Integrative Mechanisms for Addressing Spatial Justice and Territorial Inequalities in Europe

D 3.2. Report on Economic Growth in EU Territories

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Authors: Alfredo Cartone, Domenica Panzera, Paolo Postiglione, Ana Viñuela

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Acronyms and Abbreviations

AMECO	Annual Macro-Economic database
AIC	Akaike Information Criterion
AII	Average Indirect Impact
ADI	Average Direct Impact
ATI	Average Total Impact
BIM	Bayesian Interpolation Method
CV	Coefficient of Variation
CAR	Conditional Auto Regressive
ERD-CE	European Regional database by Cambridge Econometrics
EU	European Union
EU-REGIO	Eurostat Regional Statistics database
ESDA	Exploratory Spatial Data Analysis
GNS	General Nesting Spatial
GWR	Geographically Weighted Regression
GDP	Gross Domestic Product
GS2SLS	Generalized Spatial Two Stage Least Squares
IV/GMM	Instrumental Variable Generalized Method of Moments
ISPRA	Istituto Superiore per la Protezione e la Sicurezza Ambientale
LISA	Local Indicators of Spatial Association
MRW	Mankiw, Romer, Weil Model
ML	Maximum Likelihood
MCMC	Markov Chain Monte Carlo
NUTS	Nomenclature of Territorial Units for Statistics
OLS	Ordinary Least Squares
OECD	Organisation for Economic Co-operation and Development
PPS	Purchasing Power Standard
SA	Simulated Annealing
SARAR	First-order Autoregressive Spatial Model with First-order Autoregressive Disturbances
SDEM	Spatial Durbin Error Model
SDM	Spatial Durbin Model
SEM	Spatial Error Model
SLM	Spatial Lag Model
SVCP	Spatially Varying Coefficient Processes
TEC	Treaty establishing the European Community
UGT	Unified Growth Theory
WP	Work Package

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NON-TECHNICAL SUMMARY

The analysis of differences in development across regional territories is an explicit concern of policy makers operating at different spatial levels. Development is also actively studied in many fields, as in the case of regional economics and development economics. To analyse growth at local scale, new analytical tools have been introduced in recent years, which can support policy makers in reducing disparities at the local level.

The persistence of regional disparities across European Union (EU) regions, exacerbated by the global financial crisis, requires new regional policies that can enhance growth and regional equity, both within countries and across the EU. The promotion of economic growth is still a key objective in policy makers' agendas. For example, the targets of helping less-developed regions and promoting territorial cooperation have inspired the EU Cohesion policy. However, the achievement of these goals requires the reduction of regional and local disparities, specifically income and living standards, as well as the promotion of social inclusion and opportunities of employment.

Considering space in the analysis of economic development

The spatial dimension includes natural disparities located in different geographic contexts. It is important to consider what elements in the field of regional sciences are denoted as part of the spatial dimension. The spatial dimension sheds light on relevant mechanisms useful to achieve an in-depth understanding of the growth paths of regional economies. It entails the contextual differences of, as well as potential interdependences between, regions, localities and cities. For these reasons, geographical location is likely to play a role in their specific development trajectories. Both the absolute location as well as the relative location have significance. In fact, spatial proximity of regions could determine similarities in the levels of growth, or enable socio-economic heterogeneity.

The importance of relative locations, and the relevance of considering neighbourhoods' effects when analysing regional economies, encouraged a flourishing empirical and theoretical literature to introduce spatial effects in the study of regional growth. Some contributions proposed extending growth models to account for spatial effects.

The introduction of spatial effects in the study of regional economic growth has been extensively linked to the evolution and development of spatial econometrics. The set of tools cited in the current report offers a variety of techniques to model economic growth; it accounts for spatial effects and avoids potential bias and misspecification that could lead to misinformed policies. A review of the main literature is presented in Section 2 of the report. Moreover, the research found that considering spatial information is helpful to assess the effectiveness of the Cohesion Policy, which requires verification of the catch-up process in less-developed regions and the reduction of disparities across regional economies.

Spatial effects pertain to the values' similarity in space (i.e., spatial dependence) as well as to the differences in economic behaviours and relationships experienced by regional economies (i.e., spatial heterogeneity). Tools for the identification of the presence of spatial effects identify the exploratory spatial data analysis (ESDA) at NUTS 3 level, that we applied, finding the presence of relevant spatial effects in the analysis in the growth of GDP per worker.

Economic growth, convergence and interdependencies

The aforementioned spatial effects have been introduced to analyse the convergence process among EU regions. Focusing on economic convergence offers a valuable contribution to the understanding of the reduction in disparities across Europe. The convergence process refers to the reduction of disparities on some economic variables (regional GDP per worker) experienced by regional economies, as well as to the process by which poor economies catch up to wealthier economies following a faster growth path. The former notion of convergence is referred to as σ-convergence, the latter is known as β-convergence. In this report, the β-convergence analysis is performed adopting spatial models.

β -convergence provides insight into the potential of less-developed areas of the EU to ignite growth processes. However, a key issue is the consideration of relevant spatial effects. Our results test for the relevance of classical determinants of economic growth in Europe as well as the effect between neighbouring regions. The use of an expanded theoretical model of growth that considers spatial interdependencies shows that the growth rate of GDP per worker in a region is not only a function of traditional determinants as investment and population grow, but the spillover must be quantified and considered for analysis and policy definition.

Additionally, the convergence process is analysed at different spatial scales. The geographical scales considered in this research include regions belonging to the NUTS 2 and NUTS 3 levels of the official European classification. NUTS 3 regions are considered in order to extend a wide body of literature that analyses European convergence at the NUTS 2 level and to go more “local” to support specific policies. However, the analysis of NUTS 2 is not discarded, as it is vital for analysing the Cohesion Policy.

Finally, we test for economic convergence at NUTS 2 by adopting a spatial dynamic panel analysis that considers concurrently contextual differences and, again, the significant and relevant effects of interdependencies between regions.

Local contextual differences in economic growth and convergence

Since a considerable portion of the research findings explicitly takes into account interdependencies, a deeper consideration of regional and local specificities is recommended. Structural differences in the economic relationships between variables are more commonly referenced and researched in the regional sciences as part of spatial heterogeneity.

Local differences due to the presence of spatial heterogeneity help analysts and policy makers alike to individuate local patterns in the economic convergence dynamics. As a result, analysts find utility in assessing the reasons behind these differences, while policy makers set public and political agendas. In this report, an empirical analysis of economic convergence considering spatial heterogeneity is presented. Results highlight the importance of considering local differences, to the need of ad hoc policies able to boost local development. Moreover, this analysis is again performed at NUTS 3 level to stress the extent of local structural differences. Further consideration on spatial heterogeneity is recommended to develop activities that go beyond one-size-fits-all policies and to provide more sustainable equilibriums across European regions.

Economic growth, spatial effects and territorial cohesion

A wide number of contributions by the Commissioners for Regional Policy and the Cohesion Reports give us the primary relevance that EU promises to the policy concept of “Territorial Cohesion”. An explicit acknowledgement of this relevance is offered in many of the documents produced within the IMAJINE Project. Hence, the relevance of this understanding is not surprising as the central aim of the EU set out in the Treaty is to “*promote economic and social progress and a high level of employment and to achieve a balanced and sustainable development.*” However, a “*balanced and sustainable economic and social progress*” is necessarily linked to the knowledge of the effects that spatial interdependencies and differences have on the mechanisms that describe economic growth and convergence. Moreover, even if some of those issues may appear as merely technical, the role of space in this econometrics analysis offers details that cannot be neglected to guarantee policy cohesion at regional and local levels.

1. INTRODUCTION

1.1 Definitions and motivations

The main objective of WP3 (*Territorial Inequalities and Economic Growth*) is the investigation of the levels of economic development and rates of economic growth across regions and countries of the European Union (EU). In particular, the goal is to study the assumptions of real convergence to support the EU Cohesion Policy. This cohesion should be achieved mainly through growth and the reduction of the significant economic, social and territorial disparities that still exist between Europe's regions and Member States. Cohesion policy was born with the aim of supplementing the creation of the single market, and it promotes the economic development of the less-advantaged regions in the EU. This represents a primary policy objective in the EU. The importance of this objective has not reduced over time, and it is especially relevant in the light of the economic crisis.

Economic, Social and Territorial Cohesion is essentially governed by Title XVIII of the Consolidated Version of the Treaty on the Functioning of the European Union. In particular, Article 174 (ex Article 158 TEC[1]) states that: "*In order to promote its overall harmonious development, the Union shall develop and pursue its actions leading to the strengthening of its economic, social and territorial cohesion. In particular, the Union shall aim at reducing disparities between the levels of development of the various regions and the backwardness of the least favoured regions. Among the regions concerned, particular attention shall be paid to rural areas, areas affected by industrial transition, and regions which suffer from severe and permanent natural or demographic handicaps such as the northernmost regions with very low population density and island, cross-border and mountain regions".* Article 176 (ex Article 160 TEC) adds that: "*The European Regional Development Fund is intended to help to redress the main regional imbalances in the Union through participation in the development and structural adjustment of regions whose development is lagging behind and in the conversion of declining industrial regions".*

Since the beginning of the Cohesion Policy and the first programming period (1989-1993), the objective of the reduction of disparities has been interpreted as the promotion of economic convergence between EU regions. To accomplish a successful application of these policies, we need to better understand the evolution process of growth convergence in Europe. However, we are aware that Cohesion Policy aims to reduce regional disparities in the level of development that is more than purely economic convergence. We believe that the first step of this analysis should be undertaken through an in-depth analysis of economic convergence of EU regions.

The most popular approaches in the measurement of convergence are those based on σ and β-convergence. σ -convergence is defined as a decrease in the overall dispersion of income levels across countries. Our analysis is mainly focused on the β – convergence framework, based on the idea that lower-income economies grow faster than higher-income economies, and thus experience a catching-up process. This hypothesis is investigated taking into consideration the geographical nature of data, and using two different approaches: cross-sectional and panel. Several aspects motivate the use of a β

– convergence approach. Firstly, analysing the catching-up process experienced by poorer economies is a key component in assessing the effectiveness of the EU Cohesion Policy (Monfort, 2008). In fact, this catch-up process implies a reduction of disparities across regions, a key objective of EU policies. Secondly, whether poor economies are catching up with wealthier economies requires tracking the effects of economic integration in Europe on regional disparities (Fischer and Stirböck, 2004).

In the literature, a vast amount of empirical work on regional convergence is based on the computation of basic statistical measures in which the geographical characteristics of data are not considered. In this report, our aim is to re-evaluate the question of regional economic convergence starting from a spatial approach perspective. Our goal is to show that neglecting the multidirectional dependence among neighbouring regions in the European Union leads to a misspecification of the concept of regional convergence. As a consequence, the standard estimation procedures used in many empirical studies can lead to biases and inefficiencies in the estimates.

The analysis is performed both at NUTS 2 and NUTS 3 levels, depending on the availability of the data. We employ data derived from two different sources: the Eurostat REGIO official database (EU-REGIO, https://ec.europa.eu/eurostat/web/regions/data/database) and the European Regional Database (ERD-CE, https://urban.jrc.ec.europa.eu/#/en/my-place/) by Cambridge Econometrics that is now available free of charge from the territorial dashboard of the European Commission's Joint Research Centre (ISPRA). The original variables from these two data sets have been transformed according to the definition of the economic models outlined in the following sections.

1.2 The need to take a long view on real convergence at regional level

The economic and social disparities that occurred in the EU after the crisis have stimulated a policy debate on the topic of convergence with a special focus on the so-called sustainable convergence, defined as a convergence process durable and sustainable in time. Essentially, sustainable convergence requires reduction in differences between countries or regions in the long run. As often highlighted by the European Commission, sustainable convergence represents a key fact both to deliver territorial Cohesion and to promote integration in the Monetary Union[1]. In fact, sustainable convergence is a process of reduction of disparities in terms of economic growth differentials and, in this sense, sustainable convergence contributes to support socio-economic sustainability. Additionally, political sustainability benefits from economic development, reduction in disparities, and the underlying process of convergence.

The concept of sustainable convergence can assume different specifications according to the determinants that are used to analyse convergence or divergence. For example, nominal convergence concerns economic convergence in nominal variable such as

[1] See, for example, https://ec.europa.eu/commission/sites/beta-political/files/economic-social-convergence-key-facts_en.pdf .

inflation and exchange rates. Real convergence studies convergence in well-being primarily measured through real GDP per capita. Finally, social convergence is measured in terms of poverty rates and/or inequalities.

Another important distinction is observed in the frameworks that are used to assess economic convergence. As previously mentioned, in the literature a differentiation between σ -convergence and β -convergence is usually made, where the β -convergence is considered necessary but not a sufficient condition for verifying the former. Different factors are also considered between absolute economic convergence and conditional economic convergence, where the latter includes features that characterise each unit's steady state.

Finally, sustainable convergence may be analysed at different geographical dimensions (i.e., countries and/or regions). Specifically, regional economic convergence aims to shed light on the geographical dimension of economic growth and, for this reason, is suitable to verify enhancements in the level of territorial cohesion due to reduction of disparities.

Real convergence looks at convergence in living standards, which typically includes measures such as the Gross Domestic Product (GDP) per capita.[2] Specifically, the focus on long-run real convergence has always been under the lens of scientific literature and EU monitoring as it supports the economic stability of the Union.[3] Moreover, the legacies of the financial crisis and sovereign debt crisis that involved European countries further stress the existence of real convergence. Thus, to calibrate effective policies at different geographical levels, it is useful to test for convergence by adopting consolidated schemes.

Over the last 30 years, a wide debate has involved the theme of regional real economic convergence. The reason is twofold. On one side, the growing presence of datasets available at regional level has provoked interest in the scientific literature, as in the case of β -convergence, in the field of economic geography. Alternately, the increasing interest of European policy makers in σ and β -convergence at regional level has been motivated by the need to evaluate regional policies. The EU supported regional policies to improve job creation and promote competitiveness and economic growth. For those reasons, in the current report, σ and β -convergence are studied especially at regional level. Particularly, β -convergence is considered as a robust frame to verify conditions for a sustainable convergence of the EU (and not only in the monetary union, Diaz del Hoyo et al. 2017[4]). β -convergence is also analysed to assess the existence of necessary conditions related to σ -convergence. Hence, conditional models of β-convergence are adopted as they may enhance knowledge of regional differences and different determinants of economic growth (i.e., the role of investments). A deeper insight of the

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[2] Different measures can be adopted beyond the classical use of the GDP. For a wide review on this aspect, please see deliverable D 3.1.

[3] At this purpose it is interesting to notice that convergence has been recently evaluated as one of the key goals for the European Union: (http://www.europarl.europa.eu/RegData/etudes/IDAN/2018/614502/IPOL_IDA(2018)614502_EN.pdf).

[4] The authors stress the importance of studying the presence of β -convergence as a key feature for sustainable convergence, but not to limit this attempt to a search of convergence linked to the ownership to the Monetary Union.

regional real convergence process provides important evidence to evaluate the presence of a long-run reduction in disparities in terms of economic growth and competitiveness. We are aware that the relationship between economic growth and regional disparities is complex and an exhaustive answer to this question is not expected in this report. However, focusing on the concept of β -convergence as a process in which poor regions could grow faster than wealthier regions may help to verify the existence of a catch-up effect. As a result, a progressive reduction in the under-utilisation of capacities in the so-called lagging regions[5] could lead to the successful reduction in the per-capita income gap with highly performing regions (Monfort, 2008).

Additionally, the relevance of the catch-up is not limited to the traditional concept of convergence in economic output. As highlighted in Task 1.5, the traditional concept of convergence is being progressively updated with a more “individual concept of spatial justice.” Additionally, analysing σ and β -convergence at regional level (NUTS 2 and NUTS 3) enables policy makers to extend Cohesion towards a concept of “European solidarity” and equal access to services and opportunities. Therefore, regional σ and β -convergence represents not only vital mechanisms to pursue economic convergence in output, but also as required conditions for contributing more directly to well-being and welfare regardless of the place of birth.

1.3. The economic relevance of spatial effects

Spatial dependence and spatial heterogeneity are two important characteristics of geographically distributed data that should be considered when modelling economic phenomena. Spatial dependence reflects a situation where the value of a variable observed at one location depends on the observations at near locations. Conversely, spatial heterogeneity relates to the instability across space of relationships of interest (Anselin, 1988). Modelling these specific features of spatial data assumes relevance in the light of their possible economic implications.

Spatial dependence pertains to the idea of spatial diffusion, or spatial spillovers, that relate to a situation where a given characteristic of a spatial unit does not solely remain within that unit but spreads around. A variety of spatial spillovers has been analysed in the economic literature. Knowledge, industry, and growth spillovers are among the widely studied effects (Capello, 2009). Growth spillovers concern the creation of growth potentialities in a region thanks to the growth in neighbour regions. In this perspective, proximity to growth regions is by itself a factor enhancing growth. These growth spillovers at regional level spread out through different transmission channels that are mainly attributable to demand linkages, trade linkages and interregional mobility of production factors (Capello, 2009).

The presence of growth spillovers has been considered for European regions. In fact, in the EU context, it could be identified the existence of several core regions with high level of income that are located close to each other, while a set of peripheral low-income regions appear located away from the core (Combes and Overman, 2004). While core

[5] Europe's “lagging regions” include “low-income” areas in central and eastern Europe as well as “low-growth” regions in southern Europe that are experiencing stagnant productivity and job destruction.

regions consist of the most powerful countries among which Germany and France, but also the UK, Italy, the Netherlands, Belgium, and Luxembourg, the periphery regions mainly consist of countries lying to the south and east of Europe. Spatial spillovers could stem from pure physical proximity as well as by similarities in other characteristics. Specifically, for European regions, Benos et al. (2015) found that interregional externalities matter for growth, based on different definition of proximity, that involve geographical, economic, and technological distances. This implies that the geographical proximity among territories serves as a transmission channel for growth, as well as the proximity shaped by technological and economic linkages. Thus, regions surrounded by dynamic entities are likely to grow faster than otherwise. It should be noticed that the growth potentialities developed in a region could also negatively influence the growth paths in neighbouring regions (Capello, 2009), describing a negative spatial association.

Furthermore, it should be considered that growth processes across regions or countries could be not necessarily governed by a common relationship. In fact, differences in the political and economic context experienced by countries of regions, are likely to determine differences in the growth paths. The idea of identifying common growth paths only for regions that share similar initial characteristics leads to the identification of spatial regimes or clusters (Durlauf and Johnson, 1995; Galor, 2007), that represents a way to model spatial heterogeneity.

Spatial clusters correspond to groups of regions that reach different equilibrium depending on their initial conditions (Azariadis and Drazen, 1990). The differences in the endowment of human and physical capital, local technological and knowledge spillovers, market imperfection and coordination failure could explain the existence of groups of EU regions (Ramajo et al. 2008). The presence of regimes has been also verified for EU regions, mainly based on differences in the initial level of income (Ertur et al. 2006) and different initial endowments of human capital (Bartkowska and Riedl, 2012).

Taking into consideration the presence of spatial spillovers as well as the heterogeneity in the economic relationship helps in modelling and interpreting the dynamics of economic growth and convergence. This is especially relevant for regions, which represent a level of analysis that potentially emphasizes both spatial similarities and local contextual differences. Considering the territorial dimension, the interactions among regions, and their differences, also assume relevance in a policy perspective. In fact, considering specific needs, characteristics and potentialities of regions, helps in defining place-based policies. Furthermore, the diffusion of growth could not be considered as a solely spontaneous process, being the result of common EU policies inspired by the ideas of solidarity and cooperation. Accounting for the links between economy and space is also connected with the idea of spatial justice, that implies considering what the policies would mean for different territories and their development (as emphasised by the WP1). The inclusions of the spatial effects in the analysis of growth processes is the main objective of the present report.

This report includes seven sections. In Section 2, we review the literature on the concept of convergence. Section 3 concerns methods for exploratory spatial data analysis (ESDA) that are introductory for the following analyses. In Section 4, we describe the spatial approaches to measure economic convergence, incorporating the effect of spatial dependence. Section 5 is devoted to a presentation of the problem of spatial heterogeneity that can dramatically affect the economic convergence of EU regions. In Section 6, we present the empirical studies performed at different spatial scales using both cross-sectional and panel data. Section 7 provides conclusions.

2. REVIEW OF THE LITERATURE

2.1 Concepts of convergence

Economic convergence represents a prominent theme in economic growth literature. The convergence hypothesis represents one of the most important implications of the neoclassical growth theory (Solow, 1956; Swan, 1956), and refers to the long run process where poor economies achieve higher rates of economic growth compared to wealthier economies, with a subsequent reduction of such inequalities.

A large number of studies examined the economic convergence across different geographical units, adopting different theoretical perspectives and empirical strategies. Traditional empirical methodologies for testing convergence hypothesis are the σ-convergence and β-convergence analyses (Barro and Sala-i-Martin, 1992; Islam, 2003).

The σ-convergence hypothesis refers to the decline over time of the dispersion of GDP per capita across a group of economies (countries or regions). The analysis of σ-convergence can be based upon the calculation of the dispersion of the logarithms of GDP per capita across geographical units, at time t, according to the following formula:

$$\sigma_t^2 = \frac{1}{N}\sum_{i=1}^{N}(\ln y_{it} - \bar{x}_t)^2 \qquad (1)$$

where y_{it} is the GDP per capita of the i-th economy at time t, $\bar{x}_t$ is the mean of $\ln y_{it}$ and N is the number of economies under investigation. If there is a decreasing long-term trend of the dispersion σ_t^2, then economies appear to converge at a common growth rate, and the σ-convergence hypothesis is verified. Unfortunately, the σ-convergence approach is not justified by any economic theory and, furthermore, the variance of logarithms is insensible to permutations, particularly spatial permutations. Hence, it does not allow for discriminating between very different geographical configurations. However, in empirical studies, to measure σ-convergence, the coefficient of variation $CV = \sigma_t/\bar{x}_t$ is often preferred to σ_t^2 which has no interpretable meaning on its own, and it is not useful for comparisons.

Notably, according to Gluschenko (2018), we consider CV in its unweighted version, instead of using the form weighted by the regions' proportions of the national populations. In fact, this author proved that the population-weighted inequality indices yield a rough estimate of interpersonal inequality among the whole population of the country rather than an estimate of regional inequality as it is requested in the σ-convergence investigation.

The β-convergence hypothesis refers to the existence of a negative relation between the initial level and the growth rate of GDP per capita. This approach assumes exogenous saving rates and a production function based on decreasing productivity of capital and constant returns.

When discussing the β-convergence process, a usual distinction lies between absolute, or unconditional, convergence and conditional convergence (Barro and Sala-i-Martin, 1995).

The methodology used to measure absolute β-convergence, in a cross-sectional framework, generally involves estimating a growth equation, at a fixed time t, in the following form:

$$g_i = \beta_0 + \beta_1 \ln y_{it-T} + \varepsilon_i \tag{2}$$

where, for each unit i, $g_i = \frac{1}{T}\ln\left(\frac{y_{it}}{y_{it-T}}\right)$ denotes the average growth rates of GDP, T is the time span of the growth period considered,[6] y_{it-T} is the GDP per capita at the beginning of the observation period, y_{it} is the GDP per capita at the end of the observation period, β_0, β_1 are parameters to be estimated, ε_i is a stochastic error term and $i = 1, \ldots, N$ are the spatial units. A negative estimate of β_1 gives evidence of absolute β-convergence, suggesting that the growth rate of GDP per capita is negatively correlated with its initial level. The absolute β-convergence hypothesis implies that all regions converge toward the same steady state in the long run, independently from their initial conditions.

Conversely, conditional convergence is observed when economies with similar structural characteristics converge to a common steady state, and thus requires the appropriate variables to be included on the right side of the growth-initial level regression to control for these differences. The statistical model used to measure conditional β-convergence is (Mankiw et al. 1992):

$$g_i = \beta_0 + \beta_1 \ln y_{it-T} + \beta_2 \ln s_i^k + \beta_3 \ln v_i + \beta_4 \ln s_i^h + \varepsilon_i \tag{3}$$

where, for each unit i, $\ln s_i^k$ is the natural logarithm of saving rate, $v_i = \ln(n_i + l_i + k_i)$, with n_i as the population growth rate, l_i the level of technology growth rate, and k_i the depreciation rate of capital, $\ln s_i^h$ is the natural logarithm of a measure of human capital, and the remaining variables as indicated previously. The equation (3), depending on the availability of data, can be also estimated by eliminating the variable $\ln s_i^h$.

As evidenced by Islam (2003), research on convergence has viewed the use of four different methodologies: cross-section, panel, time-series and distributional approaches. The cross-section, panel and time-series approaches (in part) have all studied β-convergence, either conditional or unconditional. The cross-sectional approach has also been used to study σ-convergence. Furthermore, the distributional approaches have analysed σ-convergence.

Concerning the cross-sectional approach, a number of studies exploring the σ and β-convergence hypotheses have been proposed in the early literature. Contributions focused on the σ-convergence hypothesis have been offered by Baumol (1986) and Barro and Sala-i-Martin (1992), among others.

[6] In the cross-sectional analysis of β-convergence, the time span T corresponds to the entire period of observation P (i.e., the number of years of the period under investigation).

Pioneering works on β-convergence, where the growth-initial level regressions were not formally derived from theoretical growth models, have been suggested by Baumol (1986) for unconditional convergence, and by Kormedi and Meguire (1985) and Grier and Tullock (1989) for conditional convergence. Model-based specifications have been accomplished by Barro and Sala-i-Martin (1992) and Mankiw et al. (1992), that proposed regression equations formally derived from the neoclassical growth model. It should be noted that β-convergence is a necessary, but not sufficient condition, for σ-convergence to occur (Sala-i-Martin, 1996). In fact, finding a negative convergence parameter does not necessarily imply a declining dispersion in GDP levels (Quah, 1993a).

The concept of conditional convergence is also related to the notion of convergence clubs, which is based on the idea of multiple equilibria. Convergence clubs identify groups of economies whose initial conditions are quite similar and that converge toward the same steady state (Durlauf and Johnson, 1995; Galor, 1996). The foremost approaches to the identification of convergence clubs select the composition of the potential regimes according to some external information, such as threshold or discriminant variables, and often apply cluster analysis (Azariadis and Drazen, 1990; Durlauf and Johnson, 1995; Feve and LePen, 2000).

Durlauf and Johnson (1995), for example, study cross-country heterogeneity, providing evidence that there are multiple poles of attraction in the growth process. They use a regression-tree procedure to determine threshold levels of initial GDP per capita and literacy rates.

In the framework of cross-sectional regression, used to test the β-convergence hypothesis, it is not possible to consider region/country specific effects. To overcome this problem, a number of researchers advocate convergence analysis using panel data. Islam (1995) reformulated the regression equation used in the study of convergence into a dynamic panel data model with individual (country) effects and used panel data procedures to estimate it. A contribution to the panel data approach in the convergence analysis, which involves using GMM estimators (Arellano and Bond, 1991), has been proposed by Caselli et al. (1996), among others.

A further perspective on economic convergence is provided by studies based on time series econometric methods (Carlino and Mills, 1993; Bernard and Durlauf, 1996; Evans and Karras, 1996; Li and Papell, 1999). In this context, convergence between two or more economies requires that the long run forecasts of GDP per capita differences tend to zero, as the forecasting horizon tends to infinity. A weaker definition of convergence in the time series context is the stochastic convergence which occurs when GDP per capita disparities between economies follow a stationary process.

Finally, the distributional approach studies the relationships between σ -convergence and β-convergence (Carree and Klomp, 1997; Lee et al. 1997), focusing on the limitations of the β-convergence approach considering the shape of the entire distribution (Quah 1993b, 1996a, 1996b).

