Eastern Journal of European Studies
DOI: 10.47743/ejes-2023-0114 | June 2023 | VOLUME **14**, ISSUE **1**

Economic and regional development through SNA: the case of the unemployment rate in NUTS 2 regions of the EU

Pagona Filenta[a*], Dimitrios Kydros[a]

[a]International Hellenic University Serres, Greece

Abstract
Economic and Regional Development refers to the process of developing regions to improve their economic, political and social prosperity. This document analyses the unemployment rate of the NUTS 2 regions for 2008-2021. A model is proposed, which applies Social Network Analysis (SNA) within the framework of Economic and Regional Analysis. SNA is a process that allows the exploration of social structures using networks and graph theory. It presents the visualization of several networks, created based on the degree of correlation of the total unemployment rate data, and calculates measures and centrality metrics to conclude about the interaction and clustering of regions. The paper shows that by using SNA the interaction between regions and hence their clustering based on the change in the unemployment rate was detected, and it offers their visualization. Therefore, the application of SNA in economic and regional analysis could be a reliable methodology for future research.

Keywords: economic and regional development, Social Network Analysis (SNA), NUTS 2, total unemployment rate

Introduction

Economic and regional development in the European Union is not a recent subject of study in the international literature. The inequalities observed in the spatial distribution of income and economic activities between regions have created much interest among scholars in recent decades (Petrakos & Saratsis, 2000). A large number of studies focus on the spatial and structural differences between regions using various methods of quantitative and statistical analysis. Economic and Regional Development is not about a static picture, but it studies the complex dynamics of regions (Nijkamp & Abreu, 2009).

Studies that focus on the regional distribution of labour and capital as well as income and wealth disparities are common. Ballas et al. (2017) have brought to light

[*]Corresponding author: Pagona Filenta, PhD candidate at the Department of Economic Sciences, International Hellenic University Serres, Greece; e-mail: pagofile2@ihu.gr.

significant economic, spatial, and social inequalities, the elimination of which requires significant social change and environmental sustainability. They also showed that the regions inside countries, towns and cities, or wealthy and poor neighbourhoods within cities present significant inequalities in the standard of living and the kinds of difficulties and problems encountered by Europe's citizens exist, rather than at national borders.

The study by (Maerinez-Galarraga et al., 2015) attempted to explain some of the immediate causes of regional inequality in Spain and provided a long-term perspective on the issue. In order to achieve this, they compared the regional GDP for the years 1860-1930 to the similar figure for the years 1930-2000. The research was thus able to examine the long-term development of regional GDP per worker inequality in the Spanish NUTS-2 areas and to dissect it into its primary causes. From 1860 to 1990, the regional income disparity in Spain followed a long-term inverted U-shaped trend, increasing until 1900 and then declining after that. It is important to note that inequality increased again between 1990 and 2000.

Bouzarovski & Herrero (2015) researched the presence of a geographical energy poverty gap in the European Union (EU) in the context of examining the connection between energy transitions and the patterns of current regional economic inequality. While energy poverty is a common issue in Europe, there are significant geographic and social disparities. The findings of their research demonstrated that, because energy poverty is more prevalent in EU Member States in Southern and Eastern Europe, the traditional division between the core and periphery of economic development continues to be accurate in this situation.

Inequality has grown over the past three decades in many Member States, and the 2008 financial crisis only made matters worse, according to a 2015 analysis by the European Commission. In some countries, income inequality is not particularly high, but wealth inequality has increased (Widuto, 2019). Eliminating regional inequality is a duty of the European Union as an institution. Various tools, like the European Structural and Investment Funds, have been devised to address imbalances in order to promote regions that are less developed than other regions. (European Union, 2020).

Social Network Analysis (SNA) or network theory refers to a theory that leads to the understanding and exploration of unities that have developed a relationship (connection) with each other (Wasserman & Faust, 1994). The theory was initiated more than a century ago by sociologists and in recent years has evolved into an important field of sociological study (Jackson, 2005). However, the theory is not limited to the scientific field of sociology, but has been successfully applied in many different fields, from computer networks, biology and economic science to political science. Furthermore, in recent years scholars have used the theory of SNA methods in works of culture and literature (Kydros & Anastasiadis, 2014). SNA has its roots in graph theory and a basic form of it is the visualization of a network.

This paper attempts to introduce SNA into economic and regional analysis. For this purpose, the total unemployment rate of the NUTS2 regions of the European

Union from 2008 to 2021 is used as raw data to generate cross-correlation tables, which will be processed to produce adjacency matrices. These in turn and in collaboration with SNA techniques are the basis for the construction of networks (graphs) via the NodeXL Pro analysis and visualization software package (Smith et al., 2010). Appropriate metrics and centrality measurements will allow us to infer the interaction, and groupings between the NUTS2 regions of the EU.

Particularly, through this paper we attempt to draw conclusions on the grouping of regions in terms of the unemployment rate of the NUTS 2 regions of the EU. In other words, can regions be grouped based on the correlation of the unemployment rate? Which regions belong to each group and how is the grouping derived? Finally, is SNA an alternative method of studying economic and regional analysis?

1. Economic and regional development and Social Network Analysis (SNA)

In this section we will briefly analyse economic and regional analysis, as well as SNA, and we will refer to key terms and concepts. We will also refer to the international literature, citing works that make use of SNA, attempting to answer the question whether SNA has been applied to the study of economic and regional development.

1.1. Economic and regional development

The concept of Economic and Regional Development refers to the geography of prosperity and its evolution. It plays a leading role in areas such as economic geography, regional economics, regional science theory, and economic development. In a competitive environment, the mobility of human resources and capital, as well as trade between regions, will reinforce the negative relationship between growth and regional imbalances (Petrakos et al., 2005). The change in welfare is not easy to measure. For this reason, statistical analysis often uses Gross Domestic Product (per capita) and its fluctuation. Alternatively, indexes such as per capita consumption, poverty rate, unemployment rate, labour force participation rate, or access to public services can be used, namely social indicators that allow comparisons (Nijkamp & Abreu, 2009).

As already mentioned, GDP per capita is the predominant measure in most articles (Capello et al. 2017; Lopez-Bazo et al., 1999; Rodriguez-Pose & Ketterer, 2020, Martinez-Galarraga et al. 2015). Ezcurra (2019) studied the regional differences and inequalities observed within the European Union Member States for the period 1996-2010 and investigated the determinants of these inequalities by studying data for 272 NUTS 2 regions of the 28 Member States. His analysis broadly confirms that differences within Member States are a key factor in the overall inequalities of all European regions and that the relationship between national development and inequality within an economy is not linear.

Regional income inequality is also an indicator studied in Economic and Regional Development, as it is a permanent feature of both developed and developing countries. According to Martinez-Galarraga et al. (2015) since the 1980s, the increasing integration of the European Union has been accompanied by a reduction in individual income differences between EU Member States, but regional inequalities within countries still exist. After 1990, as countries started the economic transition from a centrally planned to a market economy and the political transition from an authoritarian to a democratic government, income disparity in the transitioning nations of Central and Eastern Europe increased (Rose & Viju, 2014).

Other measures prevalent in Economic and Regional Development research are employment/unemployment rate (Becker et al., 2018; Sardadvar & Vakulenko, 2021;), education level (Aria et al., 2019; Dima et al., 2018; Doran et al., 2016), population growth and density, and demographic composition (Rios & Gianmoena, 2020). Some other measures that are studied to a lesser extent are transport infrastructure data, highway and rail network (Rios & Gianmoena, 2020), hospital beds per 100,000 population (Ayouba et al., 2020), life expectancy (Rizzi et al., 2018), wage flexibility (Abraham, 1996), inflation rate (Capello et al., 2017; Formánek, 2019), etc.

