least one year missing

Descriptive statistics	N(valid)	N(missing)	%(missing)	Min.	Max.	Mean	Median	Std.Dev	CV	Skewness	Kurtosis
2000	124	36	22,5	2,95	59,02	14,43	10,81	10,39	0,72	1,79	3,73
2019	134	26	16,25	1,83	80,19	10,71	6,4	12,31	1,15	2,77	9,04

Histograms of Teenage pregnancy



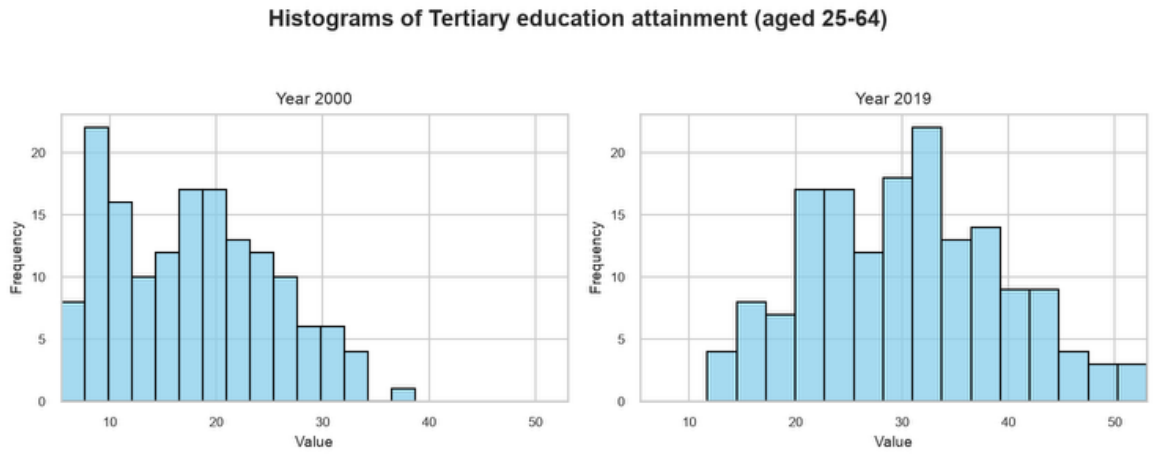


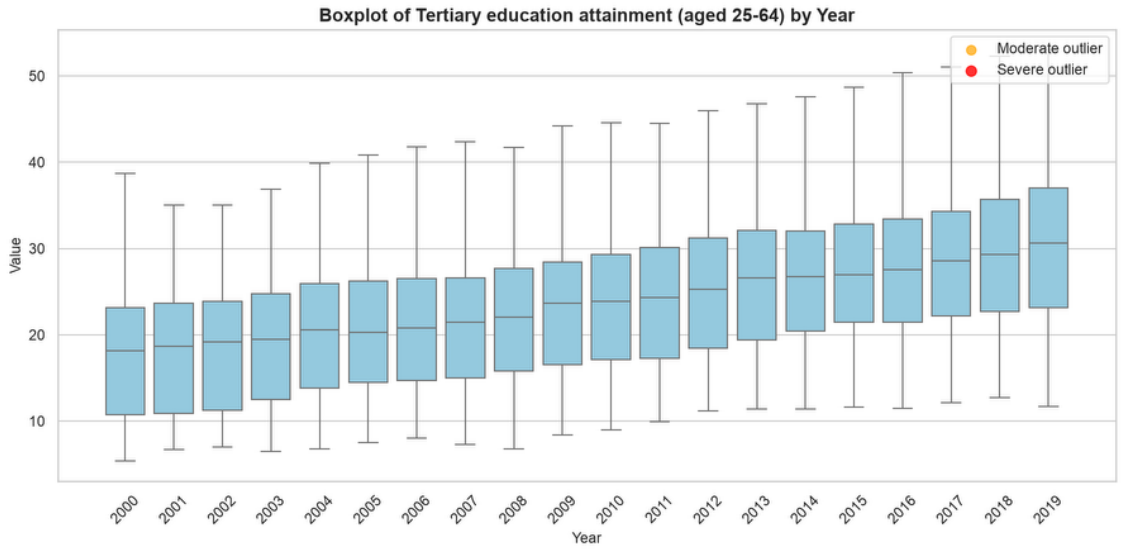
Indicator name	Tertiary education attainment (aged 25-64)
Reference	EU-SPI 2.0, 2024

Description	Percentage of population aged 25-64 with tertiary education (ISCED 5-8) attainment.
Unit of measure	Percentage
Data source	Eurostat: Population by educational attainment level, sex and NUTS 2 region (%).