In this report, we primarily study σ -convergence and β-convergence, drawing upon the cross-sectional and panel approaches.

2.2 Convergence analysis and spatial effects

In most of the aforementioned research on economic convergence, regional economies, the units of analysis in this research, have been considered as independent entities, mainly neglecting the role of spatial interaction (Rey and Montouri, 1999). This hypothesis is patently violated in all geographical and territorial studies, where "*everything is related to everything else, but near things are more related than distant things*''(as it is stated in Tobler's first law of geography; Tobler, 1970). Spatial effects refer to both spatial dependence and spatial heterogeneity (Anselin, 1988). Spatial dependence reflects a situation where values observed at one location depend on the observations at nearby locations. Spatial heterogeneity refers to the instability, over space, of economic behaviours and can be revealed in a regression model by non-constant error variances (i.e., heteroscedasticity) or by space-varying coefficients (i.e., structural instability). In recent decades, many attempts have been made to extend the economic convergence analysis to include spatial effects. A review of the empirical literature on growth and convergence that has addressed the importance of spatial factors has been proposed by Abreu et al. (2005), among others.

Among the other contributions, Moreno and Trehan (1997) performed a number of tests to examine whether location matters for growth, and a spatially-oriented analysis of the convergence processes in the EU has been proposed by López-Bazo et al. (1999). Rey and Montouri (1999) reconsidered the question of US regional income convergence from a spatial econometric perspective. The authors performed an exploratory spatial data analysis (ESDA) to assess the presence of positive spatial association and identified the spatial error model as the more appropriate specification to analyse the convergence process. ESDA tools have been applied by Le Gallo and Ertur (2003) to assess the importance of geographical location and spatial interactions in the European regional growth process. Ertur and Koch (2007) proposed a spatially augmented Solow model that includes both physical capital and spatial externalities in knowledge to model technological progress. The proposed model provides a conditional convergence equation that includes spatial effects on the dependent variable, as well as on the explanatory variables. The authors tested the convergence hypothesis assuming a speed of convergence identical for all economies (i.e., a homogeneous model), as well as a model with complete parameter heterogeneity. The use of spatial econometric specifications as generalizations of the conventional growth regression model has been emphasized by LeSage and Fischer (2008), and a spatially augmented Mankiw-Romer-Weil model (Mankiw et al. 1992) has been proposed by Fischer (2011).

The theoretical framework used to estimate β-convergence leads to an empirically testable model that evaluates the inverse relationship between the growth in GDP per capita over a defined time span and the GDP level measured at the beginning of the period (the starting point). Essentially, β - convergence model has not been conceived as a dynamic framework but is based on a static comparison.

However, very different behaviours across the spatial units considered may lead to puzzling evidence, specifically on the speed of convergence. This may cause challenges in the interpretation of the results and lead to controversial political decisions. These issues have opened a debate in the literature, and they can be considered as the main reasons why Islam (1995; 2003) suggests the application of panel data models to β - convergence problem. Additionally, as for the case of cross-sectional data, the panel estimation of economic growth models is related to increasing development of spatial econometric techniques.

The adoption of spatial panel data econometrics has helped analysts to consider the presence of cross-sectional dependence, heterogeneity across units in terms of regional specific effects, and time-specific effects. In this regard, spatial panel models may provide an additional choice for the estimation of a regional convergence model. Moreover, adding time-period specific effects is justified as they capture spatial-invariant variables required to ensure unbiased estimates, similarly to what happens in a typical time-series study (Baltagi, 2005).

Empirical analysis using panel data techniques, which accounts for both temporal and spatial dimensions of regional convergence, have been proposed in recent literature. Badinger et al. (2004) proposed a two-step procedure which involves spatial filtering of the variables, to remove spatial autocorrelation, and application of standard GMM estimators for dynamic panels in a second step. Arbia and Piras (2007) suggested the use of panel data econometrics in regional economic convergence. In particular, they extended the traditional convergence models to include a rigorous treatment of regional spillovers and to obtain more reliable estimates of the parameters, considering the spatial panel lag model and the spatial panel error model. Elhorst et al. (2010) defined an extended Solow–Swan neoclassical growth model that incorporates both space and time dynamics. They show that the econometric specification takes the form of an unconstrained spatial Durbin model. They further investigated whether the results depend on the choice of the time span and the inclusion of fixed effects. Yu and Lee (2012) introduced a spatial dynamic panel data approach to study regional growth convergence in the U.S. economy. They used annual data on personal state income from 1930-2006 for the 48 contiguous states, obtaining results that are consistent with the theoretical prediction.

3. EXPLORATORY SPATIAL DATA ANALYSIS

The main objective of this report is to analyse the economic growth of European regions using methods based on spatial analysis. The first step of this type of study consists of analysing the dynamics of the growth rates of GDP per capita across space. To this end, we use the methods of ESDA to examine the spatial distribution of the growth rates of GDP per capita of EU regions. The detection of global and local spatial autocorrelation enables visualisation of the behaviour of regional growth in the EU and changes in this pattern over the period under review.

ESDA is a collection of techniques used to describe and visualise the spatial distribution of a certain phenomenon, to discover patterns of spatial association, or suggest forms of spatial instability (Good, 1983). ESDA tools include measures of global and local spatial autocorrelation. Spatial autocorrelation refers to the extent of similarity (or dissimilarity) of observed data in space. In the presence of positive spatial autocorrelation, high or low values of the variable of interest tend to cluster in space. In the presence of negative spatial autocorrelation, the values observed in a region tend to be dissimilar to the values observed in neighbouring regions.

The most popular measure of global spatial autocorrelation is the Moran's I (Moran, 1950). This measure compares the value of the variable at any one location with the value at all other locations.

Given the growth rate $g_i^* = \frac{y_{it} - y_{it-T}}{y_{it}}$, collected at N sites, $i = 1, 2, .., N$, where y_{it} and y_{it-T} are the values of GDP per capita for the two periods under investigation, the Moran's I is specified as:

$$I = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(g_i^* - \overline{g^*})(g_j^* - \overline{g^*})}{\sum_i \left(g_i^* - \overline{g^*}\right)^2} \qquad j \neq i \tag{4}$$

where w_{ij} is an element of the matrix $\mathbf{W}$, expressing the proximity relations between spatial units, and $\overline{g^*}$ is the average of the observations g_i^*. The spatial weight matrix, usually denoted by $\mathbf{W}$, is a square matrix of dimension N, where N is the number of regions or countries, with elements w_{ij} quantifying the strength of interaction between locations i and j. Typically, the diagonal element of $\mathbf{W}$ are zero, while, for $i \neq j$, $w_{ij} = 0$ if locations i and j are not neighbours and $w_{ij} = 1$ if i and j are neighbours, according to a specified proximity criterion. Furthermore, most applications in spatial econometrics scale the individual rows (or columns) of $\mathbf{W}$ by the row totals, so that rows of $\mathbf{W}$ sum to 1. Different proximity criteria could be based on geographical contiguity, as well as on physical distance or travel time distance. Social and economic distances, such as the race and ethnicity distance or the occupational distance, could be also considered, as well as other criteria (Conley and Topa, 2002).

Under the null hypothesis of no spatial correlation, the expected value of the Moran's I is $E(I) = -1/(N-1)$. Values of I above the expected value indicate positive spatial autocorrelation, while values of I below $E(I)$ indicate negative spatial autocorrelation. Whether the value of I is statistically significant depends on its statistical distribution. Cliff and Ord (1981) derived the expression of the sample variance of the Moran's I, and showed that the index has an asymptotic normal distribution. Inference can be based also on the permutation approach, by generating empirically a reference distribution for I.

Global spatial autocorrelation analysis provides only one statistic to summarize the entire area under investigation. If the researcher aims to detect local spatial characteristics of the area, he needs to use local spatial statistics. The analysis of local spatial autocorrelation may be implemented, among others, through two different methods: the Moran scatterplot (Anselin, 1996) and the local indicators of spatial association (LISA, Anselin, 1995).

An approach toward visualizing the spatial association between the value observed at one location and the observations at neighbouring locations is offered by the Moran scatterplot (Anselin, 1996). The Moran scatterplot consists in plotting the original value of the variable g_i^* on the horizontal axis against the spatial lag $\sum_j w_{ij}\, g_j^*$ (i.e., a weighted average of the observations at neighbouring locations) on the vertical axis. This scatterplot is based on the interpretation of the Moran's I as the slope of the linear relationship between the variables depicted on the axes. It is useful to discriminate between spatial clustering of high values and spatial clustering of low values, and to detect the presence of outliers.

The four quadrants of the Moran scatterplot correspond to four different patterns of local spatial association between any one region and its neighbours: the first quadrant (top right) includes high values of the variable that are surrounded by similar values (high-high); the second quadrant (top left) includes low values of the variable that are surrounded by high values (low-high); the third quadrant (bottom left) corresponds to low values of the variables that are surrounded by similar values (low-low); the fourth quadrant (bottom right) corresponds to high values that are surrounded by low values (high-low). The first and the third quadrants of the Moran scatterplot refer to positive spatial autocorrelation (i.e., clusters of similar values); the second and the fourth quadrants indicate negative spatial association. The high-low and low-high locations are labelled as spatial outliers. Outliers are single locations; this is not the case for clusters of units.

However, the Moran scatterplot does not provide any information about the location of spatial clusters and therefore, to this end, we need to move a step ahead to define Local Indicator of Spatial Association (LISA) and LISA cluster maps.

The values of the variable for any region can be compared with the values in the neighbouring regions by using LISA indicators (Anselin, 1995). A local version of the Moran's I can be written as:

$$I(i) = \frac{N(g_i^* - \overline{g^*}) \sum_j w_{ij} (g_j^* - \overline{g^*})}{\sum_i (g_i^* - \overline{g^*})^2} \qquad j \neq i \tag{5}$$

with all quantities defined as above. A positive value for $I(i)$ indicates clustering of similar values (high or low), a negative value for $I(i)$ indicates clustering of dissimilar values. Local Moran's statistics can be used as indicators of local spatial clusters as well as to identify outliers that deviate from the global patterns of spatial association (Anselin, 1995). The interpretation of the local Moran's statistics is similar to the use of the Moran scatterplot for the identification of spatial clusters. The local clusters, identified by the LISA indicators, can be visualised in a map (LISA cluster map) that gives evidence of the positive or negative local spatial associations, between lower and higher values of the variable of interest. The additional information provided by LISA cluster map, if compared with the Moran scatterplot, consists in its capacity of visualizing the localization of the spatial clusters.

It is important to highlight that the reference to high and low is *relative* to the mean of the variable and should not be interpreted in absolute terms.

4. ANALYSIS OF SPATIAL DEPENDENCE AND ECONOMIC GROWTH

4.1 Cross-sectional data

4.1.1 Taxonomy of spatial models for the analysis of β-convergence

Modelling regional growth dynamics requires the adoption of specifications to address important methodological issues, including as spatial dependence. As previously mentioned, spatial dependence reflects a situation where values observed at one location depend on the observations at nearby locations (LeSage and Pace, 2009). Thus, standard linear regression models, commonly used to investigate the convergence hypothesis, should be modified to incorporate this spatial effect.

Consider cross-sectional data obtained observing many geographical units (i.e., countries, regions or provinces) at the same point in time. In the β-convergence models, the average growth rate of GDP per capita observed for N regions, over a given time period, is assumed to be the dependent variable, and the standard non-spatial specification takes the form:

$$g_i = \beta_0 + \mathbf{x}'_i \boldsymbol{\beta} + \varepsilon_i \qquad \varepsilon_i \sim N(0, \sigma^2) \qquad (6)[7]$$

where $i = 1,2, \ldots, N$ denotes the cross-sectional dimension (i.e., the spatial units), $g_{it} = \frac{1}{T} \ln\left(\frac{y_{it}}{y_{it-T}}\right)$ is the dependent variable, $\mathbf{x}_i$ is a vector of p explanatory variables for each spatial unit i and ε_i is independent and identically distributed error term, with zero mean and variance σ^2.

The explanatory variables vector $\mathbf{x}$ includes only the initial level of the natural logarithm of the GDP per capita (i.e., $\ln y_{it-T}$) in the unconditional β-convergence model, while the conditional β-convergence model includes additional variables (usually the list of variables defined in equation (3)) to control for structural differences.

Modelling spatial dependence usually requires including in the model (6) spatially lagged variables which represent weighted averages of observations for neighbour units of a given location. The definition of neighbours is typically carried out through the specification of a spatial weights matrix $\mathbf{W}$.

Spatially lagged variables can be included for the dependent variable, the explanatory variables and the error terms, as well as for combinations of these, yielding different linear spatial dependence models (LeSage and Pace, 2009; Elhorst, 2010).

There are two main approaches to the introduction of spatial dependence in linear regression models (Elhorst, 2014). The first approach, the standard in most empirical studies, is the specific-to-general approach. In the specific-to-general approach, one starts with the linear regression model in equation (6) and tests whether the model needs to be extended with the spatial dependence effect. The opposite approach

[7] Note that the superscript ' denotes the transpose of a vector or a matrix. All vectors and matrices are indicated in bold in the text.

consists in starting with a more general model containing a series of simpler models as special cases.

The more general approach is the Manski model (Manski, 1993), which takes the following form:

$$g_i = \beta_0 + \mathbf{x}'_i\boldsymbol{\beta} + \rho\sum_{j=1}^{N} w_{ij}g_j + \sum_{j=1}^{N} w_{ij}\mathbf{x}'_j\boldsymbol{\gamma} + u_i; \qquad u_i = \delta\sum_{j=1}^{N} w_{ij}u_j + \varepsilon_i \quad (7)$$

where, for each $i = 1, \dots, N$, $\sum_{j=1}^{N} w_{ij}g_j$ is the spatially lagged dependent variable, $\sum_{j=1}^{N} w_{ij}\mathbf{x}_j$ denotes the spatially lagged explanatory variables, and $\sum_{j=1}^{N} w_{ij}u_j$ is the spatial lag on the disturbance terms. These spatially lagged variables express the spatial interactions among the observations on the dependent variable, on the explanatory variables, and on the disturbance terms, respectively. The strength of these interactions depends on the value of the associated parameters, represented by ρ, δ and $\boldsymbol{\gamma}$, respectively. ρ is the spatial autoregressive coefficient, and δ is the spatial autocorrelation coefficient. By imposing restrictions on one or more parameters of the Manski model, a family of linear spatial econometric models can be derived. The model (7) is also known as General Nesting Spatial (GNS) model (Elhorst, 2014).

Specifically, by assuming in model (7) $\boldsymbol{\gamma} = \mathbf{0}$, we obtain the following specification:

$$g_i = \beta_0 + \mathbf{x}'_i\boldsymbol{\beta} + \rho\sum_{j=1}^{N} w_{ij}g_j + u_i; \qquad u_i = \delta\sum_{j=1}^{N} w_{ij}u_j + \varepsilon_i \quad (8).$$

This model, known as SAC (LeSage and Pace, 2009), or SARAR (first-order autoregressive spatial model with first-order autoregressive disturbances, Kelejian and Prucha, 1998), is a model with a spatially lagged dependent variable (i.e., $\sum_{j=1}^{N} w_{ij}g_j$) and a spatially autocorrelated error term (i.e., $\sum_{j=1}^{N} w_{ij}u_j$).

If in equation (7) we assume $\delta = 0$, we obtain the following specification:

$$g_i = \beta_0 + \mathbf{x}'_i\boldsymbol{\beta} + \rho\sum_{j=1}^{N} w_{ij}g_j + \sum_{j=1}^{N} w_{ij}\mathbf{x}'_j\boldsymbol{\gamma} + \varepsilon_i; \quad (9).$$

This model, known as spatial Durbin model (SDM), has been introduced by Anselin (1988), and includes among the independent variables the spatially lagged dependent variable (i.e., $\sum_{j=1}^{N} w_{ij}g_j$) as well as the spatially lagged explanatory variables (i.e., $\sum_{j=1}^{N} w_{ij}\mathbf{x}_j$).

A further specification is obtained by assuming $\rho = 0$ in (7). This approach is known as spatial Durbin error model (Elhorst, 2014), and takes the following form:

$$g_i = \beta_0 + \mathbf{x}'_i\boldsymbol{\beta} + \sum_{j=1}^{N} w_{ij}\mathbf{x}'_j\boldsymbol{\gamma} + u_i; \qquad u_i = \delta\sum_{j=1}^{N} w_{ij}u_j + \varepsilon_i \quad (10).$$

This model considers spatial lag on both the explanatory variables (i.e., $\sum_{j=1}^{N} w_{ij}\mathbf{x}_j$) and the disturbance term (i.e., $\sum_{j=1}^{N} w_{ij}u_j$).

When in (7) we assume both $\boldsymbol{\gamma} = \mathbf{0}$ and $\delta = 0$, we obtain the specification known as spatial lag model (SLM), that takes the following form:

$$g_i = \beta_0 + \mathbf{x}'_i\boldsymbol{\beta} + \rho\sum_{j=1}^{N} w_{ij}g_j + \varepsilon_i \quad (11).$$

Finally, when in equation (7) we assume both $\boldsymbol{\gamma} = \mathbf{0}$ and $\rho = 0$, we obtain the spatial error model (SEM):

$$g_i = \beta_0 + \mathbf{x}'_i \boldsymbol{\beta} + u_i; \qquad u_i = \delta \sum_{j=1}^{N} w_{ij} u_j + \varepsilon_i \qquad (12).$$

The increasing use of spatial econometrics tools has been largely theoretically and empirically motivated, as failure to consider spatial dependence may imply severe consequences on both model estimation and interpretation. Moreover, ignoring spatial dependence in the dependent variable and/or in the independent variables, if present, is equivalent to the omission of relevant explanatory variables in the regression equation. As noted in the econometric literature, this omission results in biased and inconsistent estimators of the coefficients for the remaining explanatory variables. Conversely, ignoring spatial dependence on the disturbances, if present, will result in a loss of efficiency (Elhorst, 2014).

These considerations reveal the strength of the spatial Durbin model, with respect to the other general models, such as SARAR model, which does not consider spatially lagged explanatory variables (i.e., $\sum_{j=1}^{N} w_{ij} \mathbf{x}_j$), and the spatial Durbin error model, that omits the spatially lagged dependent variable (i.e., $\sum_{j=1}^{N} w_{ij} g_j$). The SDM specification does not suffer from omitted variables bias and, as a further advantage, correctly considers the error dependence since the Spatial error model is a special case of the spatial Durbin model (LeSage and Fischer, 2008; Elhorst, 2014). As pointed out by LeSage and Fischer (2008), the specific features of the spatial Durbin model often makes this specification a natural choice over competing alternatives (LeSage and Pace, 2009).

Spatial models require special estimation techniques. There are three main estimation approaches for these models: the maximum likelihood (ML) estimation method, the instrumental variables/generalized method of moments (IV/GMM) approach, and the Bayesian Markov Chain Monte Carlo (MCMC) method. For many spatial model specifications, the ML estimation has been among the most widely used techniques (Anselin, 1988; LeSage and Pace, 2009). The ML estimation method can involve some computational difficulties. However, a number of techniques that greatly reduce these difficulties have been developed (LeSage and Pace, 2009). ML estimates rely on the assumption of normality and homoscedasticity of the disturbances. The assumption of normality is not required when IV/GMM estimators are used (Elhorst, 2010; Elhorst, 2014). Furthermore, these estimators are extremely useful when spatial models contain one or more endogenous explanatory variables, other than the spatially lagged dependent variables (Fingleton and Le Gallo, 2008). In contrast, the Bayesian MCMC estimation approach can accommodate heteroscedastic disturbances and/or outliers and allows for transforming complicated estimation problems into simpler problems. In fact, the joint posterior distribution of the model parameters can be disaggregated into a set of conditional distributions for each parameter in the model; drawing samples from these will provide valid Bayesian parameter estimates (see, among others, Gelfand and Smith, 1990; LeSage and Pace, 2009).

In models containing spatial lags of the explanatory or dependent variables, the interpretation of the parameter estimates becomes richer and more sophisticated. For example, this occurs for the SDM model, that considers other regions' dependent and explanatory variables. As pointed out by LeSage and Pace (2009), the interpretation of the SDM should be based on the estimated impacts rather than the estimated coefficients (LeSage and Fischer, 2008). For this model, analysing the effects on the dependent variable that arise from changing the explanatory variables requires calculating the average direct, indirect, and total impacts for each variable in the model (LeSage and Fischer 2008; LeSage and Pace 2009). The direct effect refers to the impact of a change in an explanatory variable in a particular unit on the dependent variable in the unit itself. The indirect, or spillover, effect refers to the impact of a change in an explanatory variable in a particular unit on the dependent variable in other units. The total effect is derived by summing up direct and indirect effects. LeSage and Pace (2009) proposed scalar summary measures for these impacts. Further details are given in Appendix 1.

4.1.2 Theoretical growth models with spatial dependence

A growth model which explicitly considers the spatial autocorrelation effect has been introduced by Ertur and Koch (2007). The authors explain at the theoretical level the spatial autocorrelation often detected in empirical growth regressions. The proposed model is an augmented Solow model (Solow, 1956) that considers spatial externalities due to technological interdependence.

The specification proposed by Ertur and Koch (2007) is defined by considering the following Cobb-Douglas production function:

$$Y_{it} = A_{it} K_{it}^{\alpha_k} L_{it}^{1-\alpha_k} \tag{13}$$

where, at time t and for economy i, Y_{it} is the output, K_{it} the level of physical capital, L_{it} the level of labour, and A_{it} the level of technology. The exponent α_k in (13) expresses the output elasticity with respect to physical capital.

Ertur and Koch (2007) model the level of technology in a particular economy as being dependent on three terms. Firstly, as in the Solow model, part of technological progress is assumed to be exogenous and identical to all economies. Secondly, the level of technology of a particular economy is related to the level of physical capital, because of knowledge spillovers generated by investment in physical capital. The parameter describing the strength of externalities generated by the physical capital accumulation is denoted by ϕ_k. Finally, it is assumed that the level of technology in a particular economy also depends on the level of technology of neighbouring economies. The degree of these spatial externalities is described by the parameter ζ.

The assumed technological interdependence implies that countries cannot be analysed in isolation but must be considered as an interdependent system. The interdependence assumed by Ertur and Koch (2007) leads to the specification that, for units i, the technological interdependence can be expressed as follows:

$$g_i = \beta_0 + \beta_1 \ln y_{it-T} + \beta_2 \ln s_i^k + \beta_3 \ln v_i + \rho \sum_{j=1}^{N} w_{ij} g_j + \rho_1 \sum_{j=1}^{N} w_{ij} \ln y_{jt-T} + \rho_2 \sum_{j=1}^{N} w_{ij} \ln s_j^k + \rho_3 \sum_{j=1}^{N} w_{ij} \ln v_j + \varepsilon_i \tag{14}$$

where $g_i = \frac{1}{T}\ln\left(\frac{y_{it}}{y_{it-T}}\right)$ expresses the average of GDP per worker growth rate, with y_{it} and y_{it-T} denoting the GDP per worker at the final time and at the initial period, respectively, and T expressing the number of periods under investigation. The variable s_i^k is the fraction of output invested in physical capital, and $v_i = n_i + l + k$, where n_i is the working population growth rate, l is the rate of technological progress, k indicates the depreciation rate of capital, with t fixed and $i = 1, \dots, N$. For all economies, l and k are assumed to be constant. The model parameters in (14) can be specified as follows: β_0 is a constant, $\beta_1 = -\frac{1-e^{-\lambda T}}{T}$, $\beta_2 = -\beta_3 = \frac{\alpha_k+\phi_k}{1-\alpha_k-\phi_k}\frac{1-e^{-\lambda T}}{T}$, $\rho_1 = \frac{\zeta(1-\alpha_k)}{1-\alpha_k-\phi_k}\frac{1-e^{-\lambda T}}{T}$, $\rho_3 = -\rho_2 = \frac{\zeta\alpha_k}{1-\alpha_k-\phi_k}\frac{1-e^{-\lambda T}}{T}$ and $\rho = \frac{\zeta(1-\alpha_k)}{1-\alpha_k-\phi_k}$. The parameter $\lambda = -\frac{\ln(T\beta_1+1)}{T}$ is the annual speed of convergence that measures how fast economies converge towards the steady state.

The model (14) predicts convergence since the growth of GDP per worker is a negative function of the initial level of income per worker (i.e., β_1 is negative), but only after controlling for the determinants of the steady state. Moreover, the GDP per worker also depends on the same variables spatially lagged because of the technological interdependence and spatial externalities. The term $\rho\sum_{j=1}^{N} w_{ij}g_j$ shows that the GDP per worker growth rate of country i positively depends on the growth rate observed for its neighbouring countries.

In model (14), as Mankiw et al. (1992) and Barro and Sala-i-Martin (1992), we suppose that the speed of convergence[8] is identical for all countries/regions. The model (14) also includes the spatially lagged dependent variable (i.e., the weighted sum of the values of the dependent variable observed in neighbouring economies) as well as the spatial lag of the independent variables. The spatially lagged variables are defined by introducing the $N \times N$ spatial weight matrix $\mathbf{W}$, with elements w_{ij} expressing the proximity relationships between the economy i, and its neighbouring economies js. The model specification (14) corresponds to the Spatial Durbin model (see Subsection 4.1.1). Ertur and Koch (2007) tested the predictions of this spatially augmented Solow model on a sample of 91 countries from 1960-1995.

Fischer (2011) introduced a spatially augmented version of the Mankiw-Romer-Weil (MRW) model (Mankiw et al. 1992). The proposed specification models technological progress along the lines suggested by Ertur and Koch (2007) but differs from this last contribution in some important features. Fischer (2011) focused on an MRW rather than a Solow model, including human capital as additional production factor. Additionally, the analysis proposed by Fischer (2011) shifts attention from countries to regions, as a more appropriate geographical scale for analysing growth processes.

The theoretical model developed by Fischer (2011) relies on the following Cobb Douglas production function:

$$Y_{it} = A_{it}K_{it}^{\alpha_k}H_{it}^{\alpha_h}L_{it}^{1-\alpha_k-\alpha_h} \qquad (15)$$

[8] The speed of convergence is defined as the rate with which economies converge to their steady state.

where H_{it} is the human capital for region i at time t, α_h represents the output elasticity with respect to human capital, and the other terms are defined as above (see equation 11). Like in Mankiw et al. (1992), it is assumed that $\alpha_k, \alpha_h > 0$, and $\alpha_k + \alpha_h < 1$, which implies that there are decreasing returns to both physical capital and human capital.

As previously mentioned, the level of technology is modelled according to Ertur and Koch (2007), and this implies that the level of technology depends on a common term that is identical for all regions, and, for region i, positively depends on the level of technology of its neighbouring regions. Furthermore, the aggregate level of technology increases with both the aggregate level of physical capital per worker, and the aggregate level of human capital per worker. The parameter describing the strength of externalities generated by the human capital accumulation is denoted by ϕ_h.