In this paper, the unemployment rate in the regions of the EU is examined. Since unemployment weakens social cohesion and strains public budgets due to increased spending on unemployment benefits and decreased tax collections, it is especially crucial to analyse regional unemployment. As a result, both researchers and policymakers have always been concerned about high unemployment rates. At both the national and regional levels, reducing unemployment and inequality in Europe is a major problem. The economic turmoil that followed the 2008 financial crisis led to a high increase in unemployment rates across Europe, leading to polarization. The weighted average of the unemployment rates in the member nations, known as the euro area, increased from 7,5% in 2007 to 11,9% in 2013. This statistic does, in fact, conceal a great deal of heterogeneity: in 2013, the unemployment rate in Spain was above 25% while it was just over 5% in Germany. Rates can differ dramatically even within regions of the same member state; for instance, they are nearly five times greater in the Belgian Brussels-Capitale region than in Oost-Vlaanderen. While unemployment rates have remained above average in some Member States and regions, the recent economic turmoil has made the labour markets in Europe more diverse (Beyer & Stemmer, 2016).

Niebuhr (2003) focused on the spatial organization of regional unemployment disparities. She contends, in particular, that the EU's low wage flexibility and restricted labour mobility imply persisting regional unemployment inequalities. The survey's findings indicated that regional labour markets in Europe exhibit a considerable degree of spatial dependence. Both areas with high unemployment rates and areas with low unemployment rates tend to be concentrated in space. The results imply that various spatial interactions have an impact on how regional unemployment has changed across Europe.

Overman et al., (2002) investigated the regional and interstate dimension of unemployment and indicated to the "neighbour effect". They referred to geographical clustering of unemployment not determined by national borders. In particular, they observed that since the 1980s, while locations with intermediate unemployment rates headed towards extreme values, locations with high or low initial unemployment rates showed little change. Indeed, this polarization was characterized by the fact that nearby regions tended to share similar outcomes due to spatially correlated changes in labour demand. Finally, policies dealing with unemployment and regional disparities have not brought the expected results.

The study by Kivi & Paas (2021) uses various spatial econometric model types to examine spatial interactions in European labour markets with a focus on the resilience of possible interactions over the period 2004-2018. The research is predicated on the hypothesis that changes in the employment rate and unobserved shocks in other regions have an impact on the employment rate in one region. After the European Union's 2004 enlargement, there have been some minor increases in spatial interactions in employment rates, which have continued to rise throughout the preceding economic crisis. The findings demonstrate that regional labour markets' spatial interactions are resilient to economic downturns, supporting the need for close regional coordination when formulating labour market and regional policy responses to various sorts of crises.

The growth potential of every region in Europe has been impacted by the process of European integration. However, distinct groups of countries' development trajectories have been highly different. The Central and Eastern EU Member States have had a largely similar path to growth since joining the Union. However, a more thorough study of this pattern is provided by the geography of development in these nations. The purpose of the research of Psycharis et al. (2020) is to give empirically supported information about regional development and inequalities in the EU, with a particular focus on the countries of Central and Eastern Europe from 2000 to 2016, with emphasis on the importance of metropolitan regions. Data on economic and demographic factors, including population, GDP, and GDP per capita in PPS, provide the basis for their analysis. Some intriguing findings from the investigation have been presented. First, compared to the average of the EU, the CEE countries are developing their economies more slowly; nonetheless, there is a significant trend toward convergence. Also, there are significant and enduring regional disparities in the CEE nations. Furthermore, metropolitan areas have levels of economic development that are above the EU average, making them the outliers in terms of level of economic development.

Regional disparities on the territory of the European Union have been extensively researched by many academics, and there is an extensive amount of literature on the subject (Petrakos & Saratsis, 2000). As the Union contains different

Member States with various rates of productivity and economic growth, convergence analysis is essential (Monford et al., 2013). The formation of a cohesion policy, which results in the reduction of disparities and regional development, is primarily aided by the obtaining, analysis, and assessment of quantitative data (Annoni et al. 2019; Cuadrado-Roura, 2001; Widuto 2019). A large number of studies have utilized various quantitative and statistical analysis techniques to concentrate on the spatial and structural disparities of regions.

There are numerous approaches and procedures in the analysis of Economic and Regional Development. Exploratory Spatial Data Analysis (ESDA) could be mentioned, which is a technique for describing and visualizing spatial distributions (Annoni et al., 2019; Dall'erba, 2005; Ertur & Koch, 2006). Also, there is Beta-convergence, a method of economic study between regions. As beta-convergence concentrates on the growth process, sigma-convergence emphasizes correcting imbalances between regions throughout time (Chocholata & Furkova, 2016). Additionally, interactions between regions that are members of the same economic union and expanding ties between regions of different Member States (such as those involving trade, technology, and transportation networks) allow for a direct correlation between the development of one region and the corresponding development of a neighbouring region. To put it differently, it is unusual for the distribution of regional production to be independent and random (Lopez-Bazo et al., 1999). Total spatial autocorrelation is typically measured using a set of statistical parameters (Ertur & Koch, 2006), and according to Mora & Moreno (2010), this measure captures the interaction between regions depending on their closeness to one another. According to Lopez-Bazo et al. (1999), the Moran's I and Geary's C indices are statistical metrics that quantify spatial autocorrelation. Dall'erba (2005) used them to evaluate the spatial distribution of regional revenue and finances, while Mora & Moreno (2010) used them to test the spatial dependence of the research variables (GDP, agricultural sector, patents, etc.). The Atkinson, Theil, and Gini indices, which measure economic inequality, are further indicators that look at regional and economic development. According to Monford (2008), the Gini index can be used to compare these numbers across populations and across geographical regions. According to Rodriguez-Pose and Tselios (2010), it is a more sensitive metric to changes in the median income distribution. Finally, Monford (2008) argues that the Atkinson index looks at income inequality and tries to identify which part of the distribution is most responsible for it.

1.2. Social Network Analysis (SNA)

The object of SNA is to study the relationships between individuals, social groups or organizations and the behavioural interactions associated with the formation of social relationships (O'Malley & Marsden, 2008). A social network can be compared to a web, which captures the interactions of people. Such networks include social or professional relationships/contacts between individuals, companies, organizations, etc. through which information and favours circulate on a systematic basis (Jackson, 2005).

There are two methods to represent a network: a matrix or a graph. A social network consists of individuals or groups, the "nodes" or "vertices" that interact with each other in social relationships. These interactions are called “links” or “edges”. An n x n adjacency matrix can represent a network G. The values of the table are 1 or 0. In particular, the value $g_{ij} = 1$ is given when there is a link between the nodes i and j and $g_{ij} = 0$ in case there does not exist a link (Jackson, 2005). A graph provides us with a visualization of a social network as a model of a social system, which consists of a number of nodes connected to each other by links (Wasserman & Faust, 1994).