Data availability (2000-2019)	99.50 %	Missing data (2000-2019)	6 regions with at least one year missing	

Descriptive statistics	N(valid)	N(missing)	%(missing)	Min.	Max.	Mean	Median	Std.Dev	CV	Skewness	Kurtosis
2000	154	6	3,75	5,4	38,7	17,75	18,15	7,41	0,42	0,34	-0,7
2019	160	0	0	11,7	53	30,33	30,65	9,08	0,3	0,22	-0,52

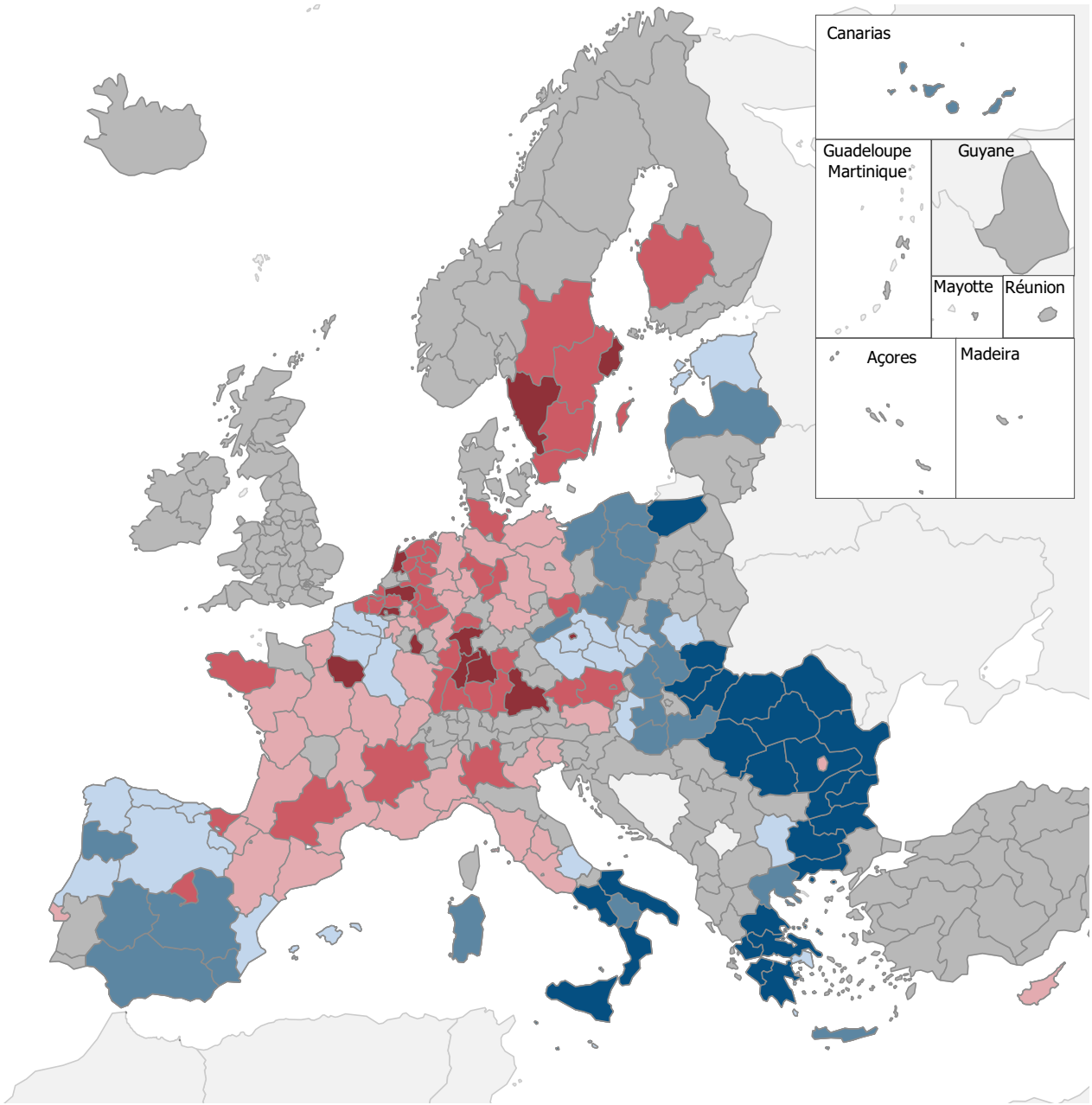




Appendix F

Spatial distribution of the A1 component scores across EU NUTS2 regions

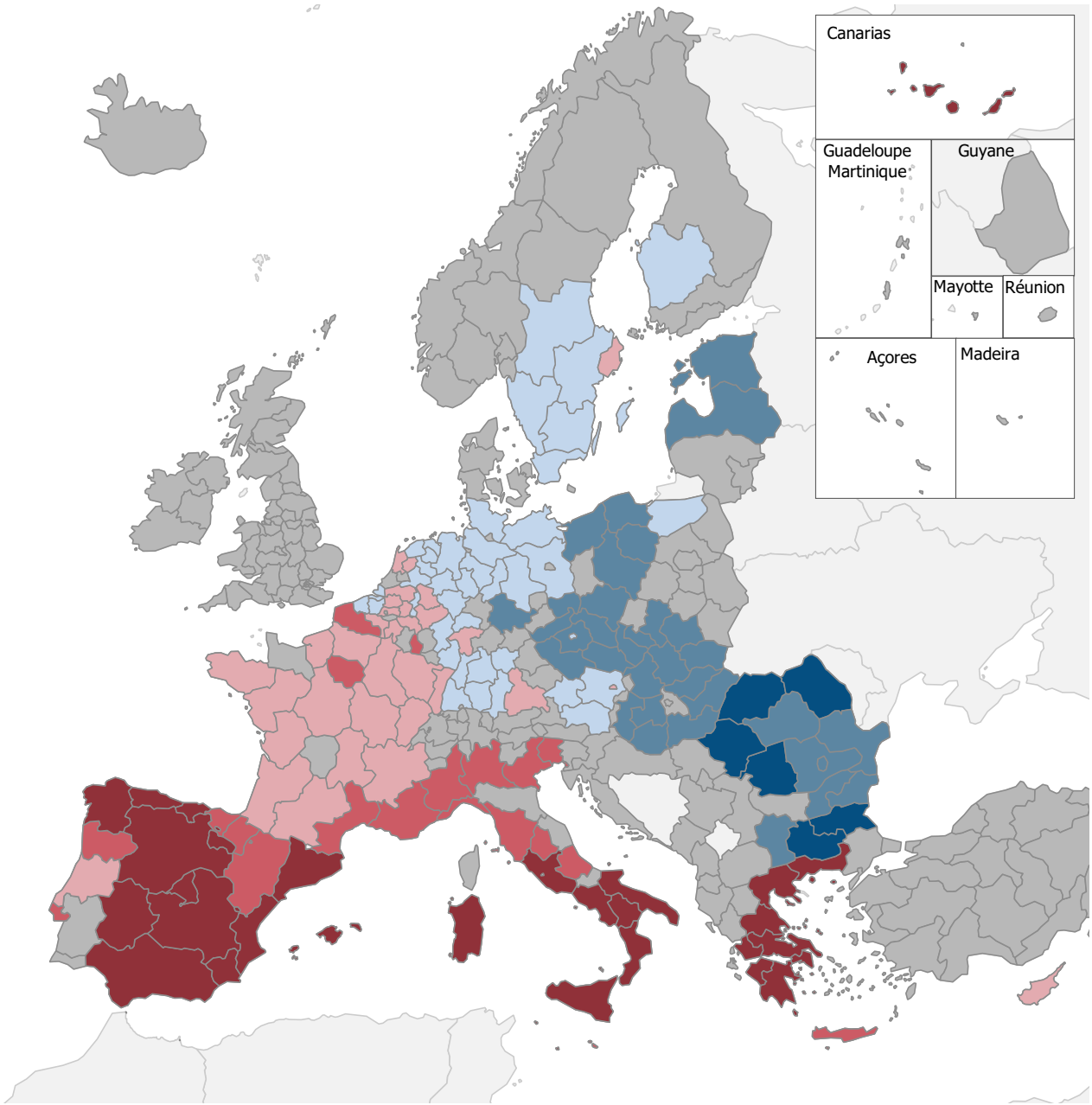
Regional scores in component A1



Appendix G

Spatial distribution of the A2 component scores across EU NUTS2 regions

Regional scores in component A2



Appendix H

Main characteristics of the selected regions

NUTS 2 code	NUTS 2 label	Country	Capital region	EU accession	Category 2007-13	Category 2014-20	Category 2021-27	Geographic area	RIS	RCI	SPI	Q2000	Q2019
AT12	Niederösterreich	Austria	Non-capital region	1995	Competitiveness	More developed	More developed	North-wester	Above EU_avg	-	Above EU_avg	3	4
AT13	Wien	Austria	Capital region	1995	Competitiveness	More developed	More developed	North-wester	Above EU_avg	-	Above EU_avg	4	1
AT22	Steiermark	Austria	Non-capital region	1995	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	3	4
AT31	Oberösterreich	Austria	Non-capital region	1995	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	4	4
BE21	Prov. Antwerpen	Belgium	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	1	4