The empirical model that derives from the aforementioned assumptions can be written for region i in the following form:

$$g_i = \beta_0 + \beta_1 \ln y_{it-T} + \beta_2 \ln s_i^k + \beta_3 \ln v_i + \beta_4 \ln s_i^h + \rho \sum_{j \neq i}^{N} w_{ij} g_j + \rho_1 \sum_{j=1}^{N} w_{ij} \ln y_{jt-T} + \rho_2 \sum_{j=1}^{N} w_{ij} \ln s_j^k + \rho_3 \sum_{j=1}^{N} w_{ij} \ln v_j + \rho_4 \sum_{j=1}^{N} w_{ij} \ln s_i^h + \varepsilon_i \quad (16)$$

where s_i^h denotes the fraction of output invested in human capital and the other terms are defined as above (see equation (14)). The specification in the model (16) corresponds to a spatial Durbin model, which introduces among the explanatory variables the spatial lag of the dependent variables as well as the spatially lagged independent variable. The model parameters are specified as follows: $\beta_1 = -\frac{1-e^{-\lambda T}}{T}$, $\beta_2 = \frac{\alpha_k+\phi_k}{1-\eta}\frac{1-e^{-\lambda T}}{T}$, $\beta_3 = -\frac{\eta}{1-\eta}\frac{1-e^{-\lambda T}}{T}$, $\beta_4 = \frac{\alpha_h+\phi_h}{1-\eta}\frac{1-e^{-\lambda T}}{T}$; $\beta_3 = -\beta_2 - \beta_4$, $\rho_1 = \frac{\gamma(1-\alpha_k-\alpha_h)}{1-\eta}\frac{1-e^{-\lambda T}}{T}$, $\rho_2 = -\frac{\zeta\alpha_k}{1-\eta}\frac{1-e^{-\lambda T}}{T}$, $\rho_3 = \frac{\zeta(\alpha_k+\alpha_h)}{1-\eta}\frac{1-e^{-\lambda T}}{T}$, $\rho_4 = -\frac{\zeta\alpha_h}{1-\eta}\frac{1-e^{-\lambda T}}{T}$, and $\rho = \frac{\zeta(1-\alpha_k-\alpha_h)}{1-\eta}\frac{1-e^{-\lambda T}}{T}$, $\rho_3 = -\rho_2 - \rho_4$, with $\eta = \alpha_k + \alpha_h + \phi_k + \phi_h$. When $\phi_k = \phi_h = 0$, equation (15) collapses to the standard MRW model, where non spatial interaction is present (see equation (3), Mankiw et al., 1992). Furthermore, the model (16) collapses to the specification proposed by Ertur and Koch (2007) if $\alpha_h = \phi_h = 0$. Fischer (2011) tested this model on a sample of 198 NUTS 2 regions belonging to 22 European countries from 1995–2004.

Since the availability of data, the equation defined in model (14) will be the reference model for our cross-sectional estimation of conditional β-convergence hypothesis for European regions at NUTS 3 level.

4.2 Panel data

4.2.1 Taxonomy of spatial models for the analysis of β-convergence

Spatial panel models are a relevant tool in economics as well as in related scientific fields of regional sciences, geography, health economics, and so on (Kelejian and Piras, 2017). In the field of economic growth, the increasing use of panel data is presumably connected to the increased availability of data sets and to the fact that panel data are generally more informative (Hsiao, 2014).

The first step to define a panel model for conditional β- convergence model is considering a pooled linear regression expressed as:

$$g_{it} = \beta_0 + \mathbf{x}'_{it}\boldsymbol{\beta} + \varepsilon_{it} \quad (17)$$

where $i = 1,2,\ldots..,N$ denotes the cross-sectional dimension (i.e., the spatial units), $t = 1,\ldots,L$[9] is the time dimension, $g_{it} = \frac{1}{T}\ln\left(\frac{y_{it}}{y_{it-T}}\right)$ is the dependent variable, T is the time span of the growth period considered, $\mathbf{x}_{it}$ is a vector of p explanatory variables for each spatial unit i for each time t, $\boldsymbol{\beta}$ is the corresponding vector of parameters, and ε_{it} is an independent and identically distributed error with zero mean and variance σ^2. Estimation of model (17) can be obtained following the same procedure of a standard cross-sectional model.

However, the model (17) may lead to severe bias connected to space-time heterogeneity that is often highlighted by geographically distributed data. For this reason, it can be extended including for spatial and time-period specific effects as:

$$g_{it} = \beta_0 + \mathbf{x}'_{it}\boldsymbol{\beta} + \varphi_i + \xi_t + \varepsilon_{it} \quad (18)$$

where φ_i is a spatial effect that controls for all time invariant variables and ξ_t is a spatial-invariant time specific effect (Elhorst, 2014).

If the researcher needs to specify interaction between units, it is possible to consider alternative spatial augmented models. First, we can consider the static spatial lag model (SLM) defined, for each unit i and time t, as:

$$g_{it} = \beta_0 + \mathbf{x}'_{it}\boldsymbol{\beta} + \rho\sum_{j=1}^{N} w_{ij}g_{jt} + \varphi_i + \xi_t + \varepsilon_{it} \quad (19)$$

where ρ is the spatial autoregressive coefficient, w_{ij} is the element of the $N \times N$ spatial weight matrix $\mathbf{W}$ and measures the connectivity between spatial units as introduced above for the cross-sectional case.

Other spatial model that can be also defined in the panel framework is the static spatial error model (SEM) defined, for each unit i and time t, as:

$$g_{it} = \beta_0 + \mathbf{x}'_{it}\boldsymbol{\beta} + \delta\sum_{j=1}^{N} w_{ij}u_{jt} + \varphi_i + \xi_t + \varepsilon_{it} \quad (20)$$

where $\sum_{j=1}^{N} w_{ij}u_{jt}$ is the spatially autocorrelated error term, and δ is the spatial autocorrelation coefficient. The spatial error modelling is considered as a special case of a non-spherical error covariance matrix (Anselin et al. 2006).

Furthermore, spatial dependence both in the dependent variable and in the error term may be considered defining a static SARAR model (Kelejian and Piras, 2017), combining model (19) and (20) as:

[9] In the panel analysis of β-convergence, the number of periods considered L is defined as $L = P/T$ where P are the total number of years of the entire period of observation.

$$g_{it} = \beta_0 + \mathbf{x}'_{it}\boldsymbol{\beta} + \rho \sum_{j=1}^{N} w_{ij} g_{jt} + \delta \sum_{j=1}^{N} w_{ij} u_{jt} + \varphi_i + \xi_t + \varepsilon_{it} \quad (21)$$

However, as evidenced by Elhorst (2014), the empirical relevance of the SARAR has been relatively low.

Finally, a static panel version of the spatial Durbin model with specific time and space effect is defined, for each unit i and time t, as:

$$g_{it} = \beta_0 + \mathbf{x}'_{it}\boldsymbol{\beta} + \rho \sum_{j=1}^{N} w_{ij} g_{jt} + \sum_{j=1}^{N} w_{ij} \mathbf{x}'_{jt}\boldsymbol{\gamma} + \varphi_i + \xi_t + \varepsilon_{it} \quad (22)$$

where, additionally, $\boldsymbol{\gamma}$ is the $k \times 1$ vector of parameters of the spatially lagged explanatory variables. The SDM extends the SLM by allowing for a spatial relationship not only in the dependent variable, but also in the independent variables, obtaining more flexible spatial effects (LeSage and Pace, 2009).

In all mentioned models, the specific effects in space and time can be treated as fixed or random. In the fixed effects model, a dummy variable is introduced for each spatial unit and for each time period, while in the random effects model, φ_i and ξ_t are treated as random variables that are independently and identically distributed with zero mean and variance σ_φ^2 and σ_ξ^2, respectively. Furthermore, it is assumed that the random variables φ_i, ξ_t, and ε_{it} are independent of each other.

The aforementioned models are all static since they involve contemporaneous values of the dependent and independent variables. It is also possible to define dynamic panel models where the lagged (in time) dependent variable and/or the lagged (in both time and space) dependent variable can be included in the specification. This model is described in more detail in Section 4.2.2.

The static models described can be essentially estimated following two key approaches. The first is based on the ML method, while the second is constituted by IV/GMM procedure. Specifically, in the case of a spatial lag model containing fixed effects, the parameters corresponding to the covariates can be estimated by a procedure called demeaning (Baltagi, 2005) that allows the analyst to pursue maximum likelihood estimation (Anselin, 1988) in the panel context.

4.2.2 Theoretical growth models with spatial dependence

A panel growth model which explicitly considers the spatial dependence effect has been introduced by Elhorst et al. (2010). This framework can be considered as the extension to the panel case of the Ertur and Koch (2007) model for cross-sectional data described in Section 4.1.2. The model is an augmented Solow model (Solow, 1956) that entails spatial externalities due to technological interdependence.

The use of a cross-sectional approach, however, as evidenced by Elhorst et al. (2010), has some potential shortcomings. First, the model employs only data at the beginning and the end of the time period under investigation. Second, it assumes that s_i^k, n_i are constant across the period. The panel approach overcomes these limitations.

Considering that $g_{it} = \frac{1}{T}\ln\left(\frac{y_{it}}{y_{it-T}}\right)$ and using algebra, the cross-sectional spatial regression equation (14) can be extended to include specific time and spatial effects as (Elhorst et al. 2010):

$$\ln y_{it} = T\beta_0 + (1 + T\beta_1)\ln y_{iT-t} + T\beta_2 \ln s_{it}^k + T\beta_3 \ln v_i + \rho \sum_{j=1}^{N} w_{ij} \ln y_{jt} + (T\rho_1 - \rho)\sum_{j=1}^{N} w_{ij} \ln y_{jt-T} + T\rho_2 \sum_{j=1}^{N} w_{ij} \ln s_j^k + T\rho_3 \sum_{j=1}^{N} w_{ij} \ln v_j + \varphi_i + \xi_t + \varepsilon_{it} \quad (23)$$

Let $\theta_0 = T\beta_0$,$\tau = (1 + T\beta_1)$, $\upsilon = (T\rho_1 - \rho)$, $\theta_2 = T\beta_2$, $\theta_3 = T\beta_3$, $\widetilde{\rho_2} = T\rho_2$, $\widetilde{\rho_3} = T\rho_3$, then equation (23) can be re-specified as:

$$\ln y_{it} = \theta_0 + \tau \ln y_{it-T} + \theta_2 \ln s_{it}^k + \theta_3 \ln v_{it} + \rho \sum_{j=1}^{N} w_{ij} \ln y_{jt} + \upsilon \sum_{j=1}^{N} w_{ij} \ln y_{it-T} + \widetilde{\rho_2} \sum_{j=1}^{N} w_{ij} \ln s_{jt}^k + \widetilde{\rho_3} \sum_{j=1}^{N} w_{ij} \ln v_{jt} + \varphi_i + \xi_t + \varepsilon_{it} \quad (24)$$

Equation (24) represents a dynamic[10] spatial panel Durbin specification, and it is appropriate for the analysis of conditional β – convergence in a panel setting (Elhorst et al. 2010).

The estimation of dynamic spatial panel model (24) is not trivial and depends on the number of spatial units and on the time span that are available in the analysis. For further details about the estimation procedure and some interesting comparisons between different estimations, see Elhorst (2012).

The equation defined in model (24) will be the reference for our panel estimation of conditional β-convergence hypothesis for European regions at NUTS 2 level.

5. ANALYSIS OF SPATIAL HETEROGENEITY AND ECONOMIC GROWTH

5.1 Spatial heterogeneity and the modelling of economic growth

In the last decade, significant effort was devoted to the analysis of regional economic convergence by using spatial dependence as the only conceptual approach for modelling.

Surprisingly, in the regional convergence literature, the presence of spatial heterogeneity has been less investigated. This effect represents another relevant characteristic highlighted by geographically distributed data, and illustrates a key difference with time series modelling: dependence and heterogeneity can be pairwise considered as basic issues.

[10] The dynamic panel data models also use the temporal lags of the dependent variable as explanatory variables.

Spatial heterogeneity is linked to the absence of stability across the territory of the phenomenon under investigation, and it implies parameters to vary over space (Anselin, 1988). Its presence can be revealed in a regression model by two distinct causes, non-constant error variances (i.e., heteroscedasticity) or space-varying coefficients (i.e., structural instability). In the field of linear estimation, spatial heterogeneity may result in misspecification.

According to Anselin (2010), spatial heterogeneity can be classified into discrete heterogeneity and continuous heterogeneity. Discrete heterogeneity concerns a pre-specified set of spatially distinct units, or spatial regimes, between which model coefficients are allowed to vary. They can be simply seen as a special case of group-wise heterogeneity. Conversely, continuous heterogeneity specifies how the regression coefficients change over space, either following a predetermined functional form as in the so-called spatial expansion method of Casetti (1997), or as determined by the data through a local estimation process, as in the Geographically Weighted Regression (GWR) introduced by Fotheringham et al. (2002).

GWR relaxes the hypothesis of homogeneity in the regression parameters and it helps in estimating and visualizing spatial patterns of coefficients. The main innovation of GWR is employing a subset of data supposed to influence more the parameter estimation in each point (Wheeler and Páez, 2010).

Bayesian regression models with spatially varying coefficient processes (SVCP) have been introduced to model non-constant linear relationships between variables (Gelfand et al. 2003). Equivalently to GWR, this methodological framework allows for a deeper analysis of the varying relationships between the dependent variable and the covariates. Instead of fitting spatially local regressions, in SVCP, spatial varying coefficients are modelled as a multivariate spatial process.

The effects of spatial heterogeneity are highly relevant in growth and convergence analysis. In regional convergence analysis, the existence of structural heterogeneities may be explained, for example, with the presence of multiple regimes or convergence clubs (Durlauf and Johnson, 1995; Quah, 1996a). From a statistical point of view, convergence clubs (or multiple regimes) can be interpreted as groups of regions where the local parameters of the regional economic convergence model are constant, or as a group of regions sharing a common growth path. Unfortunately, the presence of multiple growth regimes and convergence clubs is a much-debated economic question. However, the recent Unified Growth Theory (UGT) can provide an empirically reasonable framework to interpret the latent causes of the formation of convergence clubs (Galor 2005; 2007). As highlighted by Postiglione et al. (2010), the UGT can represent an appropriate tool to interpret convergence clubs that have been previously identified through a statistical procedure. This economic theory asserts that there are three different typologies of economic groups: the first and the second clubs constituted by wealthy and impoverished economies, respectively, and a third group of regions that are in transition from one club to another.

Usually, in a cross-sectional framework, conditional β-convergence is estimated based on a multivariate regression analysis. Generally, the classical multivariate regression model considers the N spatial units as identical members of the same population where the dependent variable g_i is expressed by a set of explanatory variables and an error term ε_i.

Thus, we the conditional β-convergence model is expressed as follows:

$$g_i = \beta_0 + \mathbf{x}_i'\boldsymbol{\beta} + \varepsilon_i \tag{25}$$

where globally estimated parameters **β**s correspond to the covariates of the β-convergence model, homogenous over space. To consider spatial heterogeneity of the parameters, the standard regression model (25) can be modified as:

$$g_i = \beta_{0m} + \sum_{j=1}^{p} \beta_{jl} x_{ij} + \varepsilon_i \tag{26}$$

where m identifies the different spatial regimes (i.e., different zones of local stationarity of the parameters). In this way, the parameters are assumed to change across different groups and allow for the treatment of spatial heterogeneity.

The identification of a group of regions sharing a common path in terms of growth requires the application of non-standard econometric techniques that allow us to divide the sample into smaller groups. Fischer and Stirböck (2006) suggested a general setup for club-convergence testing that allows for modelling spatial dependence and heterogeneity of the convergence process. Ertur et al. (2006) defined spatial regimes as spatial convergence clubs and used ESDA tools to account for spatial autocorrelation in conjunction with structural instability by estimating the appropriate spatial regimes spatial error model. A Bayesian locally linear spatial estimation approach has been developed by Ertur et al. (2007). The methodology has been used to assess local convergence, a concept that the authors used to refer to a situation where rates of convergence in economic growth are similar for observations located at nearby points in space. A specification strategy to define a model that combines groupwise-heteroscedasticity, varying coefficients across regimes and spatial dependence has been developed by Ramajo et al. (2008). Bernardini Papalia and Bertarelli (2013) developed a two-stage strategy to identify convergence clubs and to estimate a convergence club model with spatial dependence using an entropy-based estimation procedure. Postiglione et al. (2010) identify convergence clubs using a regression tree-based algorithm. This paper extends the contribution by Durlauf and Johson (1995) considering explicitly spatial information in the model. The method provides a general non-parametric way of identifying convergence clubs using a set of control variables. The regression tree is constructed through a process known as binary recursive partitioning that subdivides a data set of N observations into subsets using a sequence of splits obtained by imposing linear conditions on the set of covariates. Then, the algorithm tries to divide the data, using every possible binary split on each covariate. The process creates subsets of increasing homogeneity with respect to the response variable. Postiglione et al. (2013) used a constrained optimization algorithm for detecting multiple spatial regimes in EU regions, allowing for explicit variation in the parameters of the Solow growth model. This algorithm, which extends the Simulated Annealing (SA) algorithm to account for spatial contiguity constraints, has been applied by Panzera and Postiglione (2014) in conjunction with a Spatial Durbin model specification for the simultaneous treatment of spatial heterogeneity and spatial dependence. To identify spatial regimes in the field of β-convergence, Andreano et al. (2017) define an iterative spatial method that uses the estimates provided by Geographically Weighted Regression (GWR, Fotheringham et al. 2002). This approach is based on the idea that similarity in local models suggests the aggregation of the corresponding regions into the same group. An iterative algorithm is introduced by computing new weights at each iteration, on the basis of homogeneity of the geographical estimated parameters over the sub-groups.

In this report, we analyse spatial heterogeneity in regional economic convergence through the GWR tool using cross-sectional data. The main aim is to study is to determine whether European regional economic growth process can be recognized in geographical instabilities and/or local behaviour. These findings may help practitioners to define more effective local policies.

5.2 Geographically Weighted Regression for testing economic convergence

Over the years, the Solow model has evolved into an empirical test for economic convergence (Barro and Sala-i-Martin, 1992; Mankiw et al. 1992). Empirical tests have generally relied on the basic assumptions of standard linear models and ordinary least squares. However, the relationship between a dependent variable and some independent variables often differs across regions (i.e., parameters are non-stationary). Therefore, a relevant feature to be analysed is represented by the presence of potential spatial heterogeneity between different units.

In a cross-sectional context, potential instability in the estimated parameters of the economic growth model prompts analysts to further explore the differences that affect units located in different areas. Tackling the presence of spatial heterogeneity and significant regional differences is helpful to derive more reliable and targeted local policies.

As previously mentioned, the GWR (Fotheringham et al. 2002) is one of the possible solutions that allows to solve problems of misspecification due to spatial heterogeneity that may create biased estimates of regression coefficients. GWR has been introduced by Brunsdon et al. (1996) to study the potential instabilities of the parameters of a regression model in geographical space. GWR is a locally linear, non-parametric estimation method aimed at capturing, for each observation i, the spatial variations of the regression coefficients. For this purpose, a different set of parameters is estimated for each observation, considering the characteristics of the neighbours of i.

Formally, the equation (3) of conditional $\beta-$convergence could be re-written by considering non-stationary parameters in each region i as:

$$g_i = \beta_{0i} + \beta_{1i}\ \ln y_{it-T} + \beta_{2i}\ln s_i^k + \beta_{3i}\ln v_i + \beta_{4i}\ \ln s_i^h + \varepsilon_i \qquad (27)$$

where the estimated parameters β_{pi} $(p = 1,2, \dots, 4)$ vary from locality to locality.

It is worth noting that in the GWR model (27), the regression coefficients are estimated at each data location diversely from the OLS model (3) that are obtained globally for the study area.

Estimation of the equation (27) is obtained by adopting a geographical version of weighted least squares estimator. In matrix notation, the GWR estimator is defined as:

$$\widehat{\boldsymbol{\beta}_\iota} = (\mathbf{X}^t\mathbf{C}_i\mathbf{X})^{-1}\mathbf{X}^t\mathbf{C}_i\mathbf{y} \quad (28)$$

where $\mathbf{X}$ is the matrix of the p covariates containing variables defined in the economic model (27), which includes a leading column of ones for the estimation of the intercept. $\widehat{\boldsymbol{\beta}_\iota}$ is the vector of $(p+1)$ local regression coefficients at location i.

In GWR, the local weights $c_{ij} \in \mathbf{C}_i$ are calculated according to a desirable kernel function of the distance d_{ij} between locations i and j (McMillen, 1996; McMillen and McDonald, 1997), that places more weight on locations that are closer in space than those that are more distant.

One of the most commonly used weighting functions is the Gaussian kernel that, for a given location i, is defined as:

$$c_{ij} = \exp(-\frac{1}{2}\frac{d_{ij}^2}{b^2}) \qquad j = 1,\dots,N \quad (29)$$

where b is the bandwidth that represents a measure of the distance-decay in the weighting function and indicates the extent to which the local calibration results are smoothed (Fotheringham et al. 2002). The distances d_{ij} are generally Euclidean distances. As the bandwidth b gets larger, the weights approach unity and the local GWR model approaches the global OLS model.

The truncated kernel can also be used. This method sets the weight to 0 outside a certain range d_{ij}, and obtained, for instance, according to a bi-square kernel:

$$c_{ij} = \begin{cases} [1 - \left(\frac{d_{ij}}{b}\right)^2]^2, & if\ d_{ij} < b \\ 0, & if\ d_{ij} > b \end{cases} \quad (30)$$

where b is the selected level of bandwidth. In addition to Gaussian and bi-square, many other kernel functions may be considered depending on the nature of the application.

The kernel can be fixed or adaptive. In fixed spatial kernels, all data points within a given distance were used to calibrate a model. If data are sparse, using fixed spatial kernels, the local models might be calibrated on very few data points. To overcome this challenge, an adaptive kernel, that attempt to adjust for the density of data points, can be defined. As in many cases, spatial units show an irregular spatial configuration, and an adaptive kernel where the bandwidth is referred to a certain number of neighbours is preferable.

If the specification of the kernel function itself may be considered as less relevant in the GWR estimation, the choice of the bandwidth may severely affect the results. Therefore, careful selection of an optimal bandwidth is required. Several criteria may be adopted to this end. Many studies identify the level of bandwidth by using the Akaike Information Criterion (AIC, Fotheringham et al. 2002).

Calculation of locally different parameters of β −convergence allows analysts to visualise and compute variation in parameters that can be at the basis of inconsistent estimates (Temple, 1999). A number of studies on economic convergence are based on the application of GWR model, as for the case of Germany (Bivand and Brunstad, 2003; Eckey et al. 2007). In those applications, the presence of significant varying β-convergence parameters justifies the necessity of highlighting the diversities in the structure of economic convergence.

The GWR method will be applied to NUTS 3 regions to test for the presence of spatial instabilities in modelling conditional β −convergence in the EU.

6. EMPIRICAL STUDIES AT DIFFERENT SPATIAL SCALES

6.1 Introduction

In this section we present a variety of empirical studies at different spatial scales. The analyses concern different aspects of economic growth in EU regions.

We first perform a preliminary analysis of economic growth based on pure GDP per capita in PPS values. Then, an ESDA is used to highlight possible geographical behaviour in the growth process of EU regions. This study is introductory and open to possible spatial interpretations of the phenomenon under investigation. A σ − convergence analysis is offered to study a possible reduction of disparities in terms of GDP per worker in PPS between EU regions. The β − convergence analysis enables the detection of possible catch-up processes between EU regions. This investigation is implemented making use of both cross-sectional and panel data spatial regressions. Furthermore, a spatial heterogeneity analysis of the β − convergence process of EU regions is proposed using the GWR method. This study is important, as it allows us to identify possible clusters of EU regions that share the same behaviour in terms of economic growth.

The data sets used in our studies are derived from two sources. The first data set comes from the official Eurostat Regional Statistics database (EU-REGIO). The second data set is based on the European regional database by Cambridge Econometrics (ERD-CE). EU-REGIO is the primary source of data for ERD-CE, and is supplemented with data obtained from AMECO, which is provided by the European Commission's Directorate General Economic and Financial Affairs. The main advantage of ERD-CE database is that it provides a complete and consistent historical time series for many variables starting in 1980. This allows for econometric regression modelling using historical regional trends across European regions.

By adopting EU-REGIO and ERD-CE dataset, the analyses can offer results at different spatial scales. In this report, results at both NUTS 2 and NUTS 3 level are reported. Specifically, as many contributions to analyse cross-sectional economic convergence are present at NUTS 2 level, we examine the potential of EU-REGIO and ERD-CE to promote analyses at a lower spatial scale (i.e., NUTS 3 level). Nevertheless, modelling convergence at NUTS 2 level remains relevant for policy makers because this spatial scale is significant for European policies, including Cohesion Policy. For this reason, besides a lower spatial scale cross-sectional analysis, we take advantage of increasing availability of literature in the field of economic growth and economic convergence at NUTS 2 using spatial panel econometrics to test for economic convergence (see, for example, Elhorst et al. 2010).

6.2 Preliminary analysis

GDP indicators (as the GDP per capita) merely stress economic well-being and ignore a variety of other dimensions. However, GDP unquestionably remains a first order indicator to analyse growth and to express the extent of the differences in development between countries, regions, municipalities and, based on data availability, local units. Hence, such measures are frequently adopted at the aim of constructing time series, cross-sectional analysis and panel modelling to explore the dynamic of growth in regional inequality studies.

In the current report, regional data, including GDP at NUTS2 and NUTS3 levels, will constitute the basis for further analysis on regional economic growth. Nevertheless, it is also important looking at some of the dynamics that have involved growth of GDP at national level. A special focus is on the effect of economic downturn due to the global financial crisis of 2008 is required. In fact, this crisis had a dramatic impact on GDP in the EU. The global financial crisis exposed European countries to a long-term post-crisis potential growth rate lower than their pre-crisis levels, and to the necessity of implementing policies to enhance the convergence process.

Presenting a general scenario may help to provide a better comprehension of the forces that influence regional economic convergence, and could be useful in addressing the development of policies at different geographical levels. In this regard, we briefly consider GDP per capita in PPS at country level (i.e., NUTS 0) to form considerations on general conditions of Members' economies and well-being. In Figure 1 and Figure 2, we observe that the economic growth rate maintained a positive trend in the years that preceded 2008. An exception is only represented by the decline which occurred in the mid-1990s. However, this economic slack was then followed by a recovery that involved EU countries, both from the east (see Figure 1) and the west (see Figure 2).

The financial recession in 2008 led to a significant decrease in the output of the European economy, which is likely to be more than just a cyclical deviation from potential output. As highlighted by the European Commission (2009), this exposed many countries and regions to the risk that losses in GDP levels may not be easily recovered if the economy converges to its potential level only at a slow pace. The impact of the financial crisis on output and employment might have negatively affected the living standards of the population as well as social cohesion. Additionally, the economic slowdown also caused increasing heterogeneity in the economic growth dynamics across Europe. Among others, the sovereign-debt crisis in countries as Italy, Spain and Greece has resulted in increasing differences in both financial and economic trends.

Figure 1 - Growth rate of GDP per capita in PPS for 15 European countries from 1994-2014. Source: Own elaboration on ERD-CE dataset.