According to graph theory vocabulary, a graph G= (N, A) consists of two sets of elements. First, N= $\{n_1, n_2, n_3,\ldots,n_N\}$, the set of nodes (or vertices) with n=|N| the denotation of the total number of the nodes. Second, A= $\{l_1, l_2, l_3,\ldots, l_L\}$ the set of links (or edges) denoted as lines between a pair of nodes and l=|L| the denotation of the total number of links, where $l_k = (n_i, n_j)$, n_i, $n_j \subseteq N$ and $l_k \subseteq G$ (Kydros et al., 2012). Two nodes n_1 and n_2 connected by a link l_1 are called neighbors. A neighborhood Ni (g) of a node n1 is defined as the set of nodes connected to it in the network g, so that N_i (g) = $\{n_1 \mid n_2 \subseteq g\}$ (Jackson, 2005)

If some vertices (hence edges) are removed from a graph G = (N, A) a subgraph G'= (N', A') is generated, where N' ⊆ N and A'⊆ A.

An important element of a network is its connectivity. Two nodes are connected, when we can follow a continuous sequence of links from one node to another (without interruption). Otherwise, the network is called disconnected. In case every node is connected to all other nodes of the graph, the graph is called complete (Maier & Vyborny, 2005).

The nodes of a network are examined in terms of their position relative to other nodes. The reason is to carry out inferences regarding the importance of nodes. When studying a network, there are several indicators that describe the relationships that develop. The density of a network is the ratio of the number of links present to the maximum possible number of links in a network. This metric can answer questions about the most central node of a network or about its connectedness (Maier & Vyborny, 2005). In a complete network the density will be N(N-1)/2. The density of a graph, which can take values from 0 (L=0) to 1, is calculated as:

$$S = 2L/N(N-1)$$

Centrality measures are indicators that examine the overall position, role and action of nodes in a network and identify the most important variables of it. This leads to conclusions about which node is more important in the network than the others. Degree centrality, which is a simple centrality metric determined by the number of direct connections to a given node (Kydros & Oumbailis, 2015). A node, which has no link to another node, i.e. with a degree equal to 0 is called isolated node. In a network every link is connecting two nodes, so the average degree of a network will be

$$d_i = 2L/N$$

Betweenness centrality refers to the nodes, which fall often between other nodes. A node, that has high betweenness centrality, acts as an intermediate between other nodes with respect to their shortest path. The higher the betweenness centrality of a node is, the more this vertex is needed for information flow between pairs of nodes. Consequently, removing this node from the network would interrupt its communication.

1.3. Application of SNA in regional sciences

The question arises whether there is an application of SNA in economic science and specifically in Economic and Regional Development. SNA has been used in some areas of economic theory. The majority of the articles using SNA focus on other scientific areas and not on "Economic and Regional Development". Some articles that study the transfer of knowledge in various scientific areas through social networks could be mentioned (Vittoria et al., 2014). There are articles about financial leaders (workforce innovation) (Dziadkowiec et al., 2015) and articles about R&D knowledge networks (Gama et al., 2018). According to Grabher (2006) networks have been applied extensively in studies of regional economics and economic geography in recent decades. The techniques of SNA are useful while examining the structure of the effect between regions and geographical clusters. Many researchers believe that networks are an appropriate conceptualization of the effect between organizations and the flow of knowledge (Ter Wal & Boschma, 2009). Furthermore, labor market (Calvo-Armengol & Ioannides, 2005; Calvo-Armengol & Jackson, 2007), the garment industry (Uzzi, 1996) are some examples, where networks have gained attention.

In their paper Kim et al. (2011) presented how to use SNA to explore the structural characteristics of supply networks. The main SNA indicators are related to supply network topologies in this work's theoretical framework. Since SNA had never been used in an empirical analysis of actual supply networks prior to the publishing of this research, their goal was to demonstrate how it might supplement more conventional, qualitative ways of interpretation when evaluating cases involving supply networks. They employed a variety of criteria, including density and various centrality indicators, which finally resulted in the establishment of a portfolio of prospective supply chain management strategies. They arrived at the conclusion that SNA provides numerous quantitative measurements that qualitative techniques do not. SNA can produce current, unexpected results by examining the structural aspects of supply networks, which are usually missed by qualitative approaches.

Prell et al. (2009) investigated stakeholder analysis with SNA concerning natural resource management. They observed that the increased application of stakeholder analysis in natural resource management represents an expanding understanding that stakeholders can and should affect environmental decision-making. Stakeholder analysis can be used to represent various interests fairly, stop disputes from getting worse, and ensure that certain groups are not further marginalized. Using data acquired from the research of stakeholder social networks, they made an effort to illustrate how stakeholders could be chosen to take part in natural resource management projects. They provided suggestions in their article for improving stakeholder representation in participative processes. As a result, SNA is an advanced technique that improves accuracy and fosters a more profound knowledge of social ties among stakeholders. However, if utilized in isolation from other data, the results may provide conclusions concerning stakeholder participation in natural resource management that are oversimplified.

SNA could be a suitable tool for economic geographers in the empirical study of the structure and evolution of inter-organizational interaction, as well as knowledge flows both within and between regions. According to Ter Wal and Boshma (2009) the most empirical studies based on cluster networks, study the network as a static picture in a specific point in time. However, studies based on statistical analysis in combination with dynamic networks, do not exist.

Finally, we conclude that SNA has been successfully applied in various scientific fields. Network analysis techniques have contributed to research in various scientific disciplines, but have not been applied to regional sciences. The contribution of this paper is to introduce SNA to economic and regional development. The analysis attempts to provide an empirical method of study through available techniques and metrics and argue that using centrality measures can lead to conclusions about the interaction and clustering of nodes. The application of SNA to economic and regional development could then contribute to the formulation of policies and strategies with the main focus on cohesion between EU regions.

1.4. Methodology

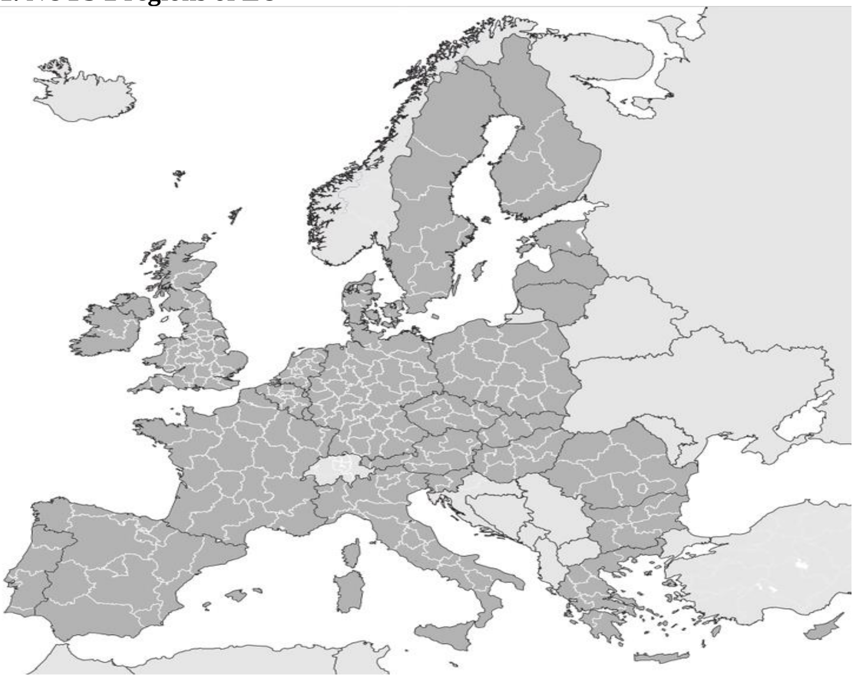
The Eurostat database was used for data collection. The sample consists of data of regional statistics by NUTS classification. Specifically, we have collected the total unemployment rates by sex, age, citizenship and NUTS 2 regions for citizens aged from 15 to 64 years for the period of 2008-2021.