BE22	Prov. Limburg (BE)	Belgium	Non-capital region	1958	Competitiveness	More developed	Transition	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	3	4
BE23	Prov. Oost-Vlaanderen	Belgium	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Top 10	Above EU_avg	4	4
BE24	Prov. Vlaams-Brabant	Belgium	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Above EU_avg	-	Above EU_avg	4	1
BE25	Prov. West-Vlaanderen	Belgium	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	4	4
BE32	Prov. Hainaut	Belgium	Non-capital region	1958	Phasing-out	Transition	Transition	North-wester	Above EU_avg	Above EU_avg	Below EU_avg	2	1
BE33	Prov. Liège	Belgium	Non-capital region	1958	Competitiveness	Transition	Transition	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	2	1
BE35	Prov. Namur	Belgium	Non-capital region	1958	Competitiveness	Transition	Transition	North-wester	Above EU_avg	Above EU_avg	Below EU_avg	2	1
BG32	Северен централен	Bulgaria	Non-capital region	2007	Convergence	Less developed	Less developed	Eastern	Below EU_avg	Below EU_avg	Bottom 10	3	3
BG33	Североизточен	Bulgaria	Non-capital region	2007	Convergence	Less developed	Less developed	Eastern	Below EU_avg	Below EU_avg	Bottom 10	3	3
BG34	Югоизточен	Bulgaria	Non-capital region	2007	Convergence	Less developed	Less developed	Eastern	Bottom 10	Bottom 10	Bottom 10	3	3
BG41	Югозападен	Bulgaria	Capital region	2007	Convergence	Less developed	Transition	Eastern	Below EU_avg	Below EU_avg	Below EU_avg	3	4
BG42	Южен централен	Bulgaria	Non-capital region	2007	Convergence	Less developed	Less developed	Eastern	Below EU_avg	Below EU_avg	Bottom 10	3	3