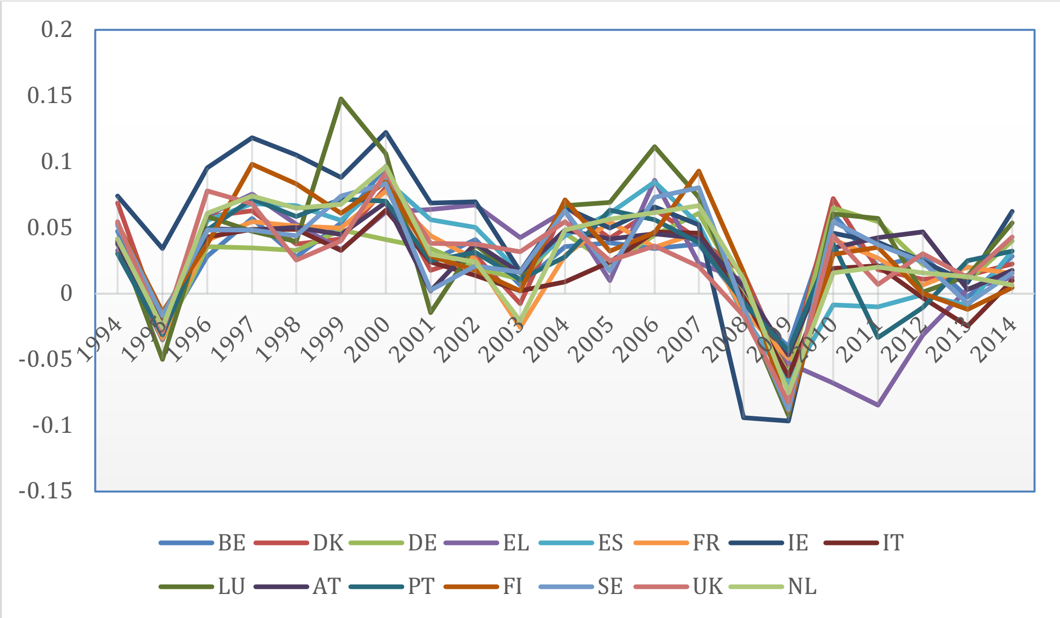
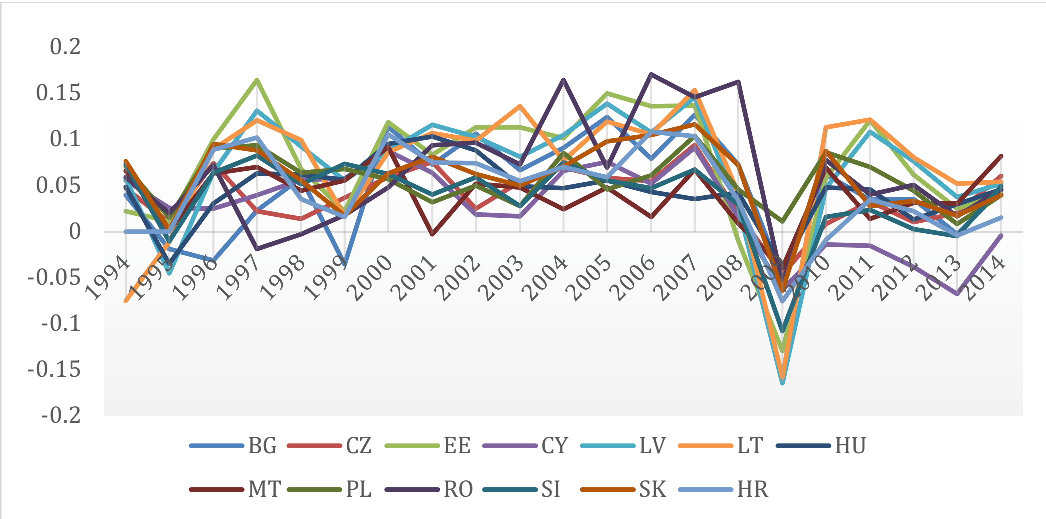


Figure 2 - Growth rate of GDP per capita in PPS for 13 European countries from 1994-2014. Source: Own elaboration on ERD-CE dataset.



The economic trends which emerged in 2008 have stimulated criticism on the sustainability of economic growth as a permanent standard for the worldwide economy (Weiss and Cattaneo, 2017). Academics and policy makers alike continue to debate whether alternative development trajectories for the global economy are possible. Among different lines of thought, the term “degrowth” has emerged as a voluntary and equitable downscaling of the economy towards a sustainable and participatory steady-state society (Schneider et al. 2010; Kallis, 2011). Degrowth postulates that indefinite economic growth on a finite planet is impossible; facilitating growth as the overarching aim of socio-economic policy will eventually lead to involuntary economic decline with far-reaching social and political consequences (Latouche, 2010). However, the concept of degrowth has evolved from a state of mere activism towards a more scientific and complex way of thinking (or re-thinking) to achieve sustainable economic pace and the steady-state economy.

Those general issues remind policy makers at both EU and country levels of the centrality of achieving social and economic cohesion. Additionally, they also lead regional policies to deal with a heterogeneous and complex piecemeal economic and political scenario. In fact, events during the last decade have determined significant differences that could complicate the European economic convergence process at both national and regional levels.

In the following sections, the analysis of regional economic convergence will be examined to shed light on significant aspects of the economic development of different regions and countries. The application of different econometrics techniques, focusing on the territorial nature of the data, will help us to understand the complexities and difficulties arising in verifying the extent of economic convergence. An in-depth analysis of convergence dynamics among regions assumes relevance in helping the development of policies and interventions that could address future challenges in promoting integration and cooperation within the EU.

6.3 σ – convergence analysis

The convergence process is a fundamental mechanism to achieve socio-economic cohesion. Faster growth of relatively poorer regions with respect to wealthier regions determines the reduction of regional inequalities, enabling more harmonious development. Reducing regional disparities is one of the main objectives of the European Cohesion Policy, which is intended to support less developed European countries and regions catch up the wealthier parts of the EU.

The evolution of regional disparities, in the long run, of EU regions can be assessed by considering a σ -convergence approach (see Section 2.1).

In our analysis, to evaluate σ -convergence, we focus on the logarithm of the GDP per worker in PPS to ensure results are more consistent with the β-convergence analysis, and based on GDP per worker in PPS. In this analysis, regional disparities are measured by the coefficient of variation (CV) of logarithms of GDP per worker in PPS, that is defined as $CV = \sigma_t/\bar{x}_t$ where $\bar{x}_t$ and σ_t are the average and the standard deviation of $\ln y_{it}$ with y_{it} as the GDP per worker in PPS, and t as the time dimension (see Section 2.1). If there is a decreasing long-term trend of CV, then regions appear to converge to a common growth rate, and σ-convergence is verified.

σ -convergence analysis is carried out on NUTS 2 EU regions, using data from the ERD-CE dataset. NUTS 2 regions are considered as units of analysis since they represent the main geographical scale eligible for support from Cohesion Policy.[11] The study is performed using two different time spans and sample regions. The first sample of spatial units is denoted as EU-15, indicating the NUTS 2 regions of the following countries:

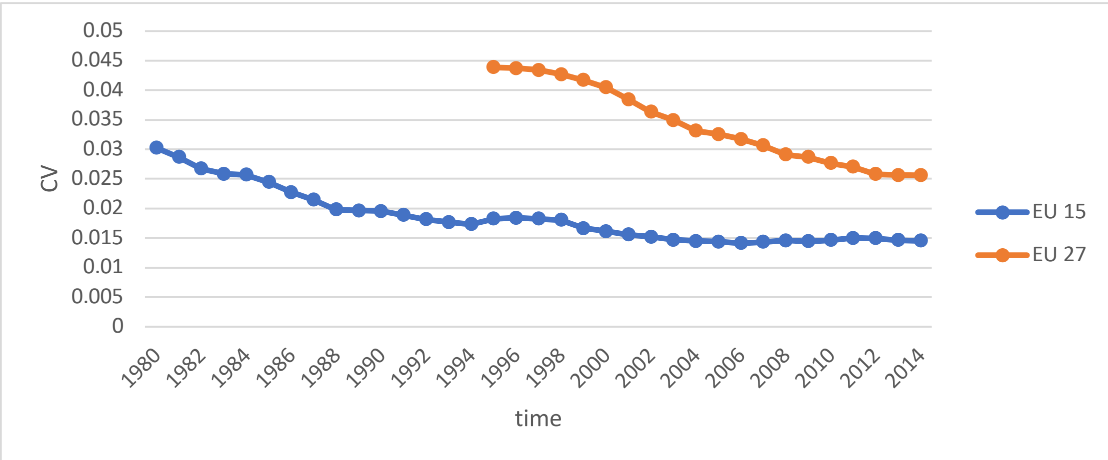
[11] https://ec.europa.eu/eurostat/web/nuts/background

Belgium (BE), Denmark (DK), France (FR), Germany (DE), Greece (EL), Ireland (IE), Italy (IT), Luxembourg (LU), Netherlands (NL), Portugal (PT), Spain (ES), the United Kingdom (UK), Austria (AT), Finland (FI) and Sweden (SE), all members of the EU since January 1995. In this case, the analysis is performed with data from 1980-2014.

The second sample of regions is specified as EU-27, indicating the NUTS 2 regions of the following countries: Belgium (BE), Denmark (DK), France (FR), Germany (DE), Greece (EL), Ireland (IE), Italy (IT), Luxembourg (LU), Netherlands (NL), Portugal (PT), Spain (ES), the United Kingdom (UK), Austria (AT), Finland (FI), Sweden (SE), Cyprus (CY), Czechia (CZ), Estonia (EE), Hungary (HU), Latvia (LV), Lithuania (LT), Malta (MT), Poland (PL), Slovakia (SK) Bulgaria (BG), Romania (RO) and Croatia (HR). In this case, the analysis is performed using data from 1995-2014.

Figure 3 presents the coefficient of variation of the logarithms of GDP per worker in PPS computed considering these two samples of EU regions considered as a whole.

Figure 3 - σ-convergence analysis – *CV* of $\ln y_{it}$, NUTS 2 regions, EU 15 and EU 27. Source: Own elaboration on ERD-CE dataset



As depicted in Figure 3, the coefficient of variation of the logarithms of GDP per worker in PPS for EU 15 NUTS 2 regions declined from 1980-2014, falling from 3% to 1.5%. The decreasing trend was stronger from 1980-1994, but disparities slightly increased in 1995, and remained stable up to 1998. Disparities continued to decrease in 1999 and remained relatively stable up to the end of the period under investigation.

In contrast, a clear decreasing trend is showed by disparities among the EU 27 NUTS 2 regions. When the sample of spatial units includes also the Eastern Europe regions, the value assumed by CV is higher with respect to the value computed for the EU 15 regions, revealing the presence of higher levels of disparities. However, these disparities rapidly declined between 1995-2014, with a CV that falls from above 4.5% to above 2.5%. These results reveal that σ-convergence occurred within the EU 27.

Conversely, the trend of CV in the EU 15 regions since 1999 reveals that the σ-convergence process is no longer taking place among the Western Europe Member

States. These results are consistent with the empirical findings of previous analyses (Neven and Gouyette, 1995; Ertur et al. 2006; Monfort, 2008; Monfort, 2012).

Moreover, these results give evidence that adding a group of countries in the analysis determines changes in the σ-convergence process. Particularly, including the new Member States from Eastern Europe has a positive contribution on the realization of the σ - convergence process, even if the initial disparities between countries were higher.

The falling of reduction of disparities in GDP per worker among the EU regions does not exclude the emerging of different trends in each considered country (i.e., analysis of the *within-country* σ - convergence process). Figure 4 shows the evolution of the CV for the NUTS 2 regions belonging to 14 of EU 15 countries. Luxembourg is not included in the analysis, having only one NUTS 2 region.

Strong evidence of σ-convergence from 1980 to the beginning of the 1990s is reported for some countries, such as Finland, the Netherlands and Portugal. These countries also reported higher levels of internal disparities, as showed by the higher values of CV. In contrast, some countries, such as Denmark, show a stable trend of CV (at a lower level) across the whole period under investigation.

Figure 5 displays the evolution of disparities in some of the countries that joined the EU in 2004 (Czechia, Hungary, Poland, Slovakia), in 2007 (Bulgaria, Romania) and in 2013 (Croatia). Cyprus, Estonia, Lithuania, Latvia and Malta are not included in the analysis, having only one region at NUTS 2 level. The trend of CV in the other seven countries does not show an important decline. The decreasing CV, observed between 1990-2014, is attributed to Romania, while a slight increasing trend is attained from Hungary. However, note that the level of disparities in Romania is higher compared with other countries. A lower level of disparities across the entire period under investigation is reported by Croatia and Hungary. A stable trend of disparities characterizes the other countries.

These results underscore the complexity of the σ -convergence analysis. The comparison between single countries add information to the analysis mentioned in the whole sample. The reduction of disparities in GDP per capita between Member States reflect the long-run convergence process that could benefit from a positive impact of the EU Cohesion Policy. In fact, the convergence process across regions is more evident when the sample of countries also include the central and eastern European countries that joined EU from 2004. These countries have set out on important growth paths, receiving support from various EU funds. The analysis of σ –convergence, focusing on the assessment of the evolution of disparities could contribute to the understanding of the effectiveness of EU Cohesion Policy. However, conclusions on the success or failure of the policies requires performing further analyses and controlling for further determinants (see Monfort, 2008, 2012).

Figure 4 - σ-convergence analysis – *CV* of $\ln y_{it}$, NUTS 2 regions, 14 countries (1980-2014). Source: Own elaboration on ERD-CE dataset

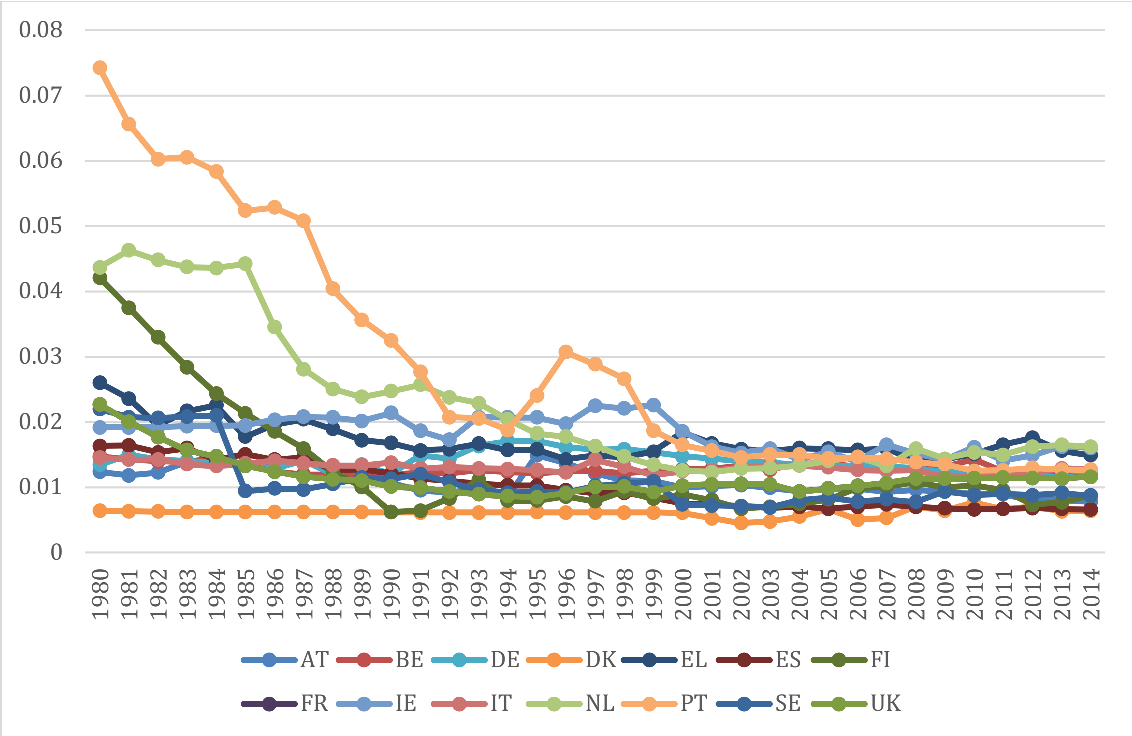
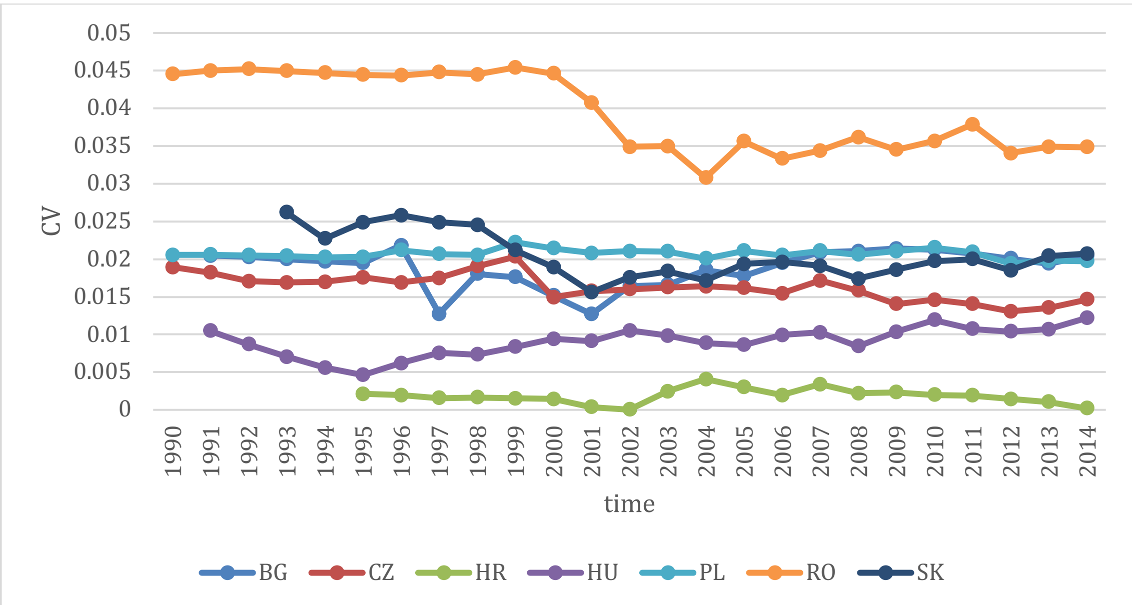


Figure 5 - σ-convergence analysis – *CV* of $\ln y_{it}$, NUTS 2 regions, 7 countries (1990-2014). Source: Own elaboration on ERD-CE dataset



6.4 Exploratory Spatial Data Analysis

Many economic variables are geographical in nature. The issues related to the analysis of geographical data lead the researcher to the necessity of an analysis that focuses on territorial aspects. Spatial interactions are important to understand the mechanisms at the basis of economic growth. For example, output productivity in a region could be affected by productivity at neighbouring sites. Additionally, geographical diversity, both natural and cultural, may represent an idiosyncratic factor that implies structural differences between regions in terms of economic growth. As such, either strong relationships or structural differences have remarkable influence on the economic growth of a region. Thus, it is crucial to emphasize the results from a spatial analysis of economic variables.

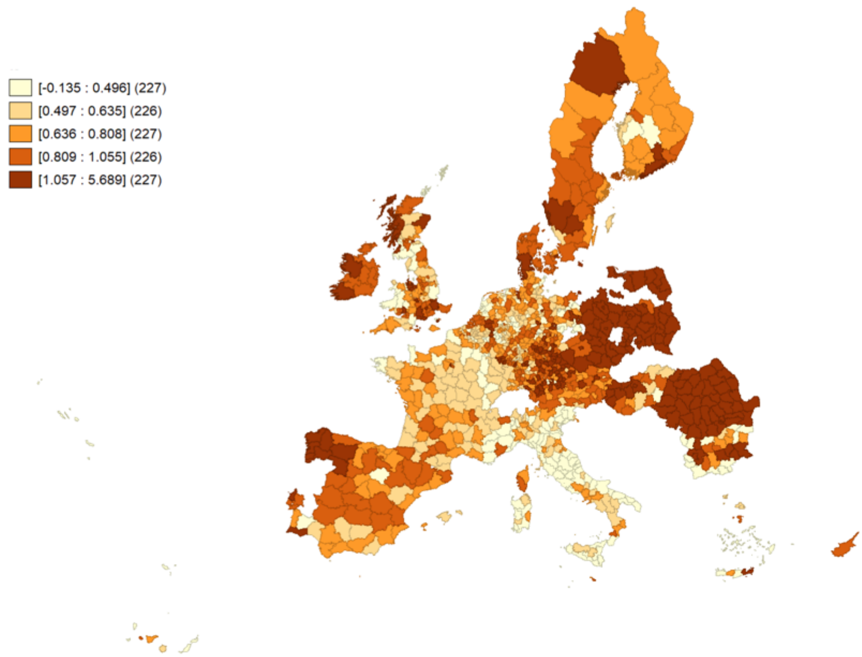
In this section, we explore spatial patterns of growth rates of GDP per worker in PPS, focusing on a large number of EU NUTS 3 regions from 1991-2014. We consider 1,133 NUTS 3 regions in the following 22 EU Countries: Austria, Belgium, Bulgaria, Cyprus, Czechia, Denmark, Germany, Greece, Spain, Finland, France, Hungary, Ireland, Italy, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Sweden and the United Kingdom.

Additionally, we also explore some dynamics in the spatial patterns focusing on possible changes in the geography of economic growth. Particularly, we consider differences in the geography of economic growth before and after the financial crisis of 2008. An analysis on NUTS 3 regions provides a more detailed picture of the spatial patterns of economic growth. As data supplied by EU-REGIO only allows for an analysis over a short period, we rely on data collected from ERD-CE dataset to consider a wider interval.

The first step of an explorative analysis generally consists of mapping the phenomenon under investigation. In our study simply showing quantile maps (denoted in literature as *choropleths maps*) of economic growth levels can help the analyst to individuate spatial patterns of the phenomenon under review. Figure 6 displays the growth rates of GDP per worker in PPS, computed at the NUTS 3 level from 1991-2014. Darker colours indicate the regions with higher values of the GDP per worker growth rates, while light colours refer to lower values of the GDP per worker growth rate. Higher growth rates are reported for some regions in northern Europe, including a number of regions belonging to Finland, Sweden, Ireland, the United Kingdom, and some regions in northern Spain. A certain dualism between eastern and western Europe is also observed, as high growth rates are reported for a large number of regions from Poland, Romania and (formerly) East Germany. Conversely, France and Italy return lower economic growth paces. Additionally, regions from Spain and Ireland experienced higher growth in the whole period with few exceptions.

Figure 7 includes a quantile map of the economic growth rates from 1991-2007, representing the spatial distribution of economic growth rates before the 2008 financial crisis. The map in Figure 6 may be compared to the one in Figure 7 without significant differences. Regions in eastern Europe are shaded darker as they appear to share relevant growth rates in the period preceding the financial crisis. Conversely, regions from Italy are ranked low in terms of economic growth, denoting slow economic growth, especially in regions located in the centre of the country and on the Adriatic coast.

Figure 6- Quantile map of GDP per worker growth rate from 1991-2014. Source: Own elaboration on ERD-CE dataset.



As a consequence of the 2008 global economic downturn, the pace of growth of many European regions slowed. Hence, the economic slack involved many regions in the following years due to the sovereign debt crisis, as was the case of Greece, Italy and Spain. In general, growth rates from 2008-2014 are considerably lower across Europe. With respect to the previous period, we can also analyse the post-crisis map (2008-2014) represented in Figure 8. Here, a decline of the growth rates for some regions in Spain emerges. The decline of growth rates is also evident in some regions in northern Europe, such as the NUTS 3 regions in Finland and Sweden. Conversely, many of the regions in Germany are better ranked in terms of economic growth compared to the previous period, a circumstance that occurs also for some units in France. Continued presence in the high group involved, again, eastern Europe, notably Poland.

Important evidence derived through the analysis of the geography of economic growth is derived from the presence of relationships between neighbours. This may suggest the presence of spatial interactions among the considered units. One method in which the degree of interdependence of European regions can be analysed, considers the presence of spatial dependence, as explained in the previous section. The analysis of spatial dependence is essential to the full comprehension of interdependences and spillover effects that may influence the dynamic of economic growth. Furthermore, spatial dependence is a key source of misspecification in a spatial model, which is relevant for the purpose of estimating economic convergence at regional level for Europe. Therefore, we investigate the presence of spatial dependence in the data by focusing on the Moran's I.

Table 1 displays the Moran's I computed for each year from 1992-2014. The index is computed for the annual growth rates of GDP per worker in PPS in the aforementioned NUTS 3 regions. In the computation of the Moran' s I, we consider a row standardised proximity matrix, based on the K nearest neighbours' criterion with $K = 7$.

Figure 7- Quantile map of GDP per worker in PPS growth rate from 1991-2007. Source: Own elaboration on ERD-CE dataset.

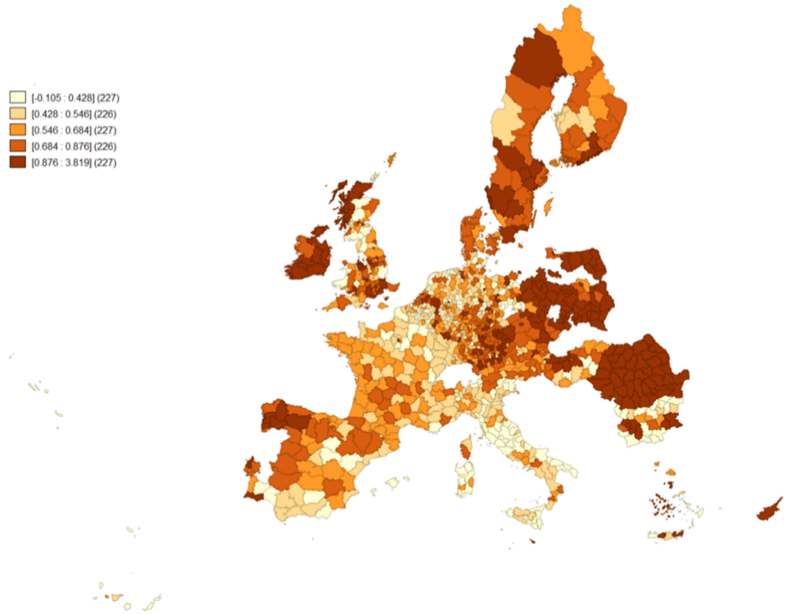
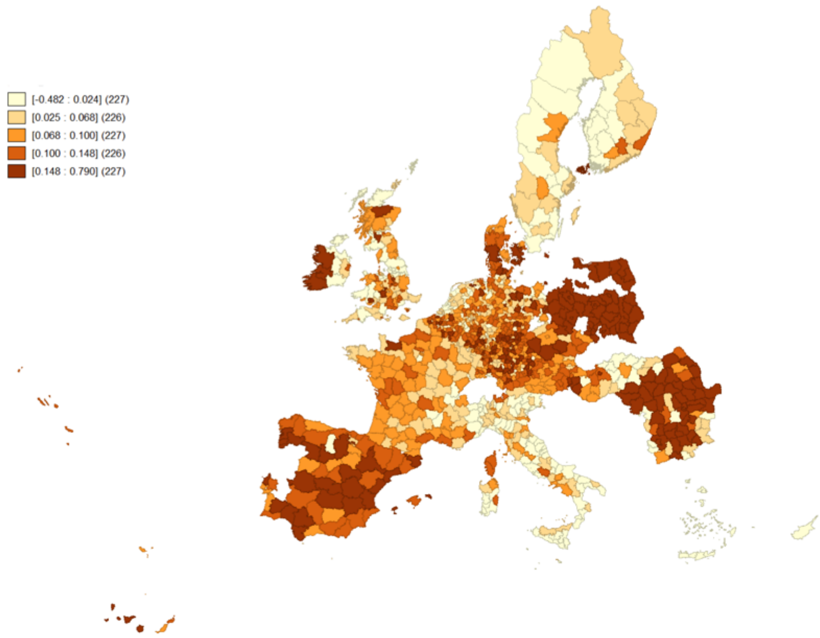


Figure 8 - Quantile map of GDP per worker in PPS growth rate from 2008-2014. Source: Own elaboration on ERD-CE dataset.



The expected value for the Moran's I statistic is constant for each year, $E(I) = -0.001$, all statistics have values larger than the expected value and are highly significant. The inference is based on a random permutation approach with 10,000 permutations. The results indicate the presence of positive spatial autocorrelation, and thus that regions with similar values of the GDP per worker growth rate tend to cluster together in space. Considering the evolution of the Moran's I between 1992-2014, we note that the index decreases over time, especially after 1995. The index reached its minimum value in 2005 ($I = 0.080$) and started to increase in the subsequent period. A larger increase is verified in the last two years under analysis. The Moran's I returns global information about the presence of positive or negative spatial association. The Moran scatterplot provides more information and insight into this explorative analysis. This is useful in order to distinguish whether the positive spatial association concerns high or low values of the GDP per worker growth rate. Figure 9 displays the Moran scatterplot for the growth rate of GDP per worker computed over the whole period under investigation. The figure shows the existence of positive spatial association for almost all the considered regions, as revealed by the slope of the regression line.