There were some values in the time series, which were not available mainly due to the amendment of the NUTS classification. The regulation of the NUTS classification ensures that the classification is stable for at least three years and also ensures that the data refer to the same regional unit for a specific period of time, which is significant for the time series. However, sometimes national interests require a change in the regional breakdown of a country. In this case the country concerned shall inform the European Commission of the changes. In addition, the Commission modifies the classification at the end of the stability period according the rules of the NUTS classification (Eurostat, 2011).

To complete the data of the total unemployment rate, which were not available, we made some calculations, which are presented in Appendix.

The overall process resulted in the final sample of the study, which consists of 239 NUTS2, i.e. the total unemployment rate of the 239 regions for the period 2008-2021.

Figure 1. NUTS 2 regions of EU



Source: Eurostat

After filling in the missing data, the data set was stored in a spreadsheet to construct a correlation matrix for the overall unemployment rates. Specifically, we worked as follows: we collected all the data, i.e. the unemployment rate of each region for the period under consideration, in a spreadsheet. Each line in the spreadsheet corresponds to a region. Each column corresponds to the value of the unemployment rate for this specific region, for one year. Hence we have 14 columns, since we deal with the time period from 2008 to 2021 Using excel, we calculated the correlation coefficient for each pair of regions i, j:

$\rho_{ij} = cov_{ij} / \sigma_i\sigma_j$, where

cov_{ij} = the Covariance of regions i and j, where $cov_{ij} = [P_i\text{-}E(P_{i)}][P_j\text{-}E(P_j)] / n\text{-}1$,

E(P) = the average of each region, n = the count of the regions,
σ_i = the standard deviation of region i and σ_j = the standard deviation of region j

Finally, based on the correlation coefficients of each pair of regions i, j we constructed a cross-correlation, rectangular, one diagonal and symmetric matrix, with dimensions 239 X 239, that includes values between -1 to 1. These values can be interpreted as follows: when the correlation coefficient tends to -1, the two regions move inversely, namely when the unemployment rate of one region increases, the rate of the second region decreases and vice versa. When the correlation coefficient tends to 1, then the two regions move to a similarly direction, namely when the unemployment rate of one region increases, then the rate of the second region increases similarly. If the coefficient is zero, no prediction can be made, because this means that the two regions vary in a random way.

The next step was to use the correlation coefficient matrices, to construct a correlation network, in which every region represents a node. For this purpose, we set a certain threshold (θ), which varies between -1 and 1. When a correlation coefficient of the matrix is greater than θ, a link is created between the two regions and thus an adjacency matrix is generated. An adjacency matrix is a NXN matrix where:

$$A_{i,j} = \begin{cases} 1, & if\ \mathrm{n}i\ is\ connected\ to\ nj \\ 0, & otherwise \end{cases}$$

We repeated this procedure for different values of θ and created different adjacency matrices with the same number of nodes (regions) and different number of links (Huang et al., 2009). Through the use of NodeXL Pro software package (Smith et al., 2010) we transformed the adjacency matrices into networks by visualizing nodes and links. Finally, NodeXL Pro was also used to calculate metrics, to conclude about the community structure and the interaction of the regions.

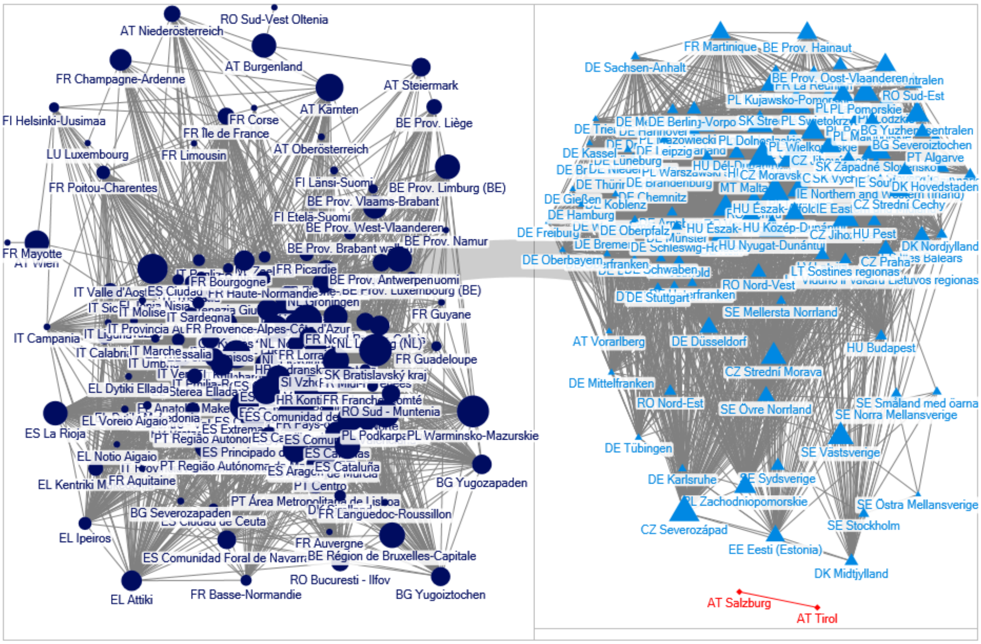
2. Data analysis

Next, we tried to study the networks created when we introduce different values of θ (threshold), as mentioned in the previous section. To study the correlation of the unemployment rate between NUTS 2 regions, we set threshold values from θ > 0,7 to θ > 0,85. In other words, have we tried to formulate to what extent the overall unemployment rate between regions tends to move in the same direction for different levels of correlation (θ), i.e. do groupings/communities of regions with similar rates of change in the unemployment rate emerge? Is there an interaction and a possible clustering between regions on the change in the unemployment rate exist? To reach conclusions we calculated metrics for each network. We used betweenness centrality, according to Brandes' algorithm (Brandes, 2001). The nodes (regions) with the highest betweenness centrality are the largest in the networks.

2.1. Analysis by network

Starting from the threshold θ> 0,7 three groups of regions can be distinguished in the generated network (Figure 2). The first group consists of 130 nodes, which are connected to each other with 3.671 links, while the second group consists of 107 nodes with 3.263 links, and the third one of 2 nodes connected by only one link. Important nodes of the network seem to be Comunidad de Madrid (ES), Bratislavský kraj (SK), due to a high degree (115 for each region). High degree centrality means that the particular node (region) has a strong interaction with the other nodes in the network, i.e. there are a large number of links between it and the other nodes. In other words, based on the correlation coefficient these regions show similar trends in the change of the unemployment rate, i.e. when the unemployment rate of one region increases, the corresponding rate of the other region increases. These two nodes have also high values in betweenness centrality (440,8 and 426,1), which means that they are located more often between other nodes. The network is quite dense (graph density = 0,290), so no substantial conclusions can be drawn. For this reason, the following network was created with an increased threshold of θ > 0,80 (Figure 3).