CY00	Κύπρος	Cyprus	Capital region	2004	Phasing-in	More developed	Transition	Southern	-	Below EU_avg	Below EU_avg	3	1
CZ01	Praha	Czechia	Capital region	2004	Competitiveness	More developed	More developed	Eastern	Above EU_avg	-	Above EU_avg	4	4
CZ02	Střední Čechy	Czechia	Non-capital region	2004	Convergence	Less developed	Transition	Eastern	Below EU_avg	-	Above EU_avg	3	4
CZ03	Jihozápad	Czechia	Non-capital region	2004	Convergence	Less developed	Transition	Eastern	Below EU_avg	Below EU_avg	Above EU_avg	3	4
CZ04	Severozápad	Czechia	Non-capital region	2004	Convergence	Less developed	Less developed	Eastern	Below EU_avg	Below EU_avg	Below EU_avg	3	3
CZ05	Severovýchod	Czechia	Non-capital region	2004	Convergence	Less developed	Less developed	Eastern	Below EU_avg	Below EU_avg	Above EU_avg	3	4
CZ06	Jihovýchod	Czechia	Non-capital region	2004	Convergence	Less developed	Transition	Eastern	Above EU_avg	Below EU_avg	Above EU_avg	3	4
CZ07	Střední Morava	Czechia	Non-capital region	2004	Convergence	Less developed	Less developed	Eastern	Below EU_avg	Below EU_avg	Above EU_avg	3	4
CZ08	Moravskoslezsko	Czechia	Non-capital region	2004	Convergence	Less developed	Less developed	Eastern	Below EU_avg	Below EU_avg	Below EU_avg	3	4
EE00	Eesti	Estonia	Capital region	2004	Convergence	Less developed	Transition	Eastern	-	Above EU_avg	Above EU_avg	3	4
FI19	Länsi-Suomi	Finland	Non-capital region	1995	Competitiveness	More developed	Transition	North-wester	Above EU_avg	Above EU_avg	Top 10	4	4