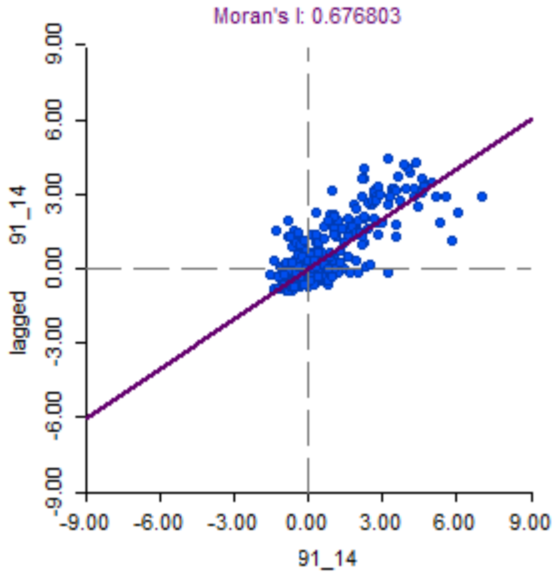
A large part of the regions under investigation is included in the first quadrant (high-high, top right), characterized by association of similar and high values. Few regions are in the third quadrant (bottom left), which includes regions with low values of the GDP per worker growth rate, surrounded by regions with similar values. Some outliers (i.e., some regions that deviate from the patterns of global positive spatial association) are also identified in the second and in the fourth quadrants.

Table 1- Moran's I statistics for the annual growth rate of GDP per worker in PPS. Connectivity matrix based on a $K = 7$ nearest neighbours. Source: Own elaboration on ERD-CE dataset.

Year	*Moran's I*	*Expectation*	*Standard deviation*	*p-value*
1992	0.543	-0.001	0.0002	0.000
1993	0.420	-0.001	0.0002	0.000
1994	0.437	-0.001	0.0002	0.000
1995	0.163	-0.001	0.0002	0.000
1996	0.273	-0.001	0.0002	0.000
1997	0.264	-0.001	0.0002	0.000
1998	0.183	-0.001	0.0002	0.000
1999	0.243	-0.001	0.0003	0.000
2000	0.211	-0.001	0.0002	0.000
2001	0.286	-0.001	0.0002	0.000
2002	0.396	-0.001	0.0002	0.000
2003	0.241	-0.001	0.0002	0.000
2004	0.398	-0.001	0.0002	0.000
2005	0.080	-0.001	0.0002	0.000
2006	0.310	-0.001	0.0002	0.000
2007	0.246	-0.001	0.0002	0.000
2008	0.315	-0.001	0.0002	0.000
2009	0.237	-0.001	0.0002	0.000
2010	0.267	-0.001	0.0002	0.000
2011	0.260	-0.001	0.0002	0.000
2012	0.274	-0.001	0.0002	0.000
2013	0.268	-0.001	0.0002	0.000
2014	0.394	-0.001	0.0002	0.000

Figures 10 and 11 display the Moran scatterplots of the GDP per worker growth rates, computed over the pre-crisis period and the post-crisis period. An evident difference between pre-crisis and post-crisis emerges from the plots. In fact, in the pre-crisis period, the positive spatial autocorrelation involves mostly units characterized by higher (and positive) growth rates. In the post-crisis period, many points are situated in the low-low quadrant, suggesting that positive autocorrelation is present, linked to the presence of slow paces of growth.

Figure 9 - Moran scatterplot of GDP per worker in PPS growth rate from 1991-2014. Connectivity matrix based on a $K = 7$ nearest neighbours. Source: Own elaboration on ERD-CE dataset.



Additionally, in the post-crisis period, the units tend to be less gathered on the scatterplot compared to the pre-crisis period, and the implied Moran's *I* is lower in the post-crisis period (i.e., 0.40). However, it is important to highlight that positive spatial autocorrelation remains a relevant feature of the geography of economic growth for European NUTS 3 regions, including in a situation of slow (or negative) economic growth.

Figure 10 - Moran scatterplot of GDP per worker in PPS growth rate from 1991-2007. Connectivity matrix based on a $K = 7$ nearest neighbours. Source: Own elaboration on ERD-CE dataset.

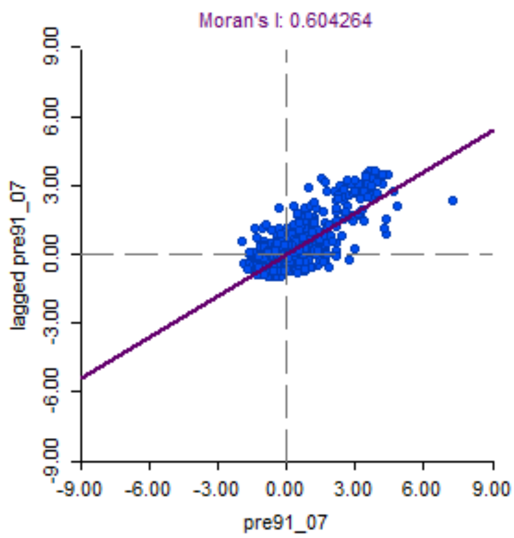
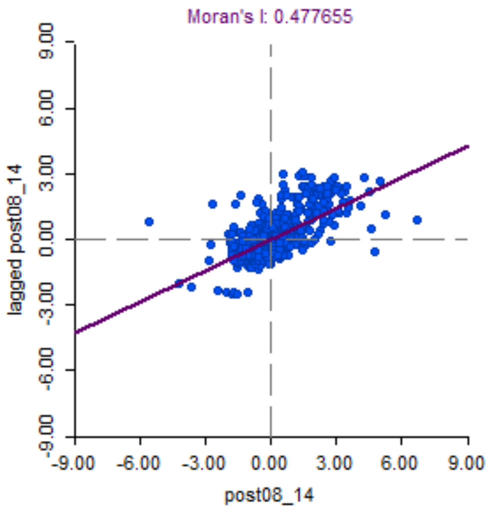


Figure 11 - Moran scatterplot of GDP per worker in PPS growth rate from 2008-2014. Connectivity matrix based on a $K = 7$ nearest neighbours. Source: Own elaboration on ERD-CE dataset.



Another relevant aspect that should be considered in the explorative analysis is spatial heterogeneity. Spatial heterogeneity is an additional component in the study of economic growth as it highlights the presence of structural differences between NUTS 3 regions. Hence, an explorative spatial analysis of spatial heterogeneity may return a more comprehensive picture of the presence of multiple spatial clusters of regions in terms of economic growth.

Spatial clusters are useful tools to identify groups of spatially contiguous units that are characterized by similar values in terms of economic growth. The local Moran statistic (i.e., LISA indicators) helps to verify the presence of local pockets of spatial dependence and, as mentioned above, may be adopted to visualise clusters. In Figure 12, it is evident that a certain presence of spatial heterogeneity affects European regions in that some spatial clusters characterize the geography of Europe at NUTS 3. In this case, high-high (in red) clusters are evident in the eastern regions of Europe while low-low (in blue) clusters affect almost the entire Italian peninsula and regions of eastern France near the German border. Some low-high regions are present especially at the southern border of Romania.

The dynamic of the LISA clusters in time is taken into consideration by computing local Moran for each year involved into the analysis (Figures 18 – 23 in Appendix 3) and some consideration in the evolution of spatial patterns can be made. Particularly, high-high clusters are situated almost continuously in eastern Europe (with some interruption as in 1993 and 1995), including many regions of east of Germany. For the case of Italy, slow growth gradually involved many regions in the country and caused a low-low cluster to appear toward the end of the period under review, especially for southern regions.

Moreover, in Figure 13 and Figure 14, LISA clusters are shown for the period pre- and post-crisis. These results confirm the analysis made on the annual growth rates. An evident difference between the pre- and post-crisis periods involves northern Europe, particularly many regions of Sweden and Finland, that during the crisis and in the following period, were affected by weak economic growth, and form a low-low cluster for that period.

Figure 12 - LISA cluster map of GDP per worker in PPS growth rate from 1991-2014. Connectivity matrix based on a $K = 7$ nearest neighbours. Source: Own elaboration on ERD-CE dataset.

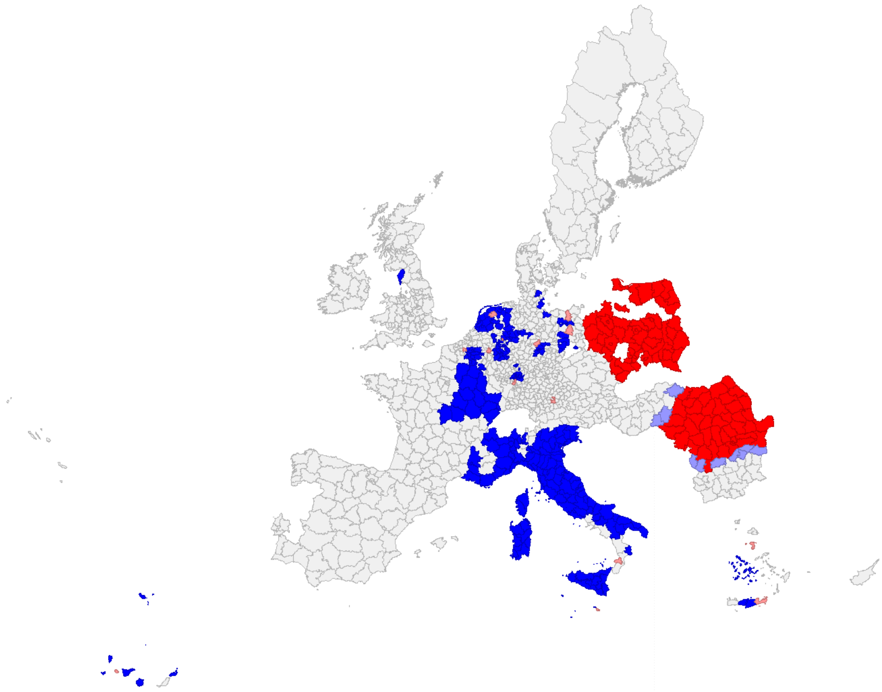


Figure 13 - LISA cluster map of GDP per worker in PPS growth rate from 1991-2007. Connectivity matrix based on a $K = 7$ nearest neighbours. Source: Own elaboration on ERD-CE dataset.

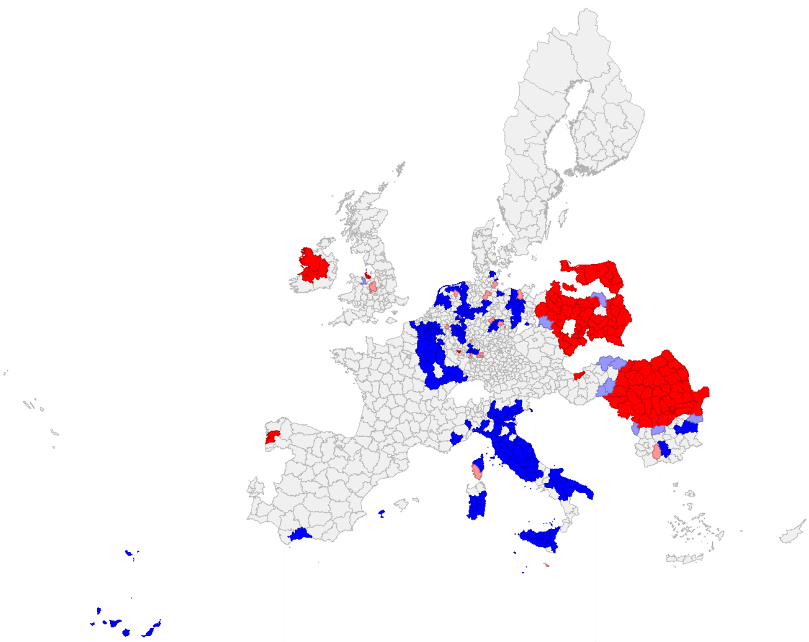
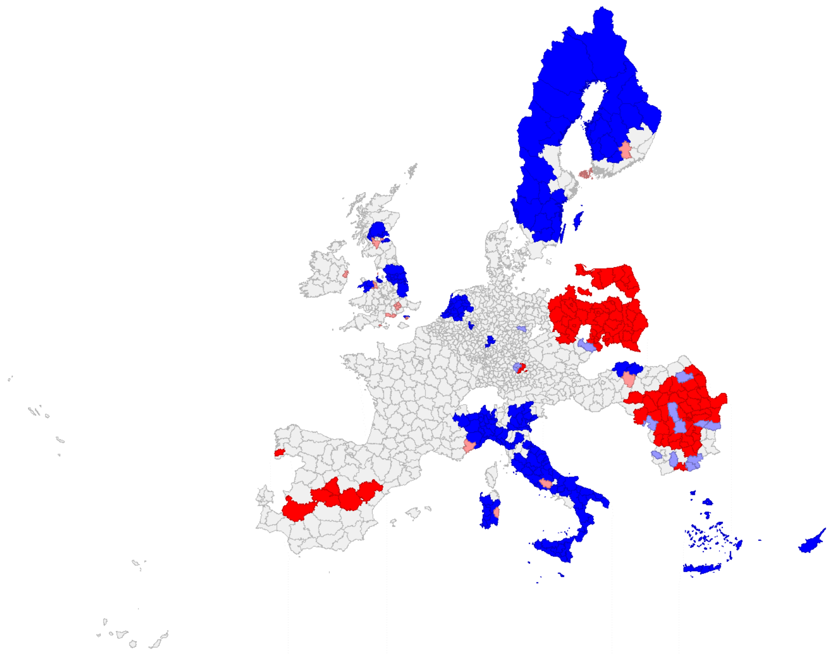


Figure 14 - LISA cluster map of GDP per worker in PPS growth rate from 2008-2014. Connectivity matrix based on a $K = 7$ nearest neighbours. Source: Own elaboration on ERD-CE dataset.



The evidence offered by an ESDA of economic growth in the EU NUTS 3 regions provides relevant evidence of the role of spatial effects in the geography of economic growth. Both types of spatial effects, namely spatial dependence and spatial heterogeneity, play a key role in the spatial distribution of growth levels and may play an important role in the determination of potential disparities and interactions. We observe that spatial dependence may be considered as an important determinant of economic growth. In this sense, regions are not independent of each other and the consideration of the influence that each region could have on the neighbours may be extremely relevant. Furthermore, we observe that regions are clustered so that structural differences must be considered while analysing economic growth in Europe. The role of both types of spatial effects in the analysis of economic growth will be considered in the following sections.

6.5 Empirical analysis of spatial dependence and economic growth

6.5.1 β – convergence analysis at NUTS 3 level

As evidenced in Section 6.3, economic convergence represents a basic measure for the evaluation of the effectiveness of the EU Cohesion Policy. Cohesion Policy targets the less developed regional economies aiming to enhance growth in these regions. The β-convergence analysis sheds light on this catch-up process, that is, the process by which poorer economies' incomes per capita tend to growth at faster rates than per capita income in wealthier economies.

The β-convergence process in the EU has been studied from different perspectives, using different methodologies, and with reference to different spatial and temporal scenarios. While most of the empirical analyses focused on assessing the convergence process across NUTS 2 regions, more limited attention has been paid to the sub-regional level. Some exceptions can be found in recent contributions examining the β-convergence hypothesis at NUTS 3 level, focusing on groups of regions in the EU or on regions belonging to single countries (Geppert and Stephan, 2008; Panzera and Postiglione, 2014; Goecke and Hüther, 2016). Some of these contributions considered spatial effects in modelling economic growth at the sub-regional level, assessing the presence of local spatial spillovers and the emerging of spatial clustering (Panzera and Postiglione, 2014).

Selecting higher levels of spatial disaggregation in analysing the convergence process may improve the analysis in several aspects. First, focusing on a more detailed geographical scale enables a proper modelling of spatial effects emerging at local level, leading to findings that could differ from the ones related to an aggregated level. Furthermore, the analysis of growth processes at a detailed spatial scale could be relevant from a policy perspective, contributing to the definition of place-based measures for the reduction of disparities.

The analysis of economic growth at a sub-regional level faces important limitations with regards to data availability. The lack of data for variables that are relevant for the analysis of growth processes could be addressed by using spatial disaggregation techniques that rely on the data available at more aggregate geographical scales. Moreover, data availability influences the choice of the time period of analysis.

In this section, we present the main results of the empirical analysis focused on β-convergence for EU NUTS 3 regions. As mentioned above, in the cross-sectional analyses, our primary aim is to extend a great number of cross-sectional analyses at NUTS 2 level by adopting spatial techniques at NUTS 3 level. This specific spatial scale appears interesting for two reasons. First, it allows to test for global economic convergence at a lower spatial scale. Second, this level is considered by policy makers for specific diagnoses that enhance the analysis offered at NUTS 2 level.

In this analysis, we estimate the spatially augmented Solow model introduced by Ertur and Koch (2007) and defined in equation (14).

The dependent variable in the model, g, expresses the average growth rate of GDP per worker in PPS over the period under investigation. The variable v is expressed as $v = n + l + k$, where n is the working population growth rate, and $l + k = 0.05$, following a fairly standard assumption in the literature (Mankiw et al. 1992). The fraction of output invested in physical capital, s^k, is defined as the average, over the period under investigation, of the investments expressed as a share of GDP. Data on investment not available at NUTS 3 level can be derived by applying the disaggregation procedure described in Appendix 2. This procedure, known as Bayesian interpolation method (BIM, Benedetti and Palma, 1994) permits the disaggregation of data on investment on physical capital (i.e., gross fixed capital formation) that are available at a more aggregate geographical level (i.e., for NUTS 2 regions). Unlike other areal interpolation methods, the BIM exploits the spatial dependence effect in the data disaggregation. Note that all the considered variables in the application are expressed in natural logarithm.

In this section, we estimate the economic model for different groups of NUTS 3 regions, considering different periods of observation. The choice of the units of analysis and of the time periods is determined by the data availability.

Sources of data are the EU-REGIO and the ERD-CE datasets.[12] The EU-REGIO data set refer to 1,256 NUTS 3 regions from 2003-2014. The regions considered in this analysis belong to 23 EU Member States: Austria, Belgium, Bulgaria, Czechia, Germany, Greece, Spain, Estonia, Finland, France, Ireland, Italy, Lithuania, Luxembourg, Latvia, Malta, the Netherlands, Poland, Portugal, Romania, Sweden, Slovakia and the United Kingdom. To include longer time periods in the analysis, we also considered data from the ERD-CE data set. These data refer to two different time spans, including 1981-2014 and 1991-2014. The regions considered over the period 1981-2014 are 901 NUTS 3 units belonging to the European countries that, since January 1995, represented the EU-15 (Austria, Belgium, Denmark, Germany, Greece, Spain, Finland, France, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Sweden and the United Kingdom). The regions considered over the period 1991-2014 are 1,133 NUTS 3 units belonging to the following 22 EU countries: Austria, Belgium, Bulgaria, Cyprus, Czechia, Denmark, Germany, Greece, Spain, Finland, France, Hungary, Ireland, Italy, Luxembourg, Malta, the Netherlands, Poland, Portugal, Romania, Sweden and the United Kingdom.

Table 2 shows the results from alternative models estimated on data from EU-REGIO. Estimation results are reported for the non-spatial absolute and conditional models. Both models are estimated using the ordinary least squares (OLS) method. The model estimation is performed using R-software. The parameters estimates are showed with some diagnostic and performance measures. Model representativeness is assessed by using conventional statistical measures such as the Akaike Information Criterion, AIC, and the coefficient of determination, R^2. The Moran's I statistics and the Breusch-Pagan tests are considered as diagnostics for spatial dependence and heteroscedasticity of error terms, respectively.

As shown in Table 2, for both the non-spatial models, the β coefficient associated to the initial level of GDP per worker is negative and highly significant, revealing the occurrence of the β-convergence process among the considered spatial units. For the other variables included in the non-spatial conditional model, we find a negative and significant impact of the saving rate on the GDP per working growth rate, while the coefficient associated with the variable v is not significant. The convergence rate for the non-spatial conditional model assumes a value that is not too different from the value estimated for the non-spatial absolute model. Moving from the absolute to the conditional model, we note an improvement of the goodness of fit of the model, as revealed by the lower value of the AIC and the higher value of R^2.

For the non-spatial conditional model, the Moran's I statistics for spatial autocorrelation applied to the OLS residuals is positive and highly significant. This reveals the presence of spatial dependence, which needs to be considered in the model specification.

[12] Note that all the variables are our transformations from the original data set available online.

Furthermore, the Breusch-Pagan test reveals the presence of heteroscedasticity (i.e., non-constant error variance). For geographically distributed data, the assumption of heteroscedasticity appears more appropriate than the assumption of error homoscedasticity, since the observational units are likely to be characterized by different sizes and by differences in other structural features (Piras et al. 2012; Panzera and Postiglione, 2014). Furthermore, non-constant error variances may reveal the presence of spatial heterogeneity (the instability over the space of economic behaviours). The detection of spatial effects motivates the use of a spatial conditional model in our analysis.

In the SDM specification defined in equation (14), the spatially lagged dependent variable as well as the spatial lags of the independent variables are included as explanatory variables. The spatial lags of the variables are defined using a proximity matrix based on the K nearest neighbour criterion, with $K = 7$. We tested different specifications of the proximity matrix, based on different numbers of neighbours. We selected the 7 nearest neighbours as the proximity structure corresponding to the lower value of the AIC, and thus to the better fit of the model. Moreover, the choice of $K = 7$ is consistent with the idea of avoiding the presence of non-connected regions (for similar considerations related to NUTS 2 regions, see Le Gallo and Ertur, 2003).

The SDM model is estimated by using the maximum likelihood method, using STATA software.

As displayed in Table 2, the results support the predicted signs for the coefficients associated with the initial level of GDP, the variable s^k and the variable v (see Section 4.1.2). The coefficients associated to the spatially lagged variables have the predicted signs, with the exception of the spatial lag of the initial level of GDP. The coefficients associated to the explanatory variables in the models are all significant, with the exception of the coefficient associated to $\ln s^k$.

The parameter governing the speed of convergence is $\lambda = 0.66\%$, and thus is smaller than the prediction of the non-spatial model. This result reveals that during the years between 2003-2014, β-convergence in the EU is present at the NUTS 3 level, but its speed is less than 1%. This result is consistent with some other empirical findings at NUTS 3 level. Analysing the β-convergence process for the EU, at different NUTS levels, Butkus et al. (2018) found that the smaller the regional units analysed, the slower the speed of convergence estimated. Over the period 2010-2014, the authors found, for NUTS 3 EU regions, a speed of convergence less than 1%.

In our analysis, the reduction of the speed of convergence appears to be linked to the introduction of spatial effects.

Table 2 – Estimation results for alternative models for β – convergence analysis (2003-2014), using cross-sectional data, 1,256 NUTS 3 European regions. Source: Own elaborations on EU-REGIO database.

	Non-spatial absolute model	Non-spatial conditional model	Weights matrix: 7 nearest neighbours	
			SDM conditional model	Conditional model with heterosc. GS2SLS[13]
Variable	Coefficient (standard error)	Coefficient (standard error)	Coefficient (standard error)	Coefficient (standard error)
Constant	0.2743*** (0.0076)	0.2550*** (0.0108)	0.1345*** (0.0148)	0.0560 (0.0555)
$\ln y_{2003}$ (Initial level GDP per worker)	-0.0238*** (0.0007)	-0.0232*** (0.0008)	-0.0063*** (0.0012)	-0.0056*** (0.0022)
$\ln s^k$		-0.0003*** (0.0002)	0.0001 (0.0002)	0.0001 (0.0002)
$\ln v = \ln(n + l + k)$		-0.0036 (0.0014)	-0.0164*** (0.0012)	-0.0171*** (0.0022)
$W \ln y_{2003}$			-0.0045*** (0.0016)	0.0013 (0.0047)
$W \ln s^k$			-0.0007* (0.0003)	-0.0004 (0.0004)
$W \ln v$			0.0219*** (0.0019)	0.0200*** (0.0029)
ρ			0.6662*** (0.0260)	0.8713*** (0.1334)
λ (Convergence Rate)	2.80%	2.72%	0.66%	0.58%
Moran's I Breusch-Pagan (heterosc.)		0.4058*** 77.619***		
Studentized Breusch-Pagan (heterosc.)		17.116***		
AIC	-7,944.237	-7,948.847	-8,599.461	
R^2	0.4732	0.4759	0.5754	0.5854

Significance levels ***1% , ** 5% , * 10%

[13] Generalized Spatial Two Stage Least Squares

This result appears inconsistent with the idea that convergence is faster when spatial effects are introduced in the analysis (Ramajo et al. 2008; Monfort, 2008). However, changes in the magnitude of economic convergence could also result, considering different periods under investigation as evidenced by Abreu et al. (2005). Presumably, the period under investigation is too short to analyse the β – convergence and to appreciate the spatial spillovers between regions. For this reason, it is interesting to test cross-sectional economic convergence under different periods and different numbers of spatial units. This is achieved using ERD-CE datasets.

In Table 2, the introduction of spatial effects determines an improvement of the goodness of fit of the model. Furthermore, with respect to the presence of heteroscedasticity, we apply a Generalised Spatial Two Stage Least Squares (GS2SLS hereafter) that treats errors as heteroscedastic, introduced by Kelejian and Prucha (2010).

Using this approach, we found that all the variables in the model have the predicted signs. Most of the variables are highly significant. A slight improvement in model representativeness with respect to the SDM specification is also reported. As highlighted in Section 4.1.1, the correct interpretation of spatial regression models requires consideration of the estimated impacts rather than the estimated coefficients (see Appendix 1 for further details on the interpretation of the coefficient of spatial regressions). The average direct, indirect and total impacts for the spatial heteroscedastic model are reported in Table 3.

Comparing the direct impact estimates with the coefficients associated with the non-spatially lagged variables in Table 2, we note that the two sets of estimates have the same sign and are similar in magnitude. As highlighted by LeSage and Fischer (2008), the differences between these estimates are mainly determined by a feedback effect (i.e., the effect of changes in a variable in a region that influence the same variable in neighbour regions, and feedback to influence the variable in the region itself). Larger discrepancies are reported between the coefficients associated with the spatially lagged explanatory variables and the indirect impact estimates.

Table 3 – Average direct, indirect and total impacts of the explanatory variables (2003-2014) for the spatial heteroscedastic model estimated with GS2SLS, 1,256 NUTS 3 European regions. Source: Own elaborations on EU-REGIO database.

Model	Variable	Average Direct Impact	Average Indirect Impact	Average Total Impact
Conditional model with heterosc. GS2SLS	$\ln y_{2003}$	- 0.0068 *** (0.0022)	-0.0270 *** (0.0081)	-0.0338*** (0.0081)
	$\ln s^k$	0.0001 (0.0002)	-0.0018 (0.0020)	-0.0017 (0.0021)
	$\ln v$	-0.0155*** (0.0022)	0.0380** (0.0155)	0.0225 (0.0155)
	Significance levels ***1% , ** 5% , * 10%			

As Table 3 shows, the average total impact associated with $\ln y_{2003}$ is negative and significant. This estimate reveals that a 1% increase in the initial level of GDP per worker is associated with a decrease in the average growth rate of -0.0338%. This result appears to be consistent with the conditional β-convergence hypothesis. The total impact is obtained by summing the direct and indirect effects. The average direct impact associated with $\ln y_{2003}$ is negative and highly significant. This indicates that an increase in the initial level of GDP per worker in a specific region exerts a negative impact on its subsequent growth rate. The indirect impact estimate reveals that the initial level of GDP per worker in neighbour regions also negatively influences the GDP per worker growth rate. The total impact associated to the variable s^k is negative, but not significant. It derives from the sum of a positive direct effect and a negative indirect effect that are both not significant. A positive total impact is reported for the variable v . It results from the sum of a negative direct impact and a negative indirect effect, that are both statistically significant.