Figure 2. Betweenness Centrality, Correlation θ > 0,7

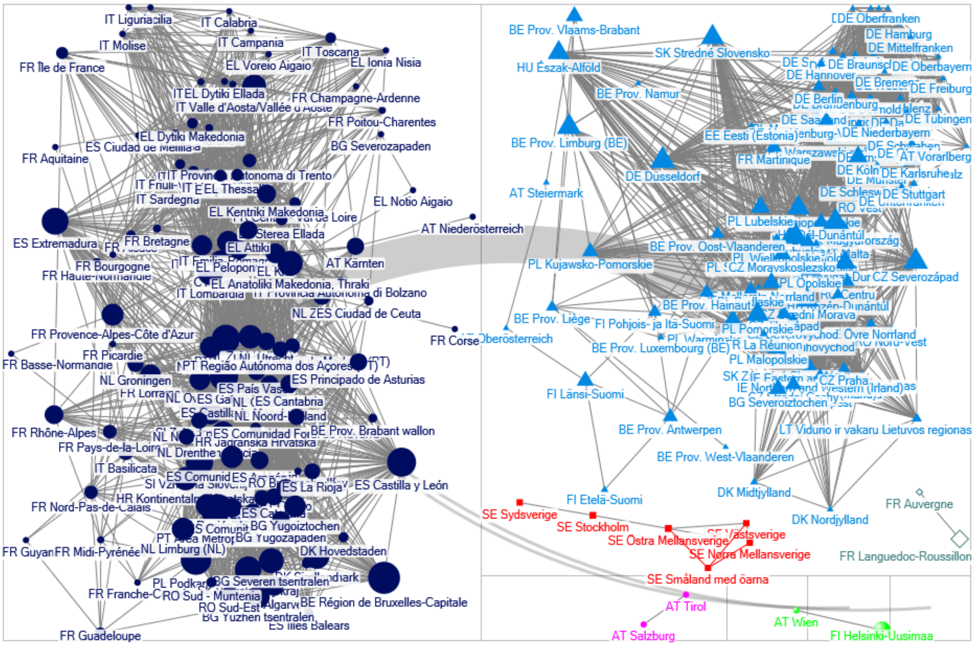


Source: Authors' representation

For θ >0,80 (Figure 3) 6 groups are created. The number of isolated nodes is equal to 6: Limousin (FR), Mayotte (FR), Luxembourg (LU), Burgenland (AT), Nord-Est (RO), and Sud-Vest Oltenia (RO), which indicates that these regions have no connection to other regions, i.e. there exist no interaction between them. In other words, to a degree of correlation above 80%, the unemployment rate of these regions does not move in the same or similar direction to the other regions. Graph density decreases to 0,175. The first group consists of 115 nodes, which are connected to each other with 2.155 links, the second group consists of 106 nodes with 2.171 links and the third group includes 6 nodes and 8 links. The last three groups have only two nodes with one link each.

The nodes with the highest degree are Norte (PT) =83, and Podkarpackie (PL) =79, which are the regions with the highest betweenness centrality, too (879,85 and 744,41).

Figure 3. Betweeness Centrality, Correlation θ > 0,8

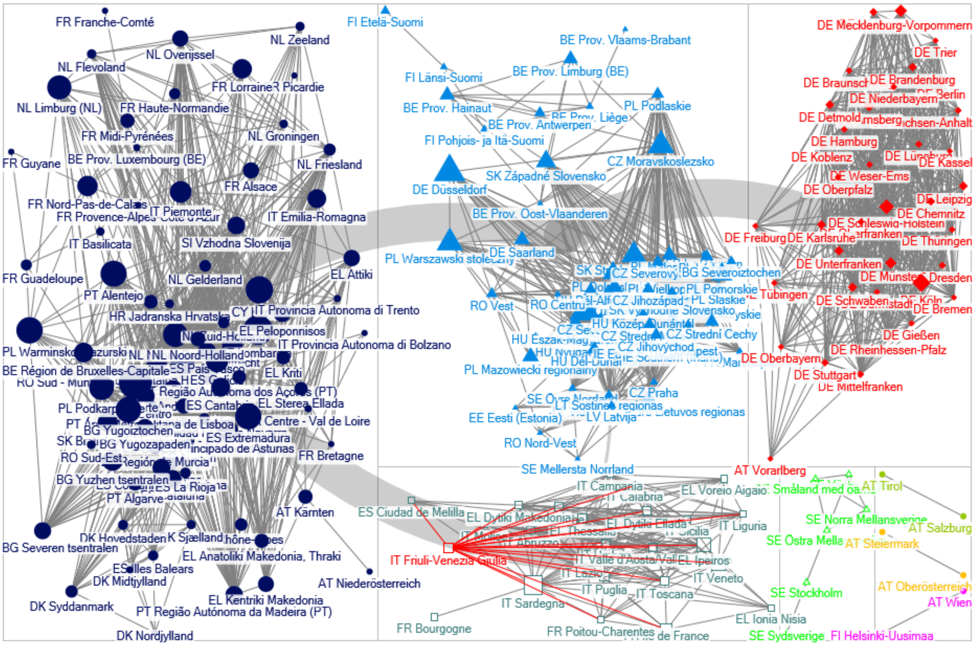


Source: Authors' representation

We then created the network where θ > 0,85 (Figure 4), namely the network with the highest correlation in this work. The number of isolated nodes of this network increased to 19. These nodes include 3 regions of Belgium, 9 regions of France, 2 regions of Romania, and 1 region of Greece, Spain, Austria, and Luxembourg. As predictable, this network is by far the sparsest, with a density of 0,123, and an increase in the number of groups. In particular, 8 groups emerged in the network. The first group consists of 85 nodes, which are connected to each other with 1.132 links; the second group consists of 61 nodes with 875 links; the third group includes 37 nodes and 574 links, the fourth group consists of 25 nodes and 203 links between them, while the other groups include only 6 to 2 nodes and a small number of links (from 8 to 1).

The regions that stand out due to the high degree are Southern (IR) =62 and Porte (PT)=62, which has also high betweenness centrality (1.274).

Figure 4. Betweenness Centrality, Correlation θ > 0,85



Source: Authors' representation

A Synoptic topology of the created networks is shown in Table 1.

Table 1. Synoptic Topology

Correlation	> 0,7	> 0,75	> 0,8	> 0,85	> 0,9
Connected Nodes	239	238	233	220	201
Edges	8.252	6.596	4.983	3.519	2.146
Connected Components	2	3	9	24	43
Isolated Nodes	0	1	6	19	38
Graph Density	0,290	0,231	0,175	0,123	0,075
Groups/ Communities	3	4	6	8	10

Source: Authors' representation

By studying the table, several conclusions can be drawn. First, it is observed that as the threshold θ increases, the number of nodes and the number of edges through which the nodes are connected decreases too. This means in practice that as the correlation coefficient increases, the tendency of regions to move in parallel decreases. Consequently, the density of the network decreases as the number of edges that exist in each network decreases, i.e., the network tends to be less dense compared to the previous network, where the threshold is smaller. Moreover, the number of isolated nodes moves in the same direction as the threshold, i.e., it increases. In other words, more and more regions are separated from the clusters, and either regions emerge that are not correlated with any other and form isolated nodes, or additional small groups are created (this is why there is an increase in groupings) as the change in the unemployment rate of some regions does not follow the pace of the other regions. Therefore, the higher the correlation coefficient, the lower the homogeneity of the networks, which means that a small number of regions are moving to a similar direction

2.2. Discussion

Having completed the analysis by network, it was considered useful to make some observations on the structure of the networks based on the resulting groupings. An attempt was made to study the results by geographical area. In particular, starting from the countries belonging to Southern Europe (Greece, Spain, Italy, Cyprus, Malta, Croatia, Portugal, and Slovenia) we observe a homogeneity in the degree of correlation of the unemployment rate, namely almost all regions of the Member States always belong to the same group. The exception is Malta. For none of the examined θ Malta does follow the other regions. Also for high (θ > 0,85) one Greek region (North Aegean), and one Spanish region (Ciudad de Ceuta) stand out. It was therefore considered important to note that in southern Europe the unemployment rate is highly correlated. This means that there is a homogeneity between the regions of these countries. There is a high correlation in the unemployment rate, i.e. the unemployment rate moves in a similar direction, either increasing or decreasing in parallel. These findings demonstrate spatial connections between regional labour markets, supporting Kivi & Paas (2021) argument that regional labour markets in Europe are spatially clustered. Business operations and the evolution of the labour market are significantly influenced by spatial interactions, demonstrating the need for coordinated policy measures.