NUTS 2 code	NUTS 2 label	Country	Capital region	EU accession	Category 2007-13	Category 2014-20	Category 2021-27	Geographic area	RIS	RCI	SPI	Q2000	Q2019
FR10	Ile-de-France	France	Capital region	1958	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Top 10	Above EU_avg	1	1
FRB0	Centre — Val de Loire	France	Non-capital region	1958	Competitiveness	More developed	Transition	North-wester	Below EU_avg	Above EU_avg	Above EU_avg	2	1
FRC1	Bourgogne	France	Non-capital region	1958	Competitiveness	More developed	Transition	North-wester	Below EU_avg	Below EU_avg	Above EU_avg	3	4
FRC2	Franche-Comté	France	Non-capital region	1958	Competitiveness	Transition	Transition	North-wester	Below EU_avg	Below EU_avg	Above EU_avg	3	4
FRD2	Haute-Normandie	France	Non-capital region	1958	Competitiveness	More developed	Transition	North-wester	Below EU_avg	Above EU_avg	Above EU_avg	2	1
FRE1	Nord-Pas de Calais	France	Non-capital region	1958	Competitiveness	Transition	Transition	North-wester	Below EU_avg	Above EU_avg	Below EU_avg	2	1
FRE2	Picardie	France	Non-capital region	1958	Competitiveness	Transition	Transition	North-wester	Below EU_avg	Above EU_avg	Below EU_avg	2	1
FRF1	Alsace	France	Non-capital region	1958	Competitiveness	More developed	Transition	North-wester	Below EU_avg	Above EU_avg	Above EU_avg	4	1
FRF2	Champagne-Ardenne	France	Non-capital region	1958	Competitiveness	More developed	Transition	North-wester	Below EU_avg	Below EU_avg	Above EU_avg	2	1
FRF3	Lorraine	France	Non-capital region	1958	Competitiveness	Transition	Transition	North-wester	Below EU_avg	Below EU_avg	Above EU_avg	2	1
FRG0	Pays de la Loire	France	Non-capital region	1958	Competitiveness	More developed	Transition	North-wester	Below EU_avg	Above EU_avg	Above EU_avg	2	1
FRH0	Bretagne	France	Non-capital region	1958	Competitiveness	More developed	Transition	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	4	4
FRI1	Aquitaine	France	Non-capital region	1958	Competitiveness	More developed	Transition	North-wester	Below EU_avg	Above EU_avg	Above EU_avg	2	1
FRI3	Poitou-Charentes	France	Non-capital region	1958	Competitiveness	Transition	Transition	North-wester	Below EU_avg	Below EU_avg	Above EU_avg	2	1
FRJ1	Languedoc-Roussillon	France	Non-capital region	1958	Competitiveness	Transition	Transition	North-wester	Above EU_avg	Below EU_avg	Above EU_avg	2	1
FRJ2	Midi-Pyrénées	France	Non-capital region	1958	Competitiveness	More developed	Transition	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	1	1
FRK1	Auvergne	France	Non-capital region	1958	Competitiveness	Transition	Transition	North-wester	Above EU_avg	Below EU_avg	Above EU_avg	2	4
FRK2	Rhône-Alpes	France	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	1	1
FRL0	Provence-Alpes-Côte d'Azur	France	Non-capital region	1958	Competitiveness	More developed	Transition	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	2	1
DE11	Stuttgart	Germany	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	4	4
DE12	Karlsruhe	Germany	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Top 10	Above EU_avg	Above EU_avg	4	4
DE13	Freiburg	Germany	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	4	4
DE14	Tübingen	Germany	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	4	4
DE21	Oberbayern	Germany	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Top 10	Above EU_avg	Above EU_avg	4	4
DE25	Mittelfranken	Germany	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	4	4
DE27	Schwaben	Germany	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	4	4
DE40	Brandenburg	Germany	Non-capital region	1958	Convergence	Transition	Transition	North-wester	Above EU_avg	-	Above EU_avg	3	4
DE71	Darmstadt	Germany	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	1	1

NUTS 2 code	NUTS 2 label	Country	Capital region	EU accession	Category 2007-13	Category 2014-20	Category 2021-27	Geographic area	RIS	RCI	SPI	Q2000	Q2019
DE72	Gießen	Germany	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	4	4
DE80	Mecklenburg-Vorpomr	Germany	Non-capital region	1958	Convergence	Transition	Transition	North-wester	Below EU_avg	Above EU_avg	Above EU_avg	3	4
DE91	Braunschweig	Germany	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	4	4
DE92	Hannover	Germany	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	4	4
DE93	Lüneburg	Germany	Non-capital region	1958	Phasing-out	Transition	Transition	North-wester	Below EU_avg	Above EU_avg	Above EU_avg	3	4
DE94	Weser-Ems	Germany	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Below EU_avg	Above EU_avg	Above EU_avg	3	4
DEA1	Düsseldorf	Germany	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	1	4
DEA2	Köln	Germany	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	4	4
DEA3	Münster	Germany	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Below EU_avg	Above EU_avg	Above EU_avg	4	4
DEA4	Detmold	Germany	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	4	4
DEA5	Arnsberg	Germany	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	4	4
DEB1	Koblenz	Germany	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	4	4
DEB3	Rheinhessen-Pfalz	Germany	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	4	4
DED2	Dresden	Germany	Non-capital region	1958	Convergence	Transition	Transition	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	4	4
DEE0	Sachsen-Anhalt	Germany	Non-capital region	1958	Phasing-out	Transition	Transition	North-wester	Below EU_avg	Above EU_avg	Above EU_avg	2	4
DEF0	Schleswig-Holstein	Germany	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	4	4
DEG0	Thüringen	Germany	Non-capital region	1958	Convergence	Transition	Transition	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	3	4
EL30	Αττική	Greece	Non-capital region	1981	Phasing-out	More developed	Transition	Southern	Below EU_avg	Below EU_avg	Below EU_avg	2	1
EL43	Κρήτη	Greece	Non-capital region	1981	Convergence	Transition	Less developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	2	2
EL51	Ανατολική Μακεδονία, Θράκη	Greece	Non-capital region	1981	Convergence	Less developed	Less developed	Southern	Below EU_avg	Bottom 10	Below EU_avg	2	2
EL52	Κεντρική Μακεδονία	Greece	Non-capital region	1981	Phasing-out	Less developed	Less developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	2	2
EL61	Θεσσαλία	Greece	Non-capital region	1981	Convergence	Less developed	Less developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	2	2
EL63	Δυτική Ελλάδα	Greece	Non-capital region	1981	Convergence	Less developed	Less developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	2	2
EL64	Στερεά Ελλάδα	Greece	Non-capital region	1981	Phasing-in	Transition	Less developed	Southern	Below EU_avg	Bottom 10	Below EU_avg	2	2
EL65	Πελοπόννησος	Greece	Non-capital region	1981	Convergence	Transition	Less developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	2	2
HU21	Közép-Dunántúl	Hungary	Non-capital region	2004	Convergence	Less developed	Less developed	Eastern	Below EU_avg	Below EU_avg	Below EU_avg	3	3
HU22	Nyugat-Dunántúl	Hungary	Non-capital region	2004	Convergence	Less developed	Less developed	Eastern	Below EU_avg	Below EU_avg	Below EU_avg	3	3
HU23	Dél-Dunántúl	Hungary	Non-capital region	2004	Convergence	Less developed	Less developed	Eastern	Below EU_avg	Below EU_avg	Below EU_avg	3	3