In order to build upon the results obtained from EU-REGIO data and consider a larger number of years in the analysis of economic convergence, we apply the same methodologies to ERD-CE data. Both ERD-CE datasets help us to deal with a larger period of investigation and different number of units included in this study. Particularly, we consider two different ERD-CE datasets, the second of which includes data from eastern Europe NUTS 3 regions since 1991.

Table 4 displays the results obtained when the economic models are estimated on data from ERD-CE. The estimates refer to the period 1981-2014, and the units of analysis are the NUTS 3 regions belonging to the EU 15. For all the considered specifications, the estimation results still confirm the convergence process. In all estimated models, the coefficients have the predicted signs, with the exception of the coefficients associated to the variable v and its spatial lag. Most of the parameter estimates are highly significant. Positive and significant estimates are found for the spatial autocorrelation parameters ρ. The values of AIC and R^2 reveal the better fit of spatial models with respect to the non-spatial specifications.

For the non-spatial specifications, we found a speed of convergence higher than the usual rate of convergence of about 2% (Sala-i-Martin, 1996). These results are consistent with empirical findings of some other analysis carried out for EU regions. For example, focusing on a sample of wealthier regions belonging to the EU 15, Fischer and Stirböck (2006) found a convergence rate of about 5%, and generally high rates of convergence for both cohesion and non-cohesion countries have been found by Ramajo et al. (2008). Additionally, for the Italian case, Panzera and Postiglione (2014) found high rate of convergence at NUTS 3 level. As emphasized by previous literature, an increase in the speed of convergence is also motivated by the introduction of spatial effects (Ramajo et al. 2008; Monfort, 2008). As displayed in Table 4, the rate of convergence tends to be faster when the estimated models account for spatial effects. Hence, the ERD-CE dataset returns different results from those obtained from EU-REGIO in terms of the effects of space on convergence speed. A potential reason for this may be the periods under study. Different numbers of years and different economic scenarios may imply substantial changes in the results of economic convergence also for spatial models.

Table 4 - Estimation results for alternative models for β – convergence analysis (1981-2014), using cross-sectional data, 901 NUTS 3 European regions. Source: Own elaborations on ERD-CE database.

	Non-spatial absolute model	Non-spatial conditional model	Weights matrix: 7 nearest neighbours	
			SDM conditional model	Conditional model with heterosc. GS2SLS
Explanatory Variable	Coefficient (standard error)	Coefficient (standard error)	Coefficient (standard error)	Coefficient (standard error)
Constant	0.2633*** (0.0048)	0.2856*** (0.0071)	0.0948*** (0.0126)	0.0191 (0.0443)
$\ln y_{2003}$ (Initial level GDP per worker)	-0.0232*** (0.0005)	-0.0239*** (0.0005)	-0.0269*** (0.0005)	-0.0271*** (0.0009)
$\ln s^k$		0.0000 (0.0000)	0.0001** (0.0000)	0.0001* (0.0000)
$\ln v = \ln(n + l + k)$		0.0053*** (0.0012)	0.0056*** (0.0012)	0.0058*** (0.0016)
$W \ln y_{1981}$			0.0194*** (0.0011)	0.0257*** (0.0038)
$W \ln s^k$			-0.0001 (0.0001)	-0.0001 (0.0001)
$W \ln v$			-0.0032* (0.0020)	-0.0049* (0.0025)
ρ			0.5973*** (0.0361)	0.9067*** (0.1781)
λ (Convergence Rate)	4.57%	4.93%	7.24%	7.48%
Moran's I		0.3291***		
Breusch-Pagan (heterosc.)		46.14***		
Studentized Breusch-Pagan (heterosc.)		23.77***		
AIC	-7,212.03	-7,226.67	-7,493.94	
R^2	0.7158	0.7216	0.7485	0.7447

Significance levels ***1% , ** 5% , * 10%

This issue may lead us to prefer results obtained from the ERD-CE dataset as they consider a period under investigation more consistent with previous analyses. In fact, the ERD-CE database covers a larger time period and facilitates performing in-depth analyses of the phenomena under study.

In Table 5, results on the average impacts of the spatial heteroscedastic model are reported. We note that the average direct and indirect impacts mainly differ from those estimated from EU-REGIO data, and that both the indirect and total impacts associated to the variables in the model are not significant. The differences between the estimation results obtained from the two datasets, can be especially explained by differences in the period under investigation as well as in the regions that have been considered. Significant average direct impacts are reported for the initial level of GDP per worker and for the variable v. The average direct impact estimate associated with $\ln y_{1981}$ indicates that a 1% increase in the initial level of GDP per worker registered by a specific region is associated with a decrease in its subsequent growth rate of -0.0266%. This supports the conditional β-convergence hypothesis. The variable v has a significant positive direct impact on the GDP per worker growth rate.

Table 5 – Average direct, indirect and total impacts of the explanatory variables (1981-2014) for the spatial heteroscedastic model estimated with GS2SLS, 901 NUTS 3 European regions. Source: Own elaborations on ERD-CE database.

Model	Variable	Average Direct Impact	Average Indirect Impact	Average Total Impact
Conditional model with heterosc. GS2SLS	$\ln y_{1981}$	-0.0266*** (0.0010)	0.0124 (0.0131)	-0.0142 (0.0134)
	$\ln s^k$	0.0001 (0.0001)	0.0002 (0.0008)	0.0003 (0.0008)
	$\ln v$	0.0060*** (0.0018)	0.0039 (0.0194)	0.0099 (0.0202)
	Significance levels ***1% , ** 5% , * 10%			

For the period 1991-2014, the group of regions under investigation include the regions belonging to eastern Europe. Table 6 displays the estimation results for the non-spatial and the spatial specifications. The goodness of fit of the model improves when the spatial effects are introduced in the analysis. The convergence process occurs between the considered regions, as confirmed by the negative and significant value of β. The speed of convergence is higher for the SDM specification and for the heteroscedastic model. All the coefficients have the expected signs, for both the SDM specification and the heteroscedastic model. Moreover, most of the parameter estimates are significant.

Table 7 shows the estimated direct, indirect and total impacts for the variables of the heteroscedastic model. For the initial level of GDP per worker, we found a negative and significant total effect. This reveals that a 1% increase in the initial level of GDP per worker determines a decrease of -0.0212% on the GDP per worker growth rate. Also, the average direct impact associated with this variable is negative and significant. The indirect impact associated with the initial level of GDP is negative and not significant. The direct, indirect and total impacts associated with all the other considered variables are not significant.

Table 6 - Estimation results for alternative models for β – convergence analysis (1991-2014), using cross-sectional data, 1,133 NUTS 3 European regions. Source: Own elaborations on ERD-CE database.

	Non-spatial absolute model	Non-spatial conditional model	Weights matrix: 7 nearest neighbours	
			SDM conditional model	Conditional model with heterosc. GS2SLS
Variable	Coefficient (standard error)	Coefficient (standard error)	Coefficient (standard error)	Coefficient (standard error)
Constant	0.2238*** (0.0047)	0.2350*** (0.0077)	0.1044*** (0.0129)	0.0172 (0.0523)
$\ln y_{2003}$ (Initial level GDP per worker)	-0.0193*** (0.0005)	-0.0199*** (0.0006)	-0.0216*** (0.0009)	-0.0211*** (0.0017)
$\ln s^k$		-0.0001 (0.0001)	0.0000 (0.0000)	0.0000 (0.0000)
$\ln v = \ln(n + l + k)$		0.0019* (0.0010)	-0.0021** (0.0009)	-0.0027** (0.0013)
$W \ln y_{1991}$			0.0135*** (0.0013)	0.0198*** (0.0042)
$W \ln s^k$			-0.0001* (0.0001)	-0.0001 (0.0001)
$W \ln v$			0.0072*** (0.0016)	0.0037 (0.0029)
ρ			0.6527*** (0.0297)	0.9473*** (0.1617)
λ (Convergence Rate)	2.60%	2.71%	3.04%	2.94%
Moran's I		0.3946***		
Breusch-Pagan (heterosc.)		373.45***		
Studentized Breusch-Pagan (heterosc.)		103.70***		
AIC	-7,973.93	-7,974.20	-8,378.15	
R^2	0.6129	0.6143	0.6484	0.6517

Significance levels ***1% , ** 5% , * 10%

Table 7 – Average direct, indirect and total impacts of the explanatory variables (1991-2014) for the spatial heteroscedastic model estimated with GS2SLS, 1,133 NUTS 3 European regions. Source: Own elaborations on ERD-CE database.

Model	Variable	Average Direct Impact	Average Indirect Impact	Average Total Impact
Conditional model with heterosc. GS2SLS	$\ln y_{1991}$	- 0.0212 *** (0.0017)	-0.0038 (0.0142)	-0.0250* (0.0143)
	$\ln s^k$	-0.0001 (0.0001)	-0.0005 (0.0014)	-0.0006 (0.0015)
	$\ln v$	-0.0020 (0.0019)	0.0206 (0.0363)	0.0186 (0.0372)
	Significance levels ***1% , ** 5% , * 10%			

The different analyses performed in this section confirm the presence of a convergence process for the EU NUTS 3 regions. Differences in the results are attributable to changes in the considered regions and in the periods under investigation; a relatively short time period seems to determine an underestimation of the speed of convergence. As a further result, we can note than the convergence process is faster when the considered regions are relatively closer in their structural characteristics. This finding may not necessarily be good news for the regions that are not able to promote structural changes by themselves. Particularly, the SDM specification presents encouraging local spillover dynamics whenever nearby units are involved into stable growth paths. However, positive local spillovers may not have any desirable effect when neighbours are characterised by low growth levels. In this sense, economic policies that would consist of helping the poorest to escape from low levels of income and making common policies more active (trade policies, single monetary policy in currency area, coordination of fiscal policies) should consider the growth level of neighbours.

Lastly, our analyses show that additional attention should be paid when including regions from the eastern Europe. When the units of analysis include both regions belonging to the EU 15 and eastern European regions, we note a lower speed of convergence, that slightly increases with the introduction of spatial effects in the model. In this direction, a progressive integration of eastern European economies could be expected to produce positive results in a more homogenous growth path at European level also thanks to the presence of spillovers. Empirical evidence in every analysis in this section supports the great importance of spatial effects in the convergence analysis.

6.5.2 β – convergence analysis at NUTS 2 level

The convergence process among the regional economies in the EU could be further analysed by the simultaneous modelling of dynamics in time and space. This implies considering both the serial dependence of observations over time and the spatial dependence among spatial units at each point in time (Elhorst, 2014). For this purpose, the Solow growth model can be extended to include specific time and space effects as described in Section 4.2.2. This results in a panel version of the spatial Durbin model.

In this section, the dynamic spatial panel data model is estimated for NUTS 2 EU regions. The data source is the ERD-CE dataset. We focus on NUTS 2 regions to diversify the geographical scales at which the convergence process is analysed. Furthermore, as previously mentioned, the NUTS 2 regions represent relevant units of analysis, as they are the main geographical scale eligible for support from the Cohesion Policy. Finally, we focus on NUTS 2 regions to facilitate the comparisons with previous analyses based upon spatial panel data approaches.

Our analysis is performed spanning two different time periods, a period of 33 years from 1982-2014, and a period of 24 years from 1991-2014. For both periods, we consider three-year time-spans. Using this panel formulation, we move from a single cross-section related to the entire time periods (see Section 6.5.1) to cross-sections for the shorter periods that constitute them (11 and 8 time-intervals, respectively). The use of time-spans larger than one year is a common approach and is motivated by the circumstance that short-time variations in growth are influenced by business cycle effect (Badinger et al. 2004).

The units of analysis for the period 1982-2014 are represented by 190 NUTS 2 regions belonging to 15 EU countries: Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, the United Kingdom, Austria, Finland and Sweden.

The spatial units analysed for the period 1991-2014 are 253 NUTS 2 regions belonging to 26 EU countries: Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, the United Kingdom, Austria, Finland, Sweden, Cyprus, Czechia, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia, Bulgaria and Romania (only Croatia and Slovenia are not considered).

Few contributions examined the convergence process in EU regions using a spatial panel approach (Badinger et al. 2004; Elhorst et al. 2010). These papers focused on shorter time periods, and considered a smaller number of spatial units, mainly at the NUTS 2 level.

Spatial panel data specifications present some advantages with respect to the cross-section specification (Badinger et al. 2004). Firstly, region specific effects that are introduced in the model allow to control for the differences in the initial level of technology. Moreover, the hypothesis that l and k are constant appears more realistic when referring to shorter time periods. Additionally, using a panel data approach allows the consideration of a larger number of observations, generally leading to increased precision of estimates.

In this section, the panel version of SDM is estimated using the quasi maximum likelihood estimation procedure developed by Lee and Yu (2010). The estimation is performed using STATA software.

Table 8 presents the results of our estimation for all the model parameters and for both periods under investigation.

Table 8 - Estimation results for β – convergence analysis (1982-2014 and 1991-2014), using a dynamic spatial panel model. Estimates of the dynamic models are expressed considering dependent variable $\ln(\frac{y_t}{y_{t-3}})/T$, where $T = 3$. Source: Own elaborations on ERD-CE database.

	1982 – 2014	1991 – 2014
Variable	Coefficient	Coefficient
$\ln y_{t-3}$	-0.0955***	-0.0569***
$\ln s^k$	-0.0175***	0.0057**
$\ln v$	0.0164**	0.0538***
$W \ln y_{t-3}$	0.0670***	0.0291***
$W \ln s^k$	0.0099	0.0009
$W \ln v$	-0.0191	-0.1246
ρ	0.5890***	0.6910***
N	190	253
L	11	8
Fixed effects	both	both
λ	11.25 %	6.24%
R^2	0.9546	0.9856
	Significance levels ***1% , ** 5% , * 10%	

For both the periods under consideration, conditional β - convergence receives support in the proposed specification. The coefficients associated to the initial level of GDP per worker are negative and highly significant. For the period 1982-2014, the speed of convergence is around 11%. From 1991-2014, the estimated speed of convergence is 6.24%. These convergence rates are higher than the rates of convergence usually found using a cross-sectional approach.

The results obtained are consistent with previous findings in the empirical literature on convergence, based on spatial panel models. In fact, based on a sample of 196 EU NUTS 2 regions, Badinger et al. (2004) found a speed of convergence of about 7% from 1985-1999. A speed of convergence of about 7% was found by Elhorst et al. (2010) who applied panel data models with fixed effects in space and time, to analyse the convergence process in a sample of 193 EU NUTS 2 regions from 1977-2002.

Note that considering a larger time period (i.e., the period 1982-2014) determines an increase in the speed of convergence. This result is consistent with the evidence obtained at NUTS 3 level (see Section 6.5.1). As previously discussed, the regions considered in the sample analysed for the longer time period are similar in their structural characteristics (i.e., the sample does not include eastern European regions), and this determines a faster convergence among regional economies.

The coefficients associated to the other variables in the model, as s^k and v, are significant for both the periods under investigation. However, they have not the expected sign, with the only exception of the coefficient associated with s^k from 1991-2014.

Moving to the interpretation of spatially lagged variables, defined by considering the 7 nearest neighbours as proximity criterion, we note that only the coefficient associated with the spatial lag of the initial level of GDP per worker is significant and with the expected sign. Furthermore, for both the periods under investigation, the spatial autocorrelation parameter is positive and highly significant.

As previously mentioned, the correct interpretation of the SDM parameters requires computing the direct, indirect and total impacts. These effects are reported in Table 9.

The average direct, indirect and total effects associated with the initial level of GDP per worker are calculated according to expressions given in Elhorst et al. (2013). Inferences regarding the statistical significance of these effects are based on the variation of 1,000 parameter combinations, drawn from the variance-covariance matrix of the parameter estimates of the dynamic spatial panel model (Elhorst, 2014).

Regarding to the other model parameters, the dynamic version of the SDM model allows for two distinct spatial dynamics (Debarsy et al. 2012): short-run and long-run impacts. The short-run impacts refer to instantaneous responses of the dependent variable to 1% change at time t in a certain explicative variable k. Long-run impacts represent the equilibrium outcomes if the change in the regressor is maintained ad infinitum.

Table 9– Direct, indirect and total impacts of the explanatory variables (1982-2014 and 1991-2014). Source: Own elaborations on EU-REGIO database.

Variable	1982 – 2014			1991-2014		
	Direct	Indirect	Total	Direct	Indirect	Total
Convergence effect $\ln y_{t-3}$	-0.2889***	0.0526	-0.2363***	-0.1753***	-0.0948*	-0.2701***
Short run effects $\ln(s^k)$ $\ln(v)$	 -0.0173*** 0.0154**	 -0.0011 -0.0208	 -0.0184 -0.0054	 0.0067** 0.0574***	 0.0150 0.0776***	 0.0217** 0.1350***
Long run effects $\ln(s^k)$ $\ln(v)$	 -0.0609*** 0.0535**	 0.0012 -0.0719	 -0.0597 -0.0184	 0.0376** 0.3244***	 0.0513 0.2258	 0.0890 0.5502**
	Significance levels ***1% , ** 5% , * 10%					

For the period 1982-2014, we found that the total impact estimate for the initial level of GDP per worker is negative and highly significant. This result supports the conditional β-converge hypothesis, indicating that a 1% increase in the initial level of GDP per worker determines a decrease in the average growth rate of -0.2336%. This total impact is derived from the sum of a direct impact, which is negative and significant, and an indirect impact, which is positive but not statistically significant. For the same period, the direct impact estimates of the other considered variables, in both the short and the long run, are significant. The direct effects of the investment, in the short run, are similar in magnitude to the estimates of the coefficient associated to the variable. Differences are attributable to feedback effects. Similar considerations apply to the direct effects of the variable v. For both the variables, the direct effects in the long run are greater than the direct effects in the short run. This result is consistent with the microeconomic theory (Elhorst, 2014). The short run and the long run indirect effects of the variables under consideration, for the period 1982-2014, are not significant, suggesting that investment and growth of natural capital spillovers effects are not present. Total impacts associated to both the variables under consideration are not significant.

From 1991-2014, the negative and statistically significant estimate of the total impact associated with the initial level of GDP per worker supports the conditional β-converge hypothesis. This total impact is derived from the sum of a direct impact and an indirect impact, which are both negative and significant. The significance of the indirect impact estimate reveals the presence of spillover effects for the initial level of GDP per worker. For the same period, we found that the direct impact estimates of the other considered variables, in both the short and the long run, are significant. The indirect effects of the variables under consideration are not significant, with the only exception of the short term spillover effect of variable v. This spillover effect is positive, indicating that changes to variable v in a spatial unit have a positive impact not only on the growth rate in the unit itself, but also on the growth rate in the neighbouring units. Total impacts associated to both the variables under consideration are significant.

The empirical findings in this section mainly support the specification adopted to model economic growth at the NUTS 2 level, as defined in Section 4.2.2. The model estimations suggest a process of β −conditional convergence, with a rate higher than what was generally found in growth regressions. As discussed previously, this result is consistent with the evidence of other empirical studies based on a spatial panel data approach. The speed of convergence is higher when we consider a smaller sample of regions, which does not include the eastern European regions. The variability in the estimated parameters, and in the estimated effects, underlines the importance of the selected units of analysis and of the time-spans under consideration.

Based on initial observation, a faster β −conditional convergence suggests that convergence process is lively. However, despite the faster convergence process, a tendency to only temporary impact growth for significant short-run development policies may arise (Islam, 1995; Bassanini and Scarpetta, 2001). As such, it is important to develop long-run policies directed to the traditional determinants of growth, as investment and population growth rates are likely to have had a conducive effect on the growth paths of EU NUTS 2 regions. This aspect reaffirms the relevance of policies based on the long run. Furthermore, panel analysis accounts for the relevance of structural local characteristics on which policies should also be directed in order to determine improvements in country-specific effects.

Specifically, the adoption of a dynamic spatial panel model helps to recognise unconsidered determinants in the economic growth mechanism. This specification addresses arguments underlying both the panel data framework and the spatial models. This implies considering the specific effects that affect regional convergence in time and space, promoting a more comprehensive analysis.

6.6 Empirical analysis of spatial heterogeneity and economic growth

Spatial heterogeneity is one of the two spatial effects that may affect geographically distributed data. In the previous sections, it was highlighted that the presence of spatial effects may affect the analysis of economic growth and the specification of β-convergence models. Specifications that incorporate the spatial dependence effect facilitates the consideration of the impact of values similarity in space. Additionally, the use of local regression may improve the analysis and represent a further tool to explore potential policies to enhance regional development. For these reasons, it is important to evaluate the instability of economic relationships that in the spatial analysis are due to the presence of spatial heterogeneity.

Many techniques may be adopted to consider the presence of spatial heterogeneity, and a common solution is to develop and estimate local models of economic convergence. Local models seek locally different parameters able to entail differences in the economic relationships. Local models are based on local regressions and build on the concept of continuous heterogeneity. While discrete heterogeneity deals with the presence of groups of regions that tend to behave equivalently, continuous heterogeneity assumes that parameters may potentially vary from one locality to another. Hence, the latter helps researchers to explore consequences of spatial heterogeneity when limited information is offered for individuating *discrete* clubs in advance (Ertur and Le Gallo, 2009). The local models can also enhance reliability of empirical test for regional economic convergence (Artelaris, 2015).

Among other techniques, the GWR has been commonly adopted. By using GWR we obtain local parameters for the convergence model and we can explore differences at units' level. Plotting results of GWR in terms of estimated parameters helps individuating contiguous zones that share similar convergence patterns at regional level across Europe.

Further, an interesting aspect would be to explore potential changes in the sign of the β parameters that might shed more light on the presence of different behaviour in terms of economic growth between regions. Additionally, considering spatial heterogeneity often leads to an increase in the model representativeness.

In the current report, to explore the consequences of spatial heterogeneity on regional economic convergence, we focus on data at NUTS 3 level from the ERD-CE dataset from 1991-2014. This dataset is selected to apply GWR and considers the wider number of regions at a lower spatial. The underlying idea is that a wide range of national and sub-national differences characterise Europe.

From a technical point of view, the application of GWR requires a series of choices regarding the shape of the kernel and the extension of the bandwidth.

In this analysis, an adaptive bi-square kernel, which considers a certain number of neighbours for each region, is preferred to a continuous one due to irregularity of the spatial configuration. The bandwidth is selected to optimize the level of a statistical criterion, the Akaike Information Criterion (AIC).

In Table 10, a summary of the results from the GWR estimation is reported.

The β -convergence parameters generally result in negative estimates, which confirms the hypothesis of β -convergence for a large number of units. However, in the last interval, positive values of the β -convergence parameter indicate the presence of divergence. Relative difference across EU regions can be also spotted for the other variables. For example, estimates obtained for $\ln s^k$ and $\ln v$ give evidence of scarce homogeneity in the modelling of economic growth.

Table 10 – GWR estimation results for β – convergence analysis (1991-2014), 1,133 NUTS 3 European regions. Results are obtained using an adaptive bi-square kernel (bandwidth= 51). Source: Own elaborations on ERD-CE database.

	Min	1st Q	Median	3rd Q	Max
Constant	-0.2195	0.1704	0.2642	0.3611	0.6699
$\ln y_{2003}$ (Initial level GDP per worker)	-0.0532	-0.0297	-0.0219	-0.0159	0.0178
$\ln s^k$	-0.0025	-0.0003	-0.0000	0.0002	0.0017
$\ln v = \ln(n + l + k)$	-0.0318	-0.0066	0.0029	0.0122	0.0420
R-squared	0.8372				
Adjusted R-squared	0.7865				

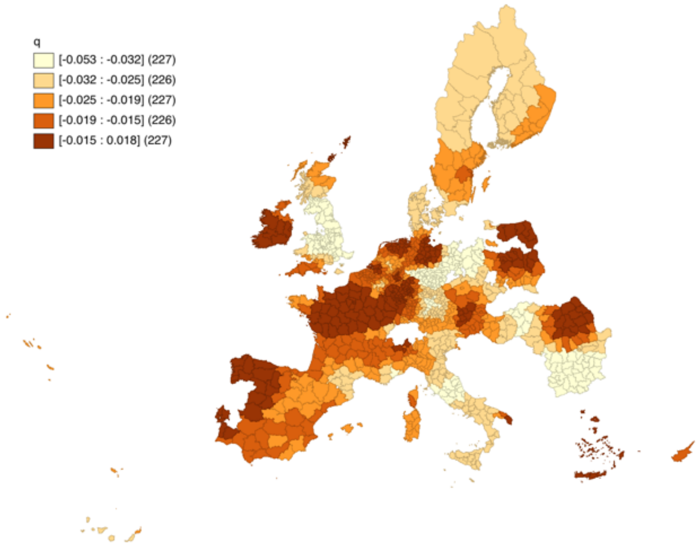
Moreover, the level of the R-squared from the GWR is about 83%, a level that outperforms the goodness of fit obtained for the global linear model in non-spatial form (R-squared for OLS is 63%). Beyond the technical issues that regard the use of GWR, a steep increase in the level of the model representativeness suggests that consideration of the existing differences across regions allows for a better representation of the phenomenon under investigation. Thus, going beyond global models for economic convergence stands as a relevant piece of evidence for policy makers (Eckey et al. 2007).

In order to ensure better comprehension of the results from GWR, quantile maps for the parameter estimated in correspondence of each variable can be visualised. Quantile maps report groups of different regions that share similar values for the considered parameter and enable both analysts and policy makers to appreciate the geographical difference in economic growth.

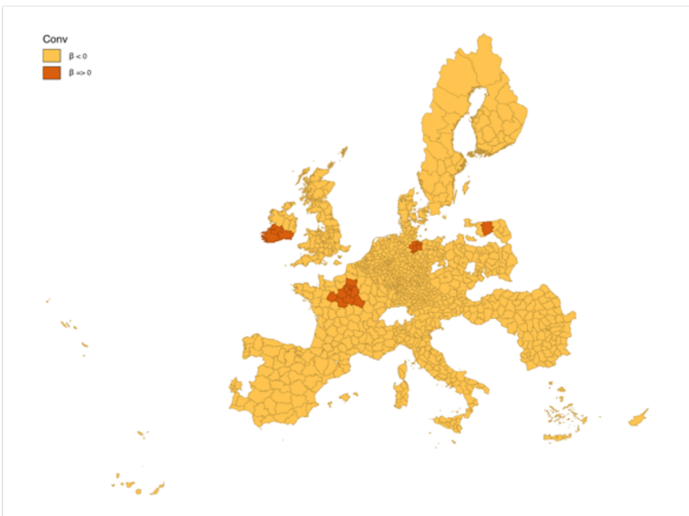
One of the main objectives of the IMAJINE Project is to promote "spatially deeper" economic analysis, to provide analysis beyond what is often performed at NUTS 2 level. In fact, local models at NUTS 3 reveals notable insights on economic growth dynamics. The NUTS 3 estimations obtained by GWR for β-convergence seem to vary across the study area from -0.0532 to 0.0172, suggesting presence of remarkable local differences. In Figure 15(a), the quantile map reports intervals for the estimated β -convergence parameter for European NUTS 3 regions. This represents a simple method to identify groups of EU regions sharing common characteristics. For many regions, the hypothesis of economic convergence seems to be empirically satisfied. This situation is consistent with a negative value of the β -convergence parameter in regions in west and southern Spain, northern Belgium, the Netherlands, Romania, southern NUTS 3 regions of Sweden, and northern Poland and Romania. Larger economic convergence involves also the northwest region of Italy and many islands of Greece. Additionally, many regions of Italy are linked to weaker convergence, as well as NUTS 3 regions in the southern Spain, regions around Toulouse and Montpellier in France, southern Germany, and northern Sweden and Finland. The last interval on the map mainly characterises regions with very low convergence and, in some cases, divergence. Particularly, those regions are situated in the centre of Italy, the United Kingdom, and east of Germany.