In Northern Europe (Ireland, Lithuania, Latvia, Finland, Sweden, Denmark, and Estonia) there is a less homogeneous correlation. The countries that make up Northern Europe behave differently from Southern Europe. The country that stands out here is Finland, as it never belongs to the group of other regions. Also, for Denmark as the threshold (θ) increases, its regions become detached from the rest of the group. Sweden partially follows the group, however as the threshold (θ) increases, some regions are detached. Therefore, the countries with all regions highly correlated are Ireland, Latvia, Lithuania, and Estonia.

Western Europe is made up of Austria, Belgium, France, Germany, Luxembourg, and the Netherlands. The situation here is more complicated. Especially for high θ, there is no homogeneity, not even between the regions of the same Member States. For France, it is true that at low θ there is homogeneity, but as θ increases several regions, most of which are overseas (La Reunion, Martinique, Guadeloupe, Guyane, Mayotte), become detached. This is consistent with Overman & Puga (2002) findings, who discovered that regional unemployment in Western Europe is considerably more strongly related with nearby regions than with more remote regions within the same country (neighbour-effect). The main feature of the group comprising the Western European countries is that Germany does not correlate with the other countries for any θ. Its regions are always unified, in other words all the regions are highly correlated with each other for the whole period under study.

Finally, an attempt was made to interpret the groupings according to another criterion, that of the historical facts of Europe. In particular, it was studied whether the countries that made up the so-called PIIGS tended to cluster in the degree of correlation of the change in the unemployment rate. The countries that make up the PIIGS (Portugal, Italy, Ireland, Greece and Spain) were the weakest economies during the financial crisis that hit the EU. From the groupings obtained from our model, it can be observed that the four southern countries belong for all θ to the same group. The Member State that stands out is Ireland, which means that in the other countries there is a high correlation of the unemployment rate.

Also, another observed grouping includes all the regions of the following countries for each θ: Czech Republic, Hungary, Estonia, Latvia, Lithuania, Malta, the majority of Poland’s regions, and Slovakia. These countries are eight of the ten Member States that joined the European Union in 2004 (the largest enlargement of the EU). The regions of these Member States therefore also share a high degree of homogeneity in the unemployment rate. The change in the rate in these regions has followed a similar direction over the period under consideration. This result is in line with the findings of Psycharis et al. (2020), who in their research highlighted how the process of European integration has impacted the capacity for development in every region of Europe. Distinct country groups, however, took very distinct developmental paths. The Central and Eastern EU nations took a largely similar path to development after joining the EU.

Conclusions

In this paper we attempted to introduce SNA in Economic and Regional Development. The existence of imbalances in the spatial distribution of income, economic opportunities and activities has attracted the interest of many scholars, who focus on spatial and structural differences between regions. Consequently, Economic and Regional Development has been studied on the basis of various approaches and methodologies. We have tried to answer the question whether SNA can be applied to Economic and Regional Analysis. For this purpose, we used indices that helps to measure regional inequalities, the unemployment rate. The analysis was based on the degree of correlation of the unemployment rate of NUTS 2 regions for the period 2008-2021. In particular, SNA techniques were used to ensure certain results. The calculation of centrality metrics, led to conclusions about the interaction and clustering between regions.

In conclusion, there is a general homogeneity in the change in the unemployment rate in the EU. In some regions this homogeneity is more pronounced, as is the case in the regions of Southern Europe. In this respect we could refer to Niebuhr (2003) research, which studied the spatial correlation of regional unemployment in European countries between 1986 and 2000 using measures of spatial autocorrelation and spatial econometric methods. The findings indicated that regional labour markets in Europe exhibit a considerable degree of geographical dependence. Both regions with high unemployment rates and those with low unemployment rates tend to be spatially concentrated. The results imply that various spatial interactions have an impact on how regional unemployment has changed across Europe. Also, Kivi & Paas's (2021) data demonstrate the spatial clustering of regional labour markets in Europe.

A visible grouping was found in the NUTS 2 regions based on the total unemployment rate. We found that SNA locates the interaction between regions and identifies the regional groupings. It would be interesting to carry out a further analysis of the corresponding rate in the male and female populations. Also, the introduction of SNA in Economic and Regional Development could be extended to other variables such as GDP per capita, population density, tertiary education attainment, income of households, etc.

The Lisbon Treaty, and in particular Article 174, included territorial cohesion for the first time, which aims to achieve overall harmonious development (European Commission, 2022), i.e. the balanced and sustainable development of the Union's regions. The main objectives of the European Union's cohesion policy are social, economic and territorial convergence and the reduction of disparities between regions. In order to reduce disparities, efforts are being made to enable the weaker regions to create better living conditions, retain and acquire talent, attract investment, increase productivity and create innovation systems. Consequently, cohesion policy is a key financial instrument of the European Union, through which it can aim to combat inequalities (Widuto, 2019).

The European Union's policy agenda places a high focus on achieving acceptable levels of employment, unemployment, and participation because these factors are essential measures of economic and social welfare. Concentrating on these labour market factors at the national level can obscure significant variations between areas within nations (Halleck Vega & Elhorst, 2014). Taking into account that the EU policy is to smooth out imbalances and differences and ensure coherence between regions, one realizes that the ideal network would consist of a single group, where no isolated nodes exist, i.e. a homogeneous network. This would practically mean that the unemployment rate would move in the same direction for all regions, with no regions that stand out.

Consequently, as future directions for research, an attempt could be made to analyse the policy and strategy options that could be implemented in specific regions in order to smooth out the imbalances. In other words, if the unemployment rate were reduced, which regions could have a corresponding impact on other regions? Which strategies (under cohesion policy) from the EU could be implemented in targeted regions in order to achieve the optimal effect in other regions, so that the unemployment rate moves in parallel? Obviously, all these questions could be applied in other macroeconomic indicators, too.