NUTS 2 code	NUTS 2 label	Country	Capital region	EU accession	Category 2007-13	Category 2014-20	Category 2021-27	Geographic area	RIS	RCI	SPI	Q2000	Q2019
HU31	Észak-Magyarország	Hungary	Non-capital region	2004	Convergence	Less developed	Less developed	Eastern	Below EU_avg	Below EU_avg	Below EU_avg	3	3
HU32	Észak-Alföld	Hungary	Non-capital region	2004	Convergence	Less developed	Less developed	Eastern	Below EU_avg	Below EU_avg	Below EU_avg	3	3
HU33	Dél-Alföld	Hungary	Non-capital region	2004	Convergence	Less developed	Less developed	Eastern	Below EU_avg	Below EU_avg	Below EU_avg	3	3
ITC1	Piemonte	Italy	Non-capital region	1958	Competitiveness	More developed	More developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	2	1
ITC3	Liguria	Italy	Non-capital region	1958	Competitiveness	More developed	More developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	2	1
ITC4	Lombardia	Italy	Non-capital region	1958	Competitiveness	More developed	More developed	Southern	Below EU_avg	Above EU_avg	Below EU_avg	1	1
ITF1	Abruzzo	Italy	Non-capital region	1958	Competitiveness	Transition	Transition	Southern	Below EU_avg	Below EU_avg	Below EU_avg	2	2
ITF3	Campania	Italy	Non-capital region	1958	Convergence	Less developed	Less developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	2	2
ITF4	Puglia	Italy	Non-capital region	1958	Convergence	Less developed	Less developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	2	2
ITF5	Basilicata	Italy	Non-capital region	1958	Phasing-out	Less developed	Less developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	2	2
ITF6	Calabria	Italy	Non-capital region	1958	Convergence	Less developed	Less developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	2	2
ITG1	Sicilia	Italy	Non-capital region	1958	Convergence	Less developed	Less developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	2	2
ITG2	Sardegna	Italy	Non-capital region	1958	Phasing-in	Transition	Less developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	2	2
ITH3	Veneto	Italy	Non-capital region	1958	Competitiveness	More developed	More developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	2	1
ITH4	Friuli-Venezia Giulia	Italy	Non-capital region	1958	Competitiveness	More developed	More developed	Southern	Above EU_avg	Below EU_avg	Below EU_avg	2	1
ITI1	Toscana	Italy	Non-capital region	1958	Competitiveness	More developed	More developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	2	1
ITI2	Umbria	Italy	Non-capital region	1958	Competitiveness	More developed	Transition	Southern	Below EU_avg	Below EU_avg	Below EU_avg	2	1
ITI4	Lazio	Italy	Non-capital region	1958	Competitiveness	More developed	More developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	2	1
LV00	Latvija	Latvia	Non-capital region	2004	Convergence	Less developed	Less developed	Eastern	-	Below EU_avg	Above EU_avg	3	4
LU00	Luxembourg	Luxembourg	Capital region	1958	Competitiveness	More developed	More developed	North-wester	-	Above EU_avg	Above EU_avg	1	1
MT00	Malta	Malta	Capital region	2004	Convergence	Transition	Transition	Southern	-	Below EU_avg	Above EU_avg	2	4
NL11	Groningen	Netherlands	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	4	4
NL12	Friesland (NL)	Netherlands	Non-capital region	1958	Competitiveness	More developed	Transition	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	4	4
NL13	Drenthe	Netherlands	Non-capital region	1958	Competitiveness	More developed	Transition	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	4	4
NL21	Overijssel	Netherlands	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	4	4
NL22	Gelderland	Netherlands	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Top 10	Above EU_avg	4	4
NL23	Flevoland	Netherlands	Non-capital region	1958	Competitiveness	More developed	Transition	North-wester	Above EU_avg	-	Above EU_avg	4	4
NL32	Noord-Holland	Netherlands	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Above EU_avg	-	Above EU_avg	4	1