Figure 15 (a) Intervals of the β-convergence parameter obtained with GWR estimation (1991-2014), 1,133 NUTS 3 European regions. (b) Regions in convergence and divergence. Results are obtained using an adaptive bi-square kernel (bandwidth=51). Source: Own elaborations on ERD-CE database.

(a)



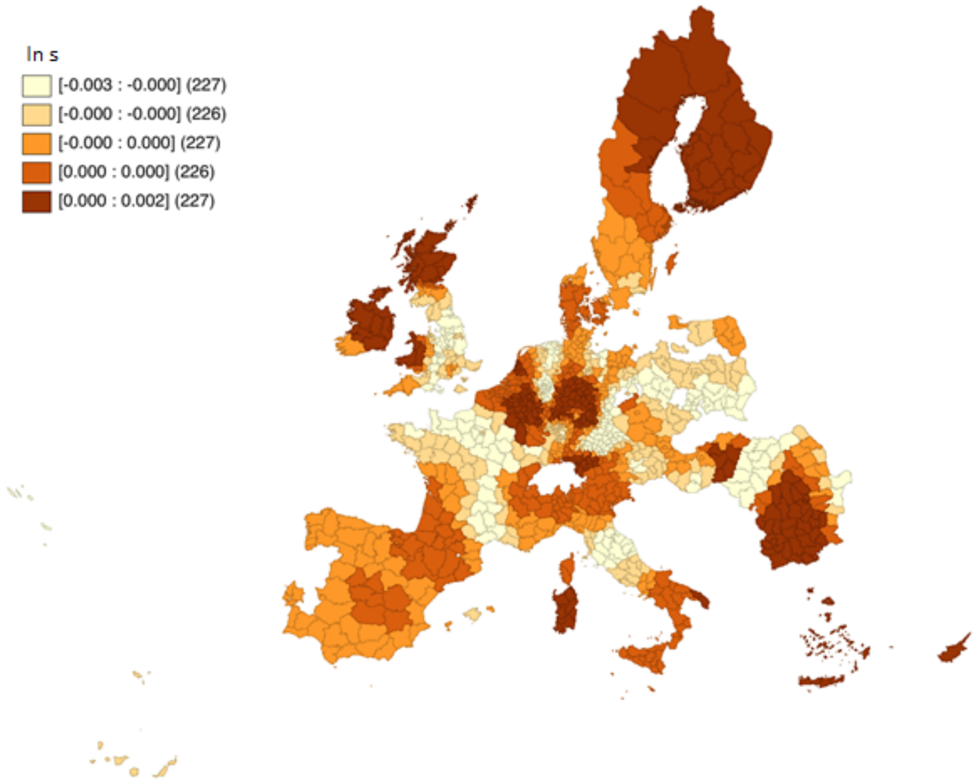
(b)



Furthermore, divergence affects some NUTS 3 regions of Germany and northern France (Paris region). Hence, some of the potential situations of divergence are located in eastern Europe. In Figure 15(b), situations of potential divergence appear as a relevant issue for policy makers as they highlight the presence of growth dynamic that outrun the classical hypothesis of convergence. This stresses the lack of the catch-up effect and points to the potential rise of disparities in eastern European regions. Lastly, potential divergence affects the southern regions of Ireland.

The use of local regression as GWR to estimate local parameters in the economic growth model can be considered as a valid starting point to visualise groups of regions sharing similar behaviours. Thus, the application of GWR is not only useful to enhance very local policies, but it also offers consideration for comparing regions within countries. For example, with reference to the β -convergence parameter, we observe that countries like Spain and France show differences between the north and south, while Germany is characterised by certain east-west differences. These features are important for reducing within countries the inequalities able to alter political scenarios.

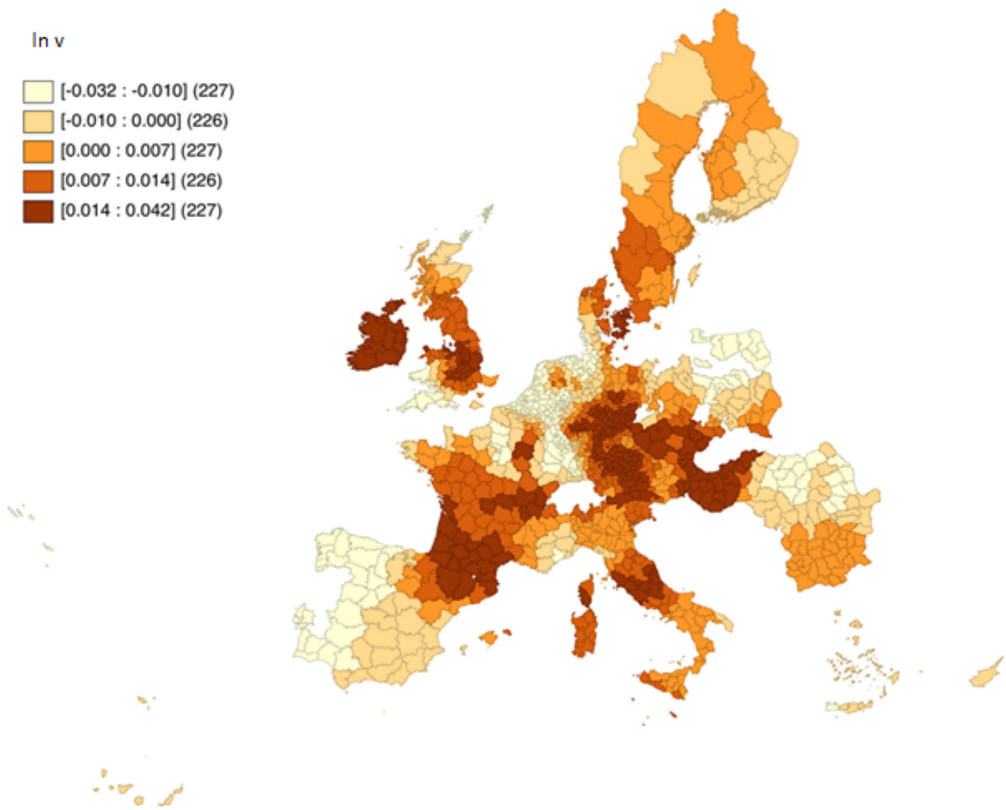
Figure 16 - Intervals of the parameter associated to $\ln(s^k)$ obtained with GWR estimation (1991-2014), 1,133 NUTS 3 European regions. Results are obtained using an adaptive bi-square kernel (bandwidth=51). Source: Own elaborations on ERD-CE database



In Figure 16, estimated parameters for $\ln(s^k)$ (i.e., investment) are displayed. This parameter is of interest for policy makers as it is strongly related to policies of European, national, and local investments to tackle the presence of between and within countries disparities. Further, the extremes of the intervals give evidence to a certain degree of spatial heterogeneity, resulting in the difference in the relationship between investment and economic growth. This relation is positive for regions in Scotland, Ireland, east of Germany, Belgium south Romania and Greece. Another interesting result is observed in the south of Italy, where the relationship between investments and economic growth is also quite positive. Moreover, in the case of Spain, differences in the estimated parameter for investment can be spotted for the areas around Madrid and Barcelona with respect to the rest of the country.

Differences in the level of the estimated parameters exist at regional level also for $\ln(v)$. Results for this variable are reported in Figure 17. In this case, the picture of European NUTS 3 regions appears highly fragmented, since some local pockets are present. This is the case, for example, of the area around Rome and in the centre of Italy, in the regions around Vienna, in the south of France, and across the whole of Ireland. For those regions characterized in the figure by darker shades, the level of the estimated parameters is positive. This strongly links the growth of per worker GDP to an increase in the level of the working population. Conversely, regions characterised by white shading, situated mainly in the West Iberian Peninsula (including regions of Portugal and Spain), many of the regions from Germany, and the Netherlands, are identified by a negative relationship of economic growth with the growth of the population. In this regard, many considerations may be offered in terms of policy support by a proper assessment in the effect of natural capital increase on the level of economic growth. This speaks to the necessity of developing local and regional policies able to support investment in the EU.

Figure 17 - Intervals of the parameter associated to $\ln(v)$ obtained with GWR estimation (1991-2014), 1,133 NUTS 3 European regions. Results are obtained using an adaptive bi-square kernel (bandwidth=51). Source: Own elaborations on ERD-CE database



GWR is able to model non-stationary regression parameters and lets the levels of the economic relationships change from unit to unit. As highlighted, this can increase model representativeness and provide a more reliable model of economic growth. This aspect can be noted while looking at the map of the residuals for GWR. While residuals in the OLS model are quite clustered, denoting potential local diversities not captured by the global model, residuals from GWR in Figure 18 are scattered, in accordance with the *iid* assumption. This evidence confirms that the definition of a model with spatial heterogeneity may be more reliable when data from the phenomenon under investigation tend to be clustered.

Further to the technical issues identified, the importance of including the role of spatial heterogeneity is a key feature in the analysis of economic convergence and economic growth. This holds true both in the presence of convergence clubs (Postiglione et al. 2013) and for the analysis of continuous heterogeneity in which we allow the parameter to change locally (Ertur and Le Gallo, 2009). In fact, this sort of analysis describes a picture in which the convergence dynamic is not homogenous, and the convergence process differs between spatial units.

Figure 18- - Intervals of residuals from GWR estimation (1991-2014), 1,133 NUTS 3 European regions. Results are obtained using an adaptive bi-square kernel (bandwidth=51). Source: Own elaborations on ERD-CE database

The analysis of local patterns in the economic convergence dynamic provides relevant support to policy makers, both to assess the reasons behind differences and to contribute significantly to the political agenda. The evidence offered in the current report is consistent with the need for *ad hoc* policies able to boost local development.

Lastly, this analysis stresses the relevance of moving beyond one-size-fits-all policies to the aim of supporting efficient local policies and more sustainable equilibriums across European regions.

7. FINAL REMARKS

In the report we aimed to demonstrate the importance of the spatial dimension and geographical location in the analysis of regional economic convergence. Different analyses were performed to measure the presence of economic convergence according to different geographical scales, number of years, and techniques. It is relevant to consider the effects of both spatial interdependencies and structural differences. The analyses based on a refined spatial scale at NUTS 3 gives us a more detailed picture on the existence of economic convergence, according to both σ and β -convergence approaches. In this sense, regional economic β -convergence holds at European level in spite of different spatial scales. Hence, there is a need to consider spatial effects, particularly dependence.

The process of convergence at NUTS 2 was not completely discarded because of its importance in the field of European Cohesion Policy. Going beyond the cross-sectional approach, we updated the current attempts of verifying convergence at NUTS 2 by adopting dynamic spatial panel models. The results confirm the convergence hypothesis, even if the role of structural differences across units (fixed effects in space) and economic contingencies (fixed effects in time) shall not be neglected to offer clearer evidence of the catch-up process. Lastly, the analysis of structural differences due to the presence of local specificities (i.e., spatial heterogeneity) reveals a general presence of economic β -convergence. However, the use of local regressions points out the presence of small pockets of divergence that should be addressed with further research.

Overall, the analyses offered support the general notion that regional economic convergence is a matter of space. Thus, because of the geographical dimension, *ad hoc* techniques explored do not represent a mere technicality; just the opposite, the use of spatial techniques supplied by the econometric literature represents a significant advancement, suitable to offer an unbiased report on convergence. Furthermore, as "spatial justice" (as highlighted by the WP1) stands as a key fact for European policies, a correct treatment of geography (and its effects) in robust models may favour both a deeper process of integration and address contextual differences. Lastly, the results in current report support the general necessity of studying economic phenomena - and especially convergence - to support cohesion and reduce disparities in the EU.

APPENDIX 1

The Interpretation of spatial regression models

In the standard regression model for the analysis of β – convergence as expressed in equation (3):

$$g_i = \beta_0 + \beta_1 \ln y_{it-T} + \beta_2 \ln s_i^k + \beta_3 \ln v_i + \beta_4 \ln s_i^h + \varepsilon_i \quad \text{(A.1)}$$

the regression parameters (i.e., $\beta_1, \beta_2, \beta_3, \beta_4$) may be interpreted as the partial derivative of the dependent variable g_i with respect to each specific exogenous variable k (i.e., $\ln y_{it-T}$, $\ln s_i^k$, $\ln v_i$, $\ln s_i^h$).

In this case, the parameter β_1 can be obtained as [14]:

$$\beta_1 = \frac{\partial g_i}{\partial \ln y_{it-T}} \quad \text{(A.2)}$$

while in general:

$$\frac{\partial g_i}{\partial \ln y_{jt-T}} = 0 \text{ for every } j \neq i \quad \text{(A.3).}$$

The coefficient β_1 can be directly interpreted as the change induced on the variable g_i for one-unit change in the variable $\ln y_{it-T}$, while holding other variables in the model constant. The model parameters are estimated under the explicit assumption that the observations are independent; changes in values for one observation (in this case unit i) do not ''spill-over'' to affect values of other observations (for every $j \neq i$).

In many empirical applications, the coefficients of spatial regression models are often interpreted incorrectly following this rationale as if they were simple partial derivatives. Note that the previous simple interpretation is still appropriate for models with only spatially lagged errors (i.e., SEM or SDEM, see LeSage and Pace, 2009).

Unfortunately, for the spatial Durbin model specification for cross-sectional data (see equation (14)) and for panel data (see equation (24)) that are the reference models for our analysis of Section 6, this interpretation no longer holds. Hence, the regression coefficients of these latter models must be interpreted differently and with caution.

This appendix briefly reviews how to derive and interpret coefficients of spatial regression models, including subjects of direct and indirect (i.e., spatial spillover) effects. For greater details about this topic, see LeSage and Pace (2009) and Elhorst (2014).

In the Spatial Durbin model, a change in a single region associated with any given explanatory variable will influence the region itself (a direct impact) and possibly influence all other regions indirectly (an indirect impact).

---

[14] For the sake of simplicity, we describe the interpretation of the model for changes of only first variable $\ln y_{it-T}$, but it is evident that the same considerations reported herein can be replaced for the other variables.

To better explain this interpretation, consider the Spatial Durbin model specified in compact form as in equation (9) and expressed in matrix notation as:

$$\mathbf{g} = \beta_0\mathbf{i} + \mathbf{X}\boldsymbol{\beta} + \rho\mathbf{W}\mathbf{g} + \mathbf{W}\mathbf{X}\boldsymbol{\gamma} + \boldsymbol{\varepsilon} \tag{A.4}$$

where $\mathbf{g}$ is the $N \times 1$ vector of the observed GDP per-worker growth rates, $\mathbf{i}$ is the $N \times 1$ unit vector, $\mathbf{X}$ is the $N \times 3$ matrix of the three covariates defined in (14) and (24), $\mathbf{W}$ is the $N \times N$ non-stochastic spatial weight matrix that specifies the proximity structure among the regions, ρ is the spatial autoregressive coefficient that evidences spatial dependence, $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are the 3×1 vectors of parameters associated to $\mathbf{X}$ and to the lagged values $\mathbf{WX}$, and $\boldsymbol{\varepsilon}$ is the $N \times 1$ vector of error terms.

Equation (A.5) can be re-written as:

$$(\mathbf{I} - \rho\mathbf{W})\mathbf{g} = \beta_0\mathbf{i} + \mathbf{X}\boldsymbol{\beta} + \mathbf{W}\mathbf{X}\boldsymbol{\gamma} + \boldsymbol{\varepsilon} \tag{A.5}$$

and so:

$$\mathbf{g} = (\mathbf{I} - \rho\mathbf{W})^{-\mathbf{1}}(\beta_0\mathbf{i} + \mathbf{X}\boldsymbol{\beta} + \mathbf{W}\mathbf{X}\boldsymbol{\gamma} + \boldsymbol{\varepsilon})$$

Therefore, in this case, for each unit $i = 1,2,\dots,N$, we obtain the following derivative:

$$\frac{\partial g_i}{\partial \ln y_{it-T}} = (\mathbf{I} - \rho\mathbf{W})^{-\mathbf{1}}\beta_1 \tag{A.6}$$

while the derivative $\frac{\partial g_i}{\partial \ln y_{jt-T}}$ for every $j \neq i$ is:

$$\frac{\partial g_i}{\partial \ln y_{jt-T}} = (\mathbf{I} - \rho\mathbf{W})^{-\mathbf{1}}\beta_1 + w_{ij}\gamma_1 \tag{A.7}$$

Equation (A.7) highlights that unlike the case of the independent data model (see equation (A.3)), the derivative of g_i with respect to $\ln y_{jt-T}$ is potentially non-zero for $j \neq i$. In other words, a change in the explanatory variable for a single region can potentially affect the dependent variable in all other observations. This is a coherent consequence of the SDM model, since this model consider other regions dependent and explanatory variables through the introduction of the lagged variables $\mathbf{Wg}$ and $\mathbf{WX}$.

However, since the impact of changes in an explanatory variable varies over all regions i, LeSage and Pace(2009) suggest some summary measures of these different impacts.

The first quantity is represented by the mean of the impacts $\frac{\partial g_i}{\partial \ln y_{it-T}}$ for $i = 1,2,\dots,N$. This is denoted as Average Direct Impact (ADI) that measures the average impact on the region's dependent variable g resulting from a change in the explanatory variable $\ln y_{t-T}$ on the same region. Note, as evidenced by LeSage and Pace (2009), that averaging over the direct impact associated with all observations i is similar in essence to typical regression coefficient interpretations that represent average response of the dependent to independent variables over the sample of observations.

The second indicator is obtained by the average across the N units of the different derivatives $\frac{\partial g_i}{\partial \ln y_{jt-T}}$ with $j \neq i$. This second measure is denoted as Average Indirect Impact (AII) and is generally interpreted as the average impact of changing the exogenous variable $\ln y_{t-T}$ of a particular region on the dependent variable g of all other regions (Elhorst, 2014). The Average Total Impact (ATI) is defined as:

$$ATI = ADI + AII \tag{A.8}$$

In summary, the spatial models for the analysis of $\beta -$ convergence have to be interpreted making use of the appropriate measures that have been outlined in this Appendix.

APPENDIX 2

The Bayesian Interpolation Method (BIM)

Some variables in our study are not available at the spatial level requested for the analysis; in many cases, this information is collected at a more aggregated spatial level. The process by which information at a coarse spatial scale is translated to finer scales, maintaining the consistency with the original dataset, is known as spatial disaggregation. The areal units corresponding to the finer spatial scale are defined target zones. Conversely, the areal units corresponding to the aggregated spatial level are labelled as source zones.

Different areal interpolation techniques can be used in this context to transform data from a set of source zones to a set of target zones (Goodchild and Lam, 1980; Goodchild et al. 1993).

Some areal interpolation techniques consider the special features of spatial data. Specifically, the spatial dependence effect could provide useful information in the spatial disaggregation procedure. Benedetti and Palma (1994) introduced a Bayesian solution to the areal interpolation problem which exploits this general property of spatial data. The method is known as Bayesian Interpolation Method (BIM).

BIM requires assumptions on the spatial data generating process. Commonly, spatially referenced data are considered to be a realization from a spatial stochastic process, that is a collection of random variables indexed by their locations.

When dealing with the areal interpolation problem, data related to both source and target zones can be interpreted as realizations of spatial stochastic processes. The spatial stochastic process generating the data related to the target zones is referred to as the original process. The spatial stochastic process generating the data for the source zones is referred to as the aggregated process. Assuming that data are available only at the aggregated spatial level, the objective is to restore the realizations of the original process given the realization of the aggregated process.

The assumption on which BIM is based concerns the joint probability distribution of the original process, which is assumed to be a Gaussian distribution. The spatial dependence effect is considered by modelling the Gaussian random field by the Conditional Autoregressive (CAR) specification (Besag, 1974). This assumption does not entail any loss of generality since any Gaussian process on a finite set of sites can be modelled according to this specification. CAR specification introduces the spatial dependence effect in the covariance structure of the process as a function of a scalar parameter of spatial autocorrelation and of a spatial weight matrix**,** which summarizes the proximity between any pairs of spatial units. Following a Bayesian approach, the prior information on the distribution of the original process is combined with the data available at the aggregated spatial level to derive the posterior probability distribution of the original process. Benedetti and Palma (1994) derive the parameters of this posterior probability distribution, that are the BIM estimates. Any inference on the original process can be based upon the specified posterior distribution.

To formalize the described methodology, consider N areal units (i.e., the units at NUTS 3 level) which describe a partition $\mathbf{\Omega}$ over a geographical domain. Denote by $\mathbf{y} = (y_1, y_2, \dots, y_N)^t$ the data related to a variable of interest Y observed on the N areal units. The vector $\mathbf{y}$ can be interpreted as a realization of the original process expressed by the random vector $\mathbf{Y} = (Y_1, Y_2, \dots, Y_N)^t$. By grouping the N units into larger areas, we obtain a set of $M < N$ areal units (i.e., the units at NUTS 2 level) which define a new partition $\mathbf{\Omega}^*$ over the same geographical domain. The data observed for this new partition can be denoted by $\boldsymbol{y}^* = (y_1^*, y_2^*, \dots, y_M^*)^t$, and the underlying spatial stochastic process, that is expressed by the random vector $\mathbf{Y}^* = (Y_1^*, Y_2^*, \dots, Y_M^*)^t$, is the aggregated process.

Assume that data are only available for the partition $\mathbf{\Omega}^*$, while we are interested in the spatial scale corresponding to $\mathbf{\Omega}$ .The issue becomes to restore the realizations of the original process given the realization $\mathbf{y}^*$ of the aggregated one.

The solution proposed by Benedetti and Palma (1994) consists in identifying the posterior probability distribution of $\mathbf{Y}|\mathbf{Y}^*$**.** According to the Bayes' rule this posterior probability distribution can be derived as follows:

$$P(\mathbf{Y}|\mathbf{Y}^*) \propto P(\mathbf{Y})P(\mathbf{Y}^*|\mathbf{Y}) \tag{A.9}$$

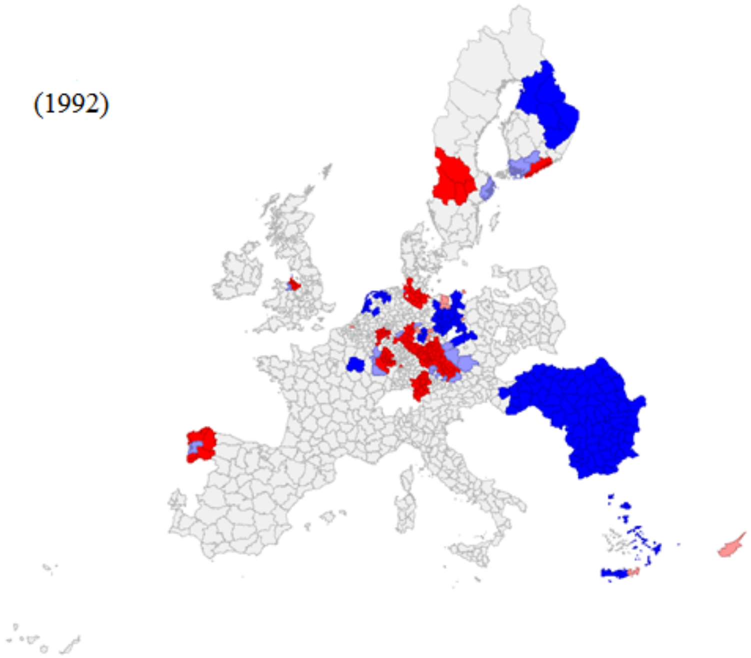
where $P(\mathbf{Y})$ is the prior probability distribution of the random vector $\mathbf{Y}$, and $P(\mathbf{Y}^*|\mathbf{Y})$ is its likelihood function. The BIM estimates $\widetilde{\mathbf{Y}}$ and $\mathbf{V}_{\widetilde{\mathbf{Y}}}$ (i.e.,, the covariance matrix of the estimates) represents the maximum a posterior estimate of $\mathbf{Y}$ and is the mode of its posterior distribution. The estimates obtained through BIM preserve the pycnophylactic property which consists in finding an estimate of $\mathbf{Y}$ such that, by applying the transformation operator $\mathbf{G}$ (i.e.,, the operation of aggregation), the observed data $\mathbf{Y}^*$ are again obtained (Tobler, 1979).

Obtaining reliable estimates of data at fine spatial scales is essential for a wide range of analyses. For instance, in our study, the variable $\ln s_i^k$ is not available at NUTS 3 level. However, the variable $\ln s_i^k$ is offered at NUTS 2 level. In this situation, the NUTS 2 regions identify the source zones, while the NUTS 3 regions are the target zones. So, in empirical analysis of $\beta -$convergence, we estimate $\ln s_i^k$ at NUTS 3 level making use of the information of the same variable available at NUTS 2 level. The pycnophylactic property, in our case, is translated as the sum of estimates of the variable $\ln s_i^k$ for NUTS 3 units reproduces the variable at NUTS 2 level, where the sum is extended to the NUTS 3 units that belong to a particular NUTS 2 region. See Panzera et al. (2016) for further details.

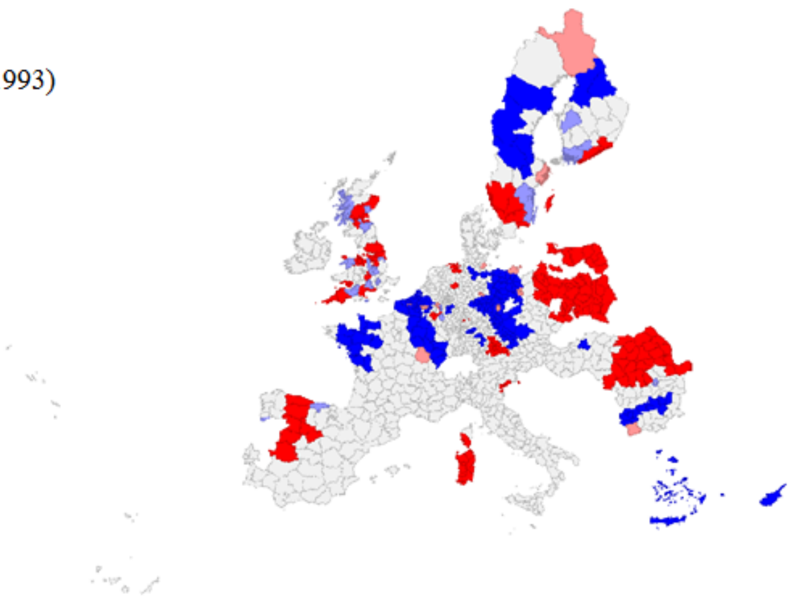
APPENDIX 3

Figure 19 - LISA cluster map of annual GDP per worker in PPS growth rate. Connectivity matrix based on a $K = 7$ nearest neighbours, years 1992-1995. Source: Own elaboration on ERD-CE dataset.