References

Abraham, F. (1996). Regional adjustment and wage flexibility in the European Union. *Regional Science and Urban Economics, 26*(1), 51-75. https://doi.org/10.1016/0166-0462(95)02110-8

Annoni, P., de Dominicis, L., & Khabirpour, N. (2019). Location matters: A spatial econometric analysis of regional resilience in the European Union. *Growth and Change*, 1-32. https://doi.org/10.1111/grow.12311

Aria, M., Gaeta, G., & Marani, U. (2019). Similarities and Differences in Competitiveness Among European NUTS2 Regions: An Empirical Analysis Based on 2010-2013 Data. *Social Indicators Research, 142*(1), 431-450. https://doi.org/10.1007/s11205-018-1909-0

Ayouba, K., Le Gallo, J., & Vallone, A. (2020). Beyond GDP: an analysis of the socio-economic diversity of European regions. *Applied Economics*, 1-20. https://doi.org/10.1080/00036846.2019.1646885

Ballas, D., Dorling, D., & Hennig, B. (2017). Analysing the regional geography of poverty, austerity and inequality in Europe: a human cartographic perspective. *Regional Studies, 51*(1), 174-185. https://doi.org/10.1080/00343404.2016.1262019

Becker, S., Egger, P., & von Ehrlich, M. (2018). Effects of EU Regional Policy: 1989-2013. *Regional Science and Urban Economics, 69*, 143-152. https://doi.org/10.1016/j.regsciurbeco.2017.12.001

Beyer, R., & Stemmer, M. (2016). Polarization or convergence? An analysis of regional unemployment disparities in Europe over time. *Economic Modelling, 55*, 373-381. https://doi.org/10.1016/j.econmod.2016.02.027

Bouzarovski, S., & Herrero, S. (2015). The energy divide: Integrating energy transitions, regional inequalities and poverty trendsi n the European Union. *European Urban and Regional Studies, 24*(1), 69-86. https://doi.org/10.1177/0969776415596449

Brandes, U. (2001). A faster algorithm for betweeness centrality. *The journal of Mathematical Sociology*, *25*(2), 163-177. https://doi.org/10.1080/0022250X.2001.9990249

Calvo-Armengol, A., & Ioannides, Y. (2005). Social Networks in Labour Market. In *The New Palgrave Dictionary of Economics* 1-4. Department of Economics. https://doi.org/10.1057/978-1-349-95121-5_2477-1

Calvo-Armengol, A., & Jackson, M. (2007). Networks in labor markets: Wage and employment dynamics and inequality. *Journal of Economic Theory, 132*(1), 27-46. https://doi.org/10.1016/j.jet.2005.07.007

Capello, R., Caragliu, A., & Fratesi, U. (2017). Modeling Regional Growth between Competitiveness and Austerity Measures: The MASST3 Model. *International Regional Science Review, 40*(1), 38-74. https://doi.org/10.1177/0160017614543850

Chocholata, M., & Furkova, A. (2016). Does the location and the institutional backround matter in convergence modelling of the EU regions? *Central European Journal of Opereations Research, 25*(3), 679-697. https://doi.org/10.1007/s10100-016-0447-6

Cuadrado-Roura, J. (2001). Regional convergence in the European Union: From hypothesis to the actual trends. *The Annals of Regional Science*, *35*, 333-356.

Dall'erba, S. (2005). Distribution of regional income and regional funds in Europe 1989-1999: An exploratory spatial data analysis. *The Annals of Regional Science, 39*, 121-148.

Dima, A., Begu, L., Vasilescu, M., & Maassen, M. (2018). The Relationship between the Knowledge Economyand Global Competitiveness in the European Union. *Sustainability*, *10*(6). https://doi.org/10.3390/su10061706

Doran, J., McCarthy, N., & O'Connor, M. (2016). Entrepreneurship and employment growth across European regions. *Regional Studies, Regional Science, 3*(1), 121-128. https://doi.org/10.1080/21681376.2015.1135406

Dziadkowiec, O., Wituk, S., & Franklin, D. (2015). A social network analysis of south central Kansas workforce innovations in regional economic development. *Journal of Place Managrment and Development*, *8*(1), 6-22. https://doi.org/10.1108/JPMD-08-2014-0012

Ertur, C., & Koch, W. (2006). Regional disparities in the European Union and the enlargement process: an exploratory spatial data analysis, 1995-2000. *The Annals of Regional Science, 40*(4), 723-745. https://doi.org/10.1007/s00168-006-0062-x

European Union. (2020). *The history of the European Union*. https://europa.eu/european-union/about-eu/history_el

Eurostat. (2011). *Statistical books, Regions in the European Union, KS-RA-11-011-EN.* Luxembourg: Publications Office of the European Union. https://ec.europa.eu/eurostat/documents/3859598/5916917/KS-RA-11-011-EN.PDF

Ezcurra, R. (2019). Regional Disparities and Within-Country Inequality in the European Union. *Revista De Econimia Mundial, 51*, 39-162. https://doi.org/10.33776/rem.v0i51.3907

Formánek, T. (2019). GDP per capita in selected EU countries: Economic growth factors and spatio-temporal interactions examined at the NUTS2 level. *Journal of International Studies, 12*(1), 119-133. https://doi.org/10.14254/2071-8330.2019/12-1/8

Gama, R., Barro, C., & Fernandes, R. (2018). Science Policy, R&D and Knowledge in Portugal: an Application of Social Network Analysis. *Journal of Knowledge Economy*, 329-358. https://doi.org/10.1007/s13132-017-0447-3

Grabher, G. (2006). Trading routes, bypasses, and risky intersections: mapping the travels of "networks" between economic sociology and economic geography. *Progress in Human Geography*, *30*(2), 163-189. https://doi.org/10.1191/0309132506ph600oa

Halleck Vega, S., & Elhorst, J. (2014). Modelling regional labour market dynamics in space and time. *Papers in Regional Science, 93*(4), 819-841. https://doi.org/10.1111/pirs.12018

Huang, W.-Q., Zhuang, X.-T., & Ya, S. (2009). A network analysis of the Chinese stock market. *Physic A: Statistical Mechanics and its Applications, 388*(14), 2956-2964. https://doi.org/10.1016/j.physa.2009.03.028

Jackson, M. (2005). The Economics of Social Networks. *Advances in Economics and Econometrics*, 1-56. https://doi.org/10.1017/CBO9781139052269.003

Kim, Y., Choi, T., Yan, T., & Dooley, K. (2011). Structural investigation of supply networks: A social network analysis approach. *Journal of Operations Management*, *29*(3), 194-211. https://doi.org/10.1016/j.jom.2010.11.001

Kivi, L., & Paas, T. (2021). Spatial interactions of employment in European labour markets. *Eastern Journal of European Studies*(12), 196-211. https://doi.org/10.47743/ejes-2021-SI09

Kydros, D., & Anastasiadis, A. (2014). Social network analysis in literature. The case of The Great Eastern by A. Empirikos. Conference: 5th European Congress of Modern Greek StudiesAt: Thessaloniki, Greece.

Kydros, D., & Oumbailis, V. (2015). A Network Analysis of the Greek Stock Market. *Procedia Economics and Finance*, *33*, 340-349. https://doi.org/10.1016/S2212-5671(15)01718-9

Kydros, D., Magoulios, G., & Trevlakis, N. (2012). A Network Analysis of the Greek Parliament and some Socio-Economic Issues. *MIBES Transactions International Journal*, *6*(1), 200-211.

Lopez-Bazo, E., Vaya, E., & Mora, A. (1999). Regional economic dynamics and convergence in the European Union. *The Annals of Regional Science*, *33*, 343-370. https://doi.org/10.1007/s001680050109

Maerinez-Galarraga, J., Roses, J., & Tirado, D. (2015). The Long-Term Patterns of Regional Income Inequality in Spain, 1860-2000. *Regional Studies*, *49*(4), 502-517. https://doi.org/10.1080/00343404.2013.783692

Maier, G., & Vyborny, M. (2005). Internal migration between US-states. A social network analysis. SRE-Discussion Papers 2005/04, WU Vienna University of Economics and Business..