NUTS 2 code	NUTS 2 label	Country	Capital region	EU accession	Category 2007-13	Category 2014-20	Category 2021-27	Geographic area	RIS	RCI	SPI	Q2000	Q2019
NL34	Zeeland	Netherlands	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	4	4
NL41	Noord-Brabant	Netherlands	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Top 10	Above EU_avg	4	4
NL42	Limburg (NL)	Netherlands	Non-capital region	1958	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	4	4
PL21	Małopolskie	Poland	Non-capital region	2004	Convergence	Less developed	Less developed	Eastern	Below EU_avg	Below EU_avg	Below EU_avg	3	4
PL22	Śląskie	Poland	Non-capital region	2004	Convergence	Less developed	Less developed	Eastern	Below EU_avg	Below EU_avg	Below EU_avg	3	4
PL41	Wielkopolskie	Poland	Non-capital region	2004	Convergence	Less developed	Transition	Eastern	Below EU_avg	Below EU_avg	Below EU_avg	3	4
PL42	Zachodniopomorskie	Poland	Non-capital region	2004	Convergence	Less developed	Less developed	Eastern	Below EU_avg	Below EU_avg	Below EU_avg	3	3
PL51	Dolnośląskie	Poland	Non-capital region	2004	Convergence	Less developed	Transition	Eastern	Below EU_avg	Below EU_avg	Below EU_avg	3	4
PL61	Kujawsko-pomorskie	Poland	Non-capital region	2004	Convergence	Less developed	Less developed	Eastern	Below EU_avg	Below EU_avg	Below EU_avg	3	3
PL62	Warmińsko-mazurskie	Poland	Non-capital region	2004	Convergence	Less developed	Less developed	Eastern	Below EU_avg	Below EU_avg	Below EU_avg	3	3
PL63	Pomorskie	Poland	Non-capital region	2004	Convergence	Less developed	Less developed	Eastern	Below EU_avg	Below EU_avg	Below EU_avg	3	4
PT11	Norte	Portugal	Non-capital region	1986	Convergence	Less developed	Less developed	Southern	Below EU_avg	Below EU_avg	Above EU_avg	3	4
PT16	Centro (PT)	Portugal	Non-capital region	1986	Convergence	Less developed	Less developed	Southern	Below EU_avg	Below EU_avg	Above EU_avg	3	4
PT17	Área Metropolitana de Lisboa	Portugal	Capital region	1986	Competitiveness	More developed	More developed	Southern	Below EU_avg	Above EU_avg	Above EU_avg	3	1
RO11	Nord-Vest	Romania	Non-capital region	2007	Convergence	Less developed	Less developed	Eastern	Bottom 10	Bottom 10	Below EU_avg	3	3
RO12	Centru	Romania	Non-capital region	2007	Convergence	Less developed	Less developed	Eastern	Bottom 10	Bottom 10	Bottom 10	3	3
RO21	Nord-Est	Romania	Non-capital region	2007	Convergence	Less developed	Less developed	Eastern	Bottom 10	Bottom 10	Bottom 10	3	3
RO22	Sud-Est	Romania	Non-capital region	2007	Convergence	Less developed	Less developed	Eastern	Bottom 10	Bottom 10	Bottom 10	3	3
RO31	Sud-Muntenia	Romania	Non-capital region	2007	Convergence	Less developed	Less developed	Eastern	Bottom 10	Bottom 10	Bottom 10	3	3
RO32	Bucureşti-Ilfov	Romania	Capital region	2007	Convergence	More developed	More developed	Eastern	Below EU_avg	Below EU_avg	Below EU_avg	3	4
RO41	Sud-Vest Oltenia	Romania	Non-capital region	2007	Convergence	Less developed	Less developed	Eastern	Bottom 10	Bottom 10	Bottom 10	3	3
RO42	Vest	Romania	Non-capital region	2007	Convergence	Less developed	Less developed	Eastern	Bottom 10	Below EU_avg	Below EU_avg	3	3
SK02	Západné Slovensko	Slovakia	Non-capital region	2004	Convergence	Less developed	Less developed	Eastern	Below EU_avg	Below EU_avg	Below EU_avg	3	3
SK03	Stredné Slovensko	Slovakia	Non-capital region	2004	Convergence	Less developed	Less developed	Eastern	Below EU_avg	Below EU_avg	Below EU_avg	3	3
SK04	Východné Slovensko	Slovakia	Non-capital region	2004	Convergence	Less developed	Less developed	Eastern	Below EU_avg	Below EU_avg	Below EU_avg	3	3
ES11	Galicia	Spain	Non-capital region	1986	Convergence	More developed	Transition	Southern	Below EU_avg	Below EU_avg	Above EU_avg	2	1
ES12	Principado de Asturias	Spain	Non-capital region	1986	Phasing-out	More developed	Transition	Southern	Below EU_avg	Below EU_avg	Above EU_avg	2	1
ES13	Cantabria	Spain	Non-capital region	1986	Competitiveness	More developed	Transition	Southern	Below EU_avg	Below EU_avg	Above EU_avg	2	1