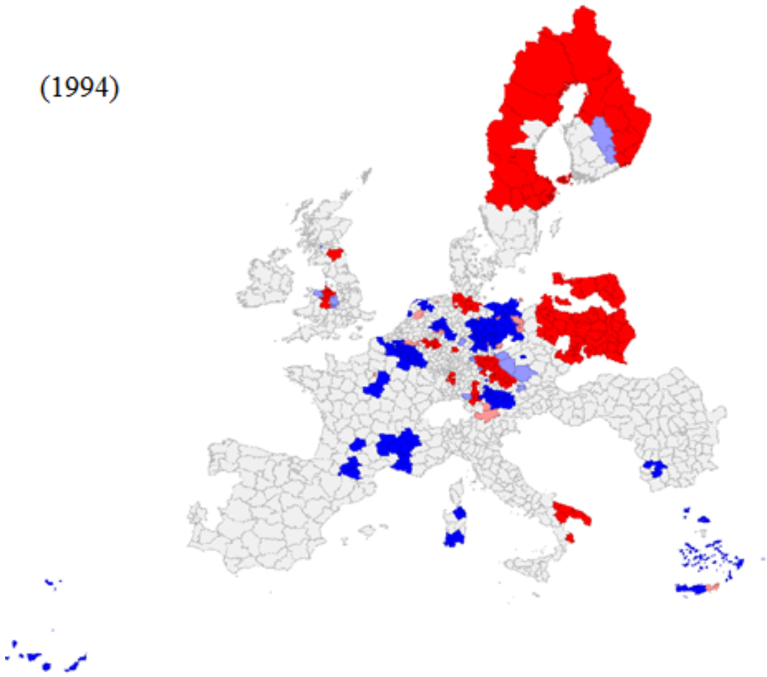
(1992)



(1993)



(1994)



(1995)

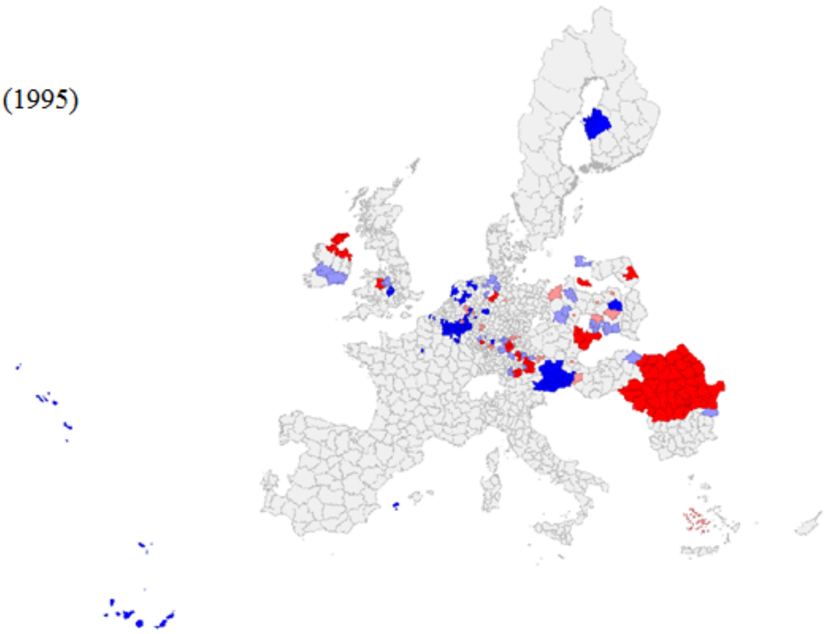
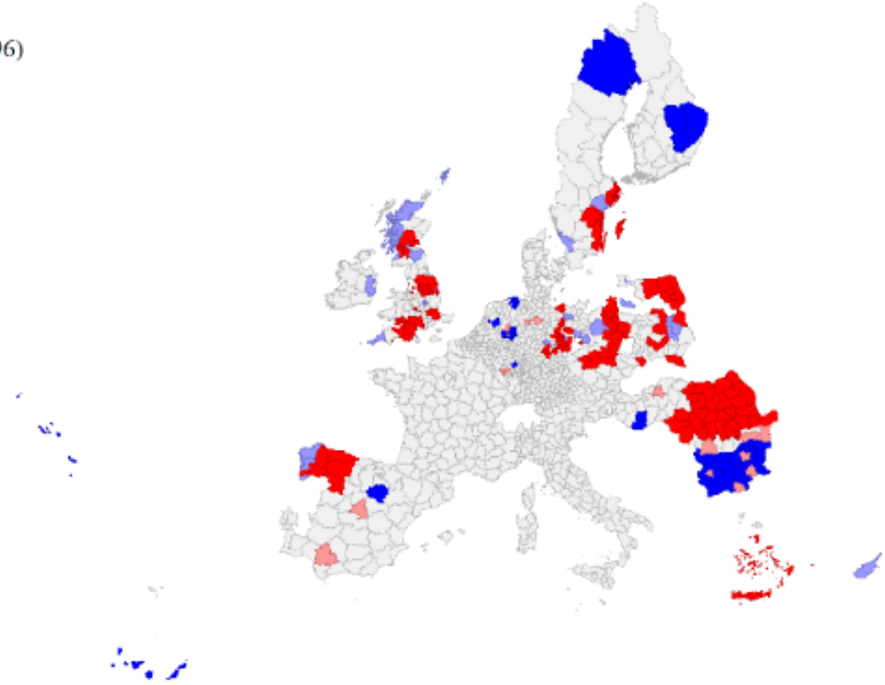
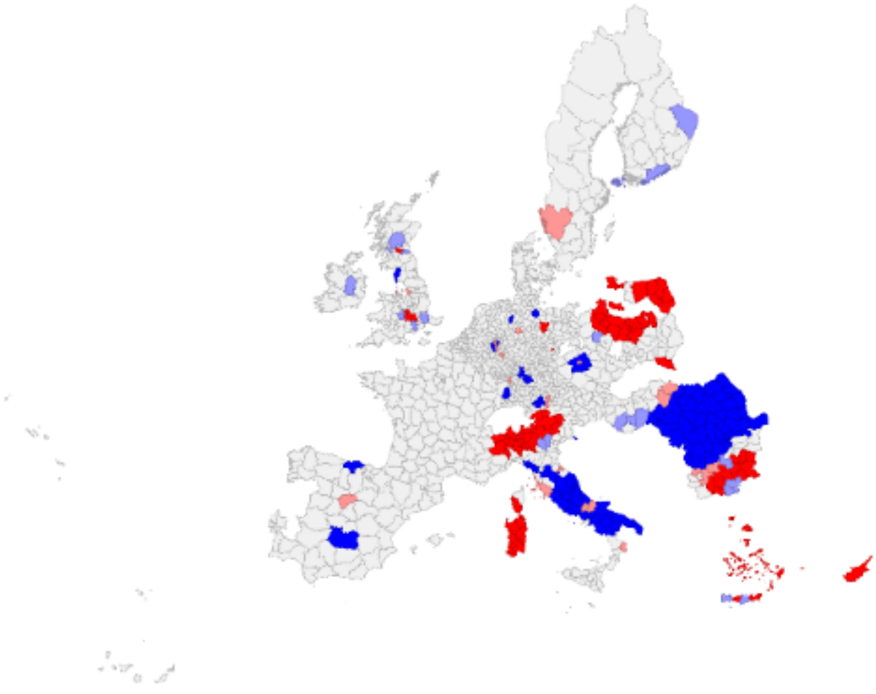


Figure 20 - LISA cluster map of annual GDP per worker in PPS growth rate. Connectivity matrix based on a $K = 7$ nearest neighbours, years 1996-1999. Source: Own elaboration on ERD-CE dataset.

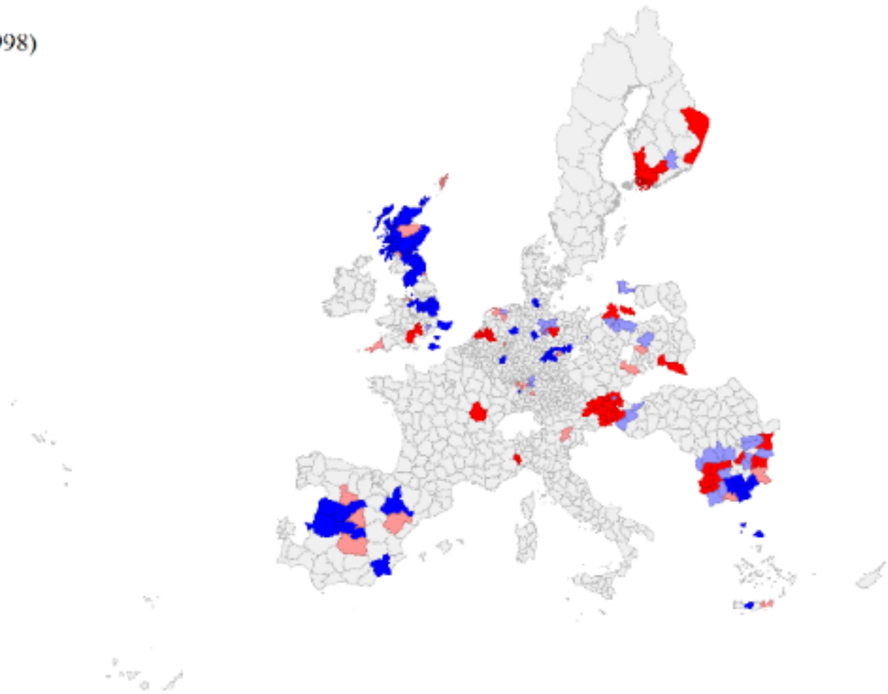
(1996)



(1997)



(1998)



(1999)

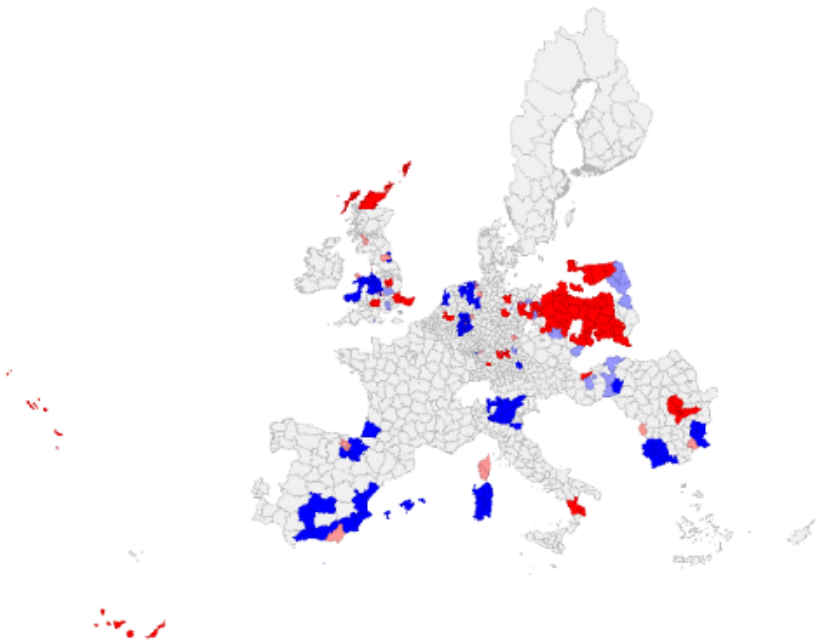
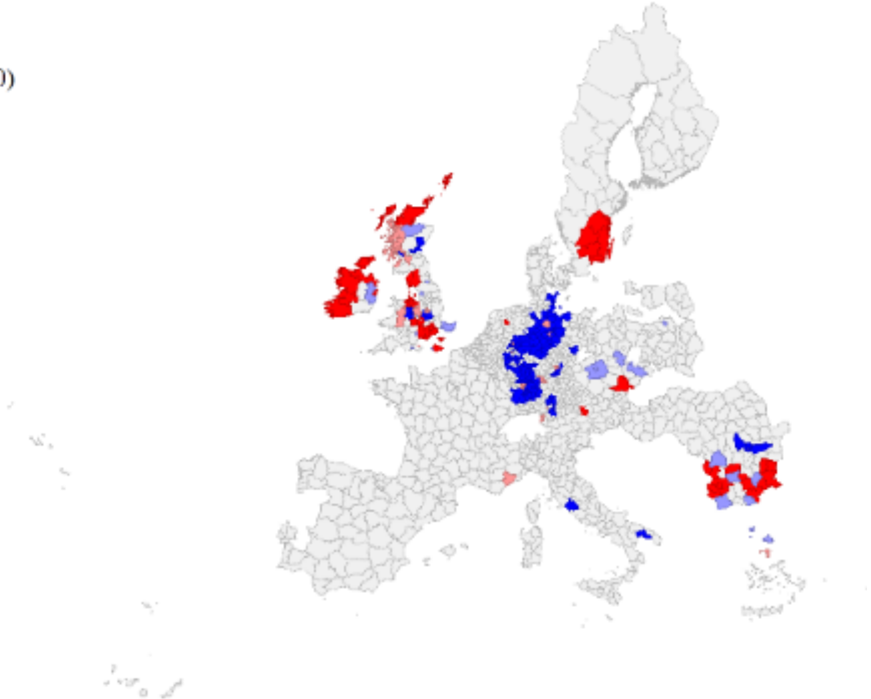
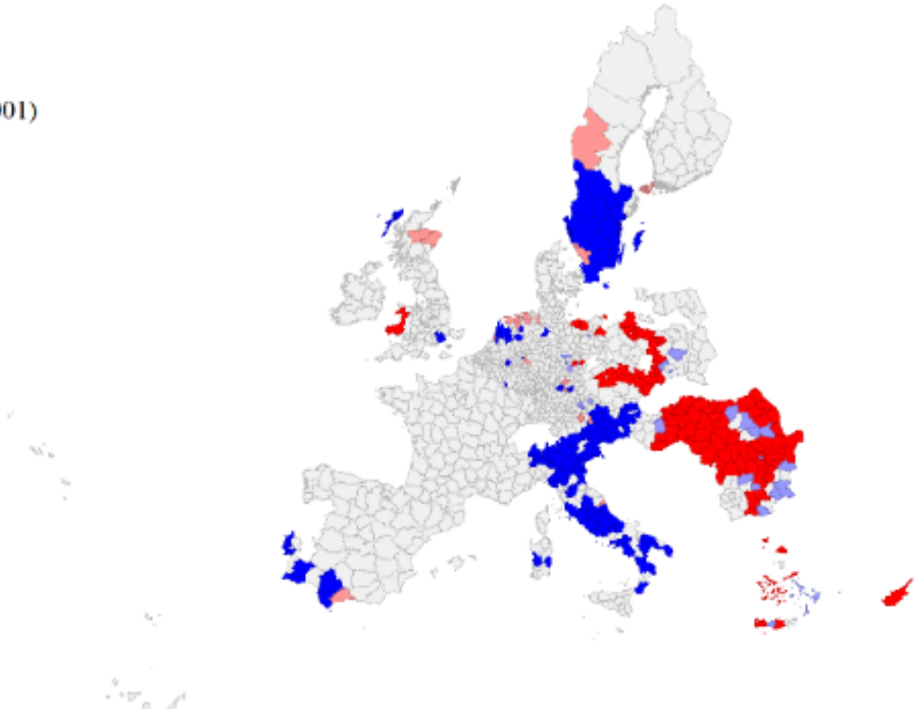


Figure 21 - LISA cluster map of annual GDP per worker in PPS growth rate. Connectivity matrix based on a $K = 7$ nearest neighbours, years 2000-2003. Source: Own elaboration on ERD-CE dataset.

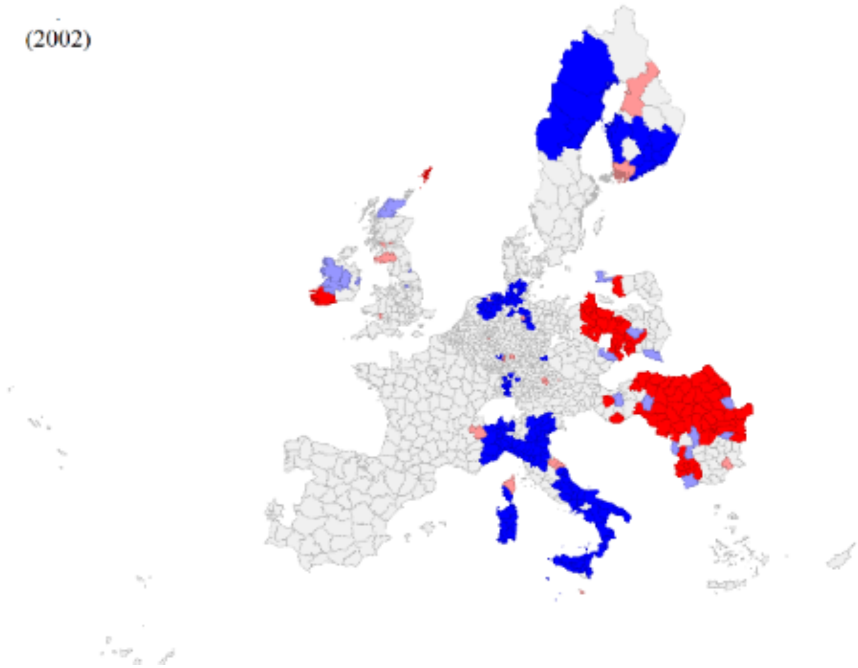
(2000)



(2001)



(2002)



(2003)

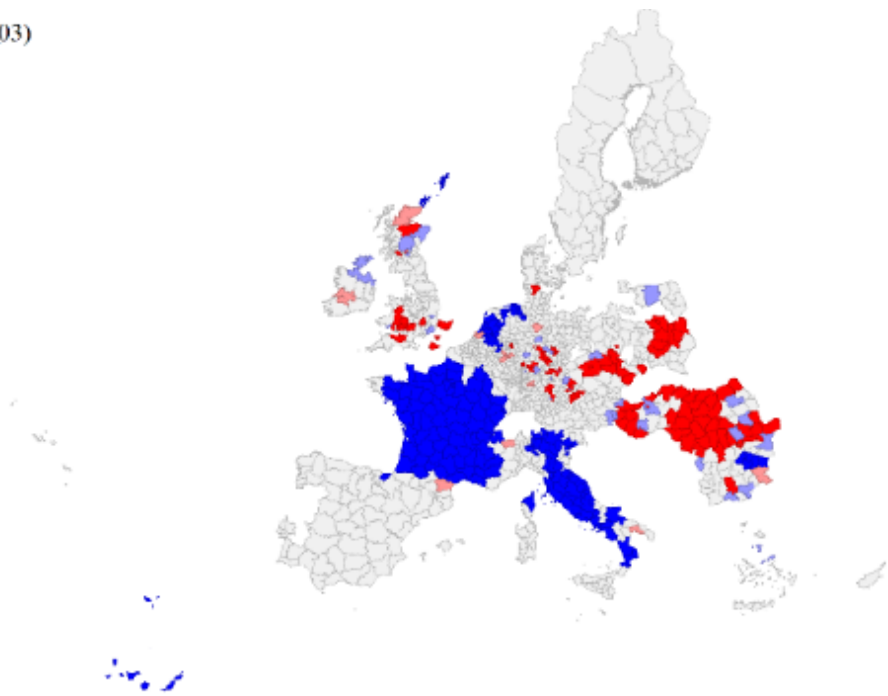
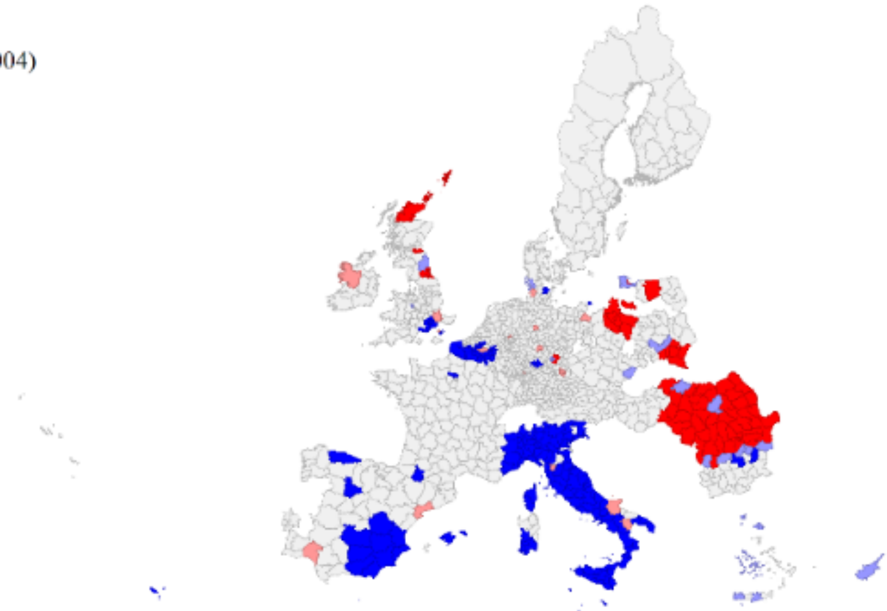
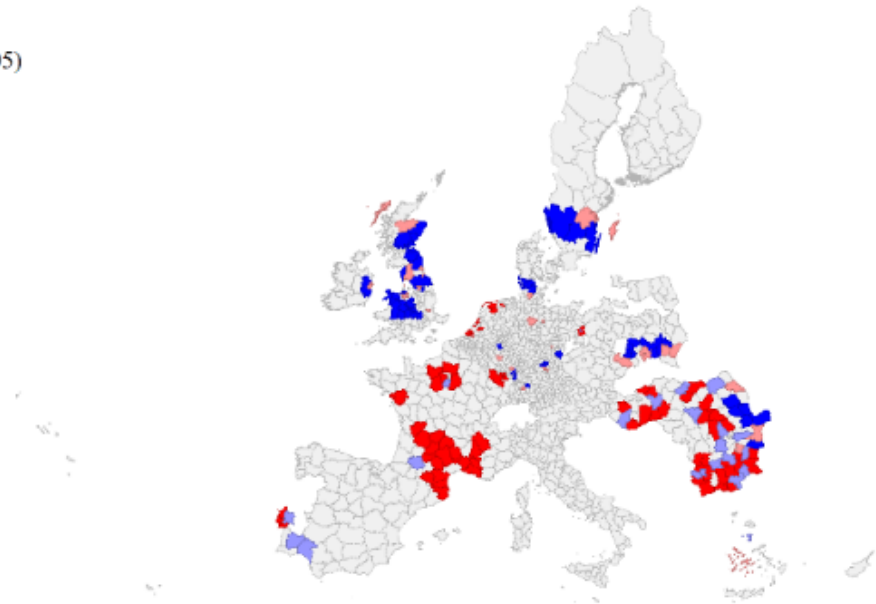


Figure 22 - LISA cluster map of annual GDP per worker in PPS growth rate. Connectivity matrix based on a $K = 7$ nearest neighbours, years 2004-2007. Source: Own elaboration on ERD-CE dataset.

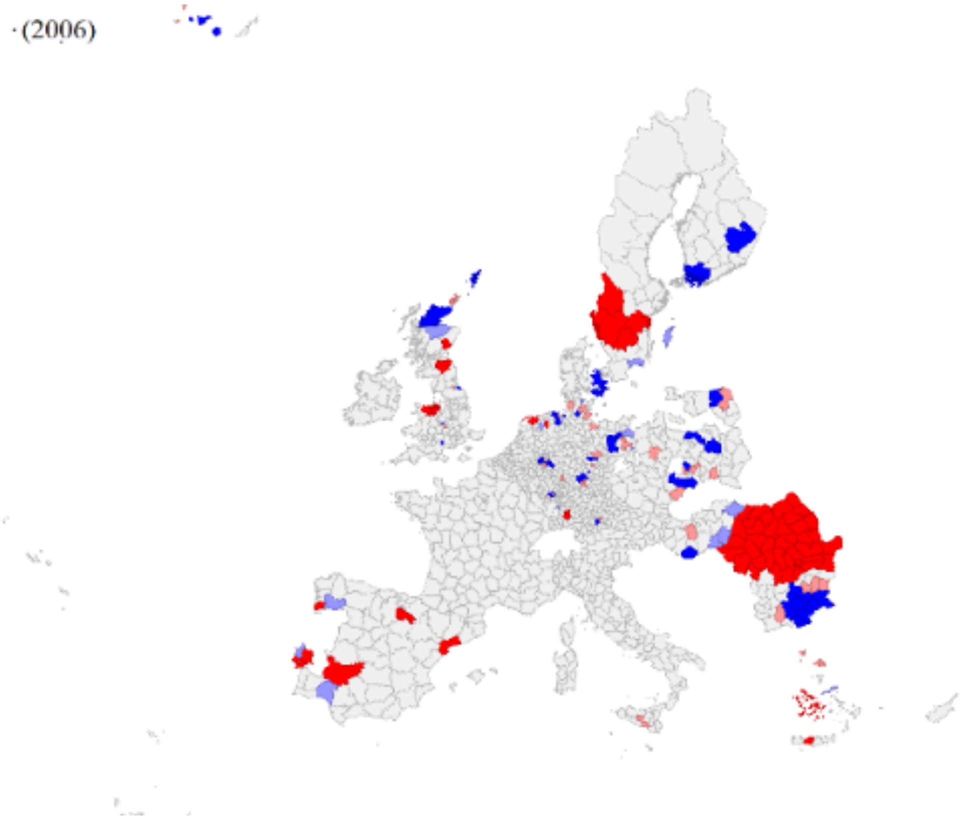
(2004)



(2005)



(2006)



(2007)

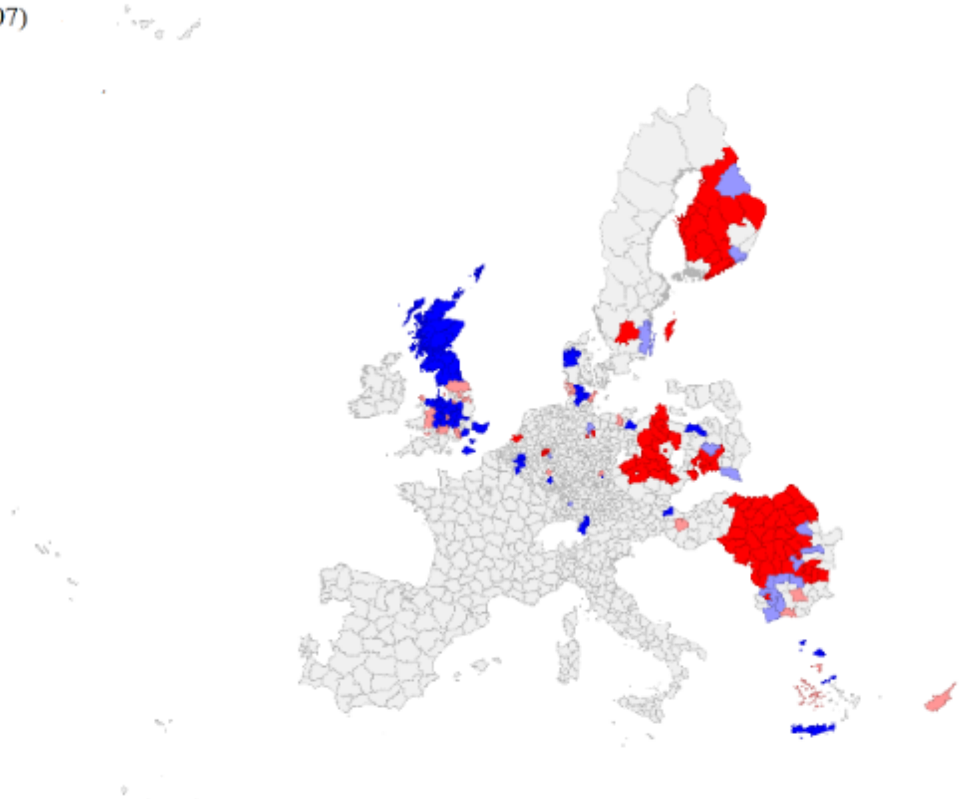