Martinez-Galarraga, J., Roses, J., & Tirado, D. (2015). The Long-Term Patterns of Regional Income Inequality in Spain, 1860-2000. *Regional Studies*, *49*(4), 502-517. https://doi.org/10.1080/00343404.2013.783692

Monford, M., Cuestas, J., & Ordonez, J. (2013). Real convergence in Europe: A cluster analysis. *Economic Modelling*, *33*, 689-694. https://doi.org/10.1016/j.econmod.2013.05.015

Monford, P. (2008). *Convergence of EU regions- Measures and evolution.* https://ec.europa.eu/regional_policy/sources/docgener/work/200801_convergence.pdf

Mora, T., & Moreno, R. (2010). Specialisation changes in European regions: the role played by externalities across regions. *Journal og Geographical Systems*, *12*(3), 311-334. https://doi.org/10.1007/s10109-009-0098-4

Niebuhr, A. (2003). Spatial interaction and regional unemployment in Europe. *European Journal of Spatial Development*, *5*(5), 117-147.

Nijkamp, P., & Abreu, M. (2009). Regional Development Theory. *International Encyclopedia of Human Geography*, 202-207.

O'Malley, A., & Marsden, P. (2008). The analysis of social networks. *Health Serv Outcomes Res Method*, *8*(4), 222-269. https://doi.org/10.1007/s10742-008-0041-z

Overman, H., Puga, D., & Vandenbussche, H. (2002). Unemployment clusters across Europe´s regions and countries. *Economy policy*, *17*(34), 115-147.

Petrakos, G., & Saratsis, Y. (2000, January). Regional inequalities in Greece. *Papers in Regional Science*, *79*(1), 57-74. https://doi.org/10.1111/j.1435-5597.2000.tb00759.x

Petrakos, G., Rodriguez-Pose, A., & Rovolis, A. (2005). Growth, inmtegration, and regional disparities in the European Union. *Environment and Planning A*, *37*, 1837-1855. https://doi.org/10.1068/a37348

Prell, C., Hubacek, K., & Reed, M. (2009). Stakeholder Analysis and Social Network Analysis in Natural Resource Management. *Society and Natural Resources*, *22*(6), 501-518. https://doi.org/10.1080/08941920802199202

Psycharis, Y., Kallioras, D., & Pantazis, P. (2020). *Regional inequalities in Central and Eastern European countries: The role of Capital regions and Metropolitan Areas*. In A. Śliwiński, P. Polychronidou & A. Karasavvoglou, A. (Eds). Economic Development and Financial Markets (pp. 3-20). Cham: Springer. https://doi.org/10.1007/978-3-030-32426-1

Rios, V., & Gianmoena, L. (2020). The link between quality of government and regional resilience in Europe. *Journal of Policy Modeling*, *42*(5), 1064-1084. https://doi.org/10.1016/j.jpolmod.2020.02.005

Rizzi, P., Graziano, P., & Dallara, A. (2018). A capacity approach to territorial resilience: the case of European regions. *The Annals of Regional Science*, *60*(2), 285-328. https://doi.org/10.1007/s00168-017-0854-1

Rodriguez-Pose, A., & Ketterer, T. (2020). Institutional change and the development of lagging regions in Europe. Regional Studies, *54*(7), 974-986. https://doi.org/10.1080/00343404.2019.1608356

Rodriguez-Pose, A., & Tselios, V. (2010). Inequalities in income and education and regional economic growth in western Europe. *The Annals of Regional Science*, *44*, 349-375. https://doi.org/10.1007/s00168-008-0267-2

Rose, S., & Viju, C. (2014). Income inequality in post-communist Central and Eastern European countries. *Eastern Journal of European Studies*, *5*(1), 5-19. https://ejes.uaic.ro/articles/EJES2014_0501_ROS.pdf

Sardadvar, S., & Vakulenko, E. (2021). Does migration depress regional human capital accumulation in the EU's new member states? Theoretical and empirical evidence. *Review of Regional Research*, *41*, 95-122. https://doi.org/10.1007/s10037-020-00147-2

Smith, M., Ceni, A., Milic-Frayling, N., ShneidermaN, B., Mendes Rodrigues, E., Leskovec, J., & Dunne, C. (2010). *NodeXL: a free and open network overview, discovery and exploration add-in for Excel 2007/2010/2013/2016 from the Social Media Research Foundation*. https://www.smrfoundation.org

Ter Wal, A., & Boschma, R. A. (2009). Applying social network analysis in economicgeography: framing some key analytic issues. *The Annals of Regional Science*, *43*, 739-756. https://doi.org/10.1007/s00168-008-0258-3

Uzzi, B. (1996). The Sources and Consequences of Embeddedness for the Economic Performance of Organizations: The Network Effect. *American Sociological Review*, *61*(4). https://doi.org/10.2307/2096399

Vittoria, M., Lavadera, L., & Lubrano Lavadera, G. (2014). Knowledge networks and dynamic capabilities as the new regional policy milieu. A social network analysis of the Campania biotechnology community in southern Italy. *Enterpreneurship and Regional Development*, *26*(7-8), 594-618. https://doi.org/10.1080/08985626.2014.964782

Wasserman, S., & Faust, K. (1994). *Social Network Analysis: Methods and Applications.* Cambridge University Press. https://doi.org//10.1017/CBO9780511815478

Widuto, A. (2019). *European Parliament Research Service*, *ERPS*. (E. Parliament, Editor) https://www.europarl.europa.eu/RegData/etudes/BRIE/2019/637951/EPRS_BRI(2019)637951_EN.pdf

Appendix

The Irish regions Border, Midland and Western (IE) and Southern and Eastern (IE) (NUTS 2013) were amended by NUTS 2016 classification to Northern and Western (IE), Southern (IE) and Eastern and Midland (IE). As a result, there were missing data in the time series for the years 2008-2011, for which an attempt was made at NUTS 3 regions level (NUTS2 sub-regions), to calculate and complete. However, no data were available for NUTS 3 regions. Finally, the average of Border, Midland and Western (IE) and Southern and Eastern (IE) were used to fill in the missing data in Northern and Western (IE), Southern (IE) and Eastern and Midland (IE) regions.

A similar methodology was applied for the following regions: Sostines regionas (LT) and Vidurio ir vakaru Lietuvos regionas (LT) (NUTS 2016), which according to the NUTS 2013 classification were included in region Lietuva (LT), for 2008-2012. Budapest (HU) and Pest (HU) (NUTS 2016), which according to the NUTS 2013 classification were included in region Közép-Magyarország (HU).

The regions of Croatia Grad Zagreb and Sjeverna Hrvatska had data gaps from 2010 to 2020, while the Kontinentalna Hrvatska region (NUTS 2016) had gap in 2020-2021. It was decided to use the data of the first two regions for 2020-2021 and average them to fill the gap in the latter region.

The FI20 Aland region of Finland did not contain any data and it was decided to delete it.

There were also data gaps, which was filled by the linear regression work by making projections: Warszawski stoleczny (PL) Mazowiecki regionalny (PL) for 2008-2012, Lubuskie (PL) for 2020-2021, Corse (FR) for 2009-2011, Mayotte (FR) for 2008-2012 and the year 2021 and for the German regions Niederbayern, Oberpfalz, Oberfranken, Unterfranken, Bremen, Kassel, Trier, Saarland and Chemnitz for the year 2020.