NUTS 2 code	NUTS 2 label	Country	Capital region	EU accession	Category 2007-13	Category 2014-20	Category 2021-27	Geographic area	RIS	RCI	SPI	Q2000	Q2019
ES21	País Vasco	Spain	Non-capital region	1986	Competitiveness	More developed	More developed	Southern	Above EU_avg	Above EU_avg	Above EU_avg	2	1
ES22	Comunidad Foral de Navarra	Spain	Non-capital region	1986	Competitiveness	More developed	More developed	Southern	Above EU_avg	Below EU_avg	Above EU_avg	2	1
ES23	La Rioja	Spain	Non-capital region	1986	Competitiveness	More developed	Transition	Southern	Below EU_avg	Below EU_avg	Above EU_avg	2	1
ES24	Aragón	Spain	Non-capital region	1986	Competitiveness	More developed	More developed	Southern	Below EU_avg	Below EU_avg	Above EU_avg	2	1
ES30	Comunidad de Madrid	Spain	Capital region	1986	Competitiveness	More developed	More developed	Southern	Above EU_avg	Above EU_avg	Above EU_avg	1	1
ES41	Castilla y León	Spain	Non-capital region	1986	Phasing-in	More developed	Transition	Southern	Below EU_avg	Below EU_avg	Above EU_avg	2	1
ES42	Castilla-La Mancha	Spain	Non-capital region	1986	Convergence	Transition	Less developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	2	2
ES43	Extremadura	Spain	Non-capital region	1986	Convergence	Less developed	Less developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	2	2
ES51	Cataluña	Spain	Non-capital region	1986	Competitiveness	More developed	More developed	Southern	Above EU_avg	Above EU_avg	Above EU_avg	2	1
ES52	Comunitat Valenciana	Spain	Non-capital region	1986	Phasing-in	More developed	Transition	Southern	Below EU_avg	Below EU_avg	Above EU_avg	2	1
ES53	Illes Balears	Spain	Non-capital region	1986	Competitiveness	More developed	Transition	Southern	Below EU_avg	Below EU_avg	Above EU_avg	2	1
ES61	Andalucía	Spain	Non-capital region	1986	Convergence	Transition	Less developed	Southern	Below EU_avg	Below EU_avg	Below EU_avg	2	2
ES62	Región de Murcia	Spain	Non-capital region	1986	Phasing-out	Transition	Transition	Southern	Below EU_avg	Below EU_avg	Below EU_avg	2	2
ES70	Canarias	Spain	Non-capital region	1986	Phasing-in	Transition	Transition	Southern	Below EU_avg	Below EU_avg	Above EU_avg	2	2
SE11	Stockholm	Sweden	Capital region	1995	Competitiveness	More developed	More developed	North-wester	Top 10	Top 10	Top 10	4	1
SE12	Östra Mellansverige	Sweden	Non-capital region	1995	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Above EU_avg	Top 10	4	4
SE21	Småland med öarna	Sweden	Non-capital region	1995	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	4	4
SE22	Sydsverige	Sweden	Non-capital region	1995	Competitiveness	More developed	More developed	North-wester	Above EU_avg	Above EU_avg	Above EU_avg	4	4
SE23	Västsverige	Sweden	Non-capital region	1995	Competitiveness	More developed	More developed	North-wester	Top 10	Above EU_avg	Above EU_avg	4	4
SE31	Norra Mellansverige	Sweden	Non-capital region	1995	Competitiveness	More developed	Transition	North-wester	Below EU_avg	Above EU_avg	Above EU_avg	4	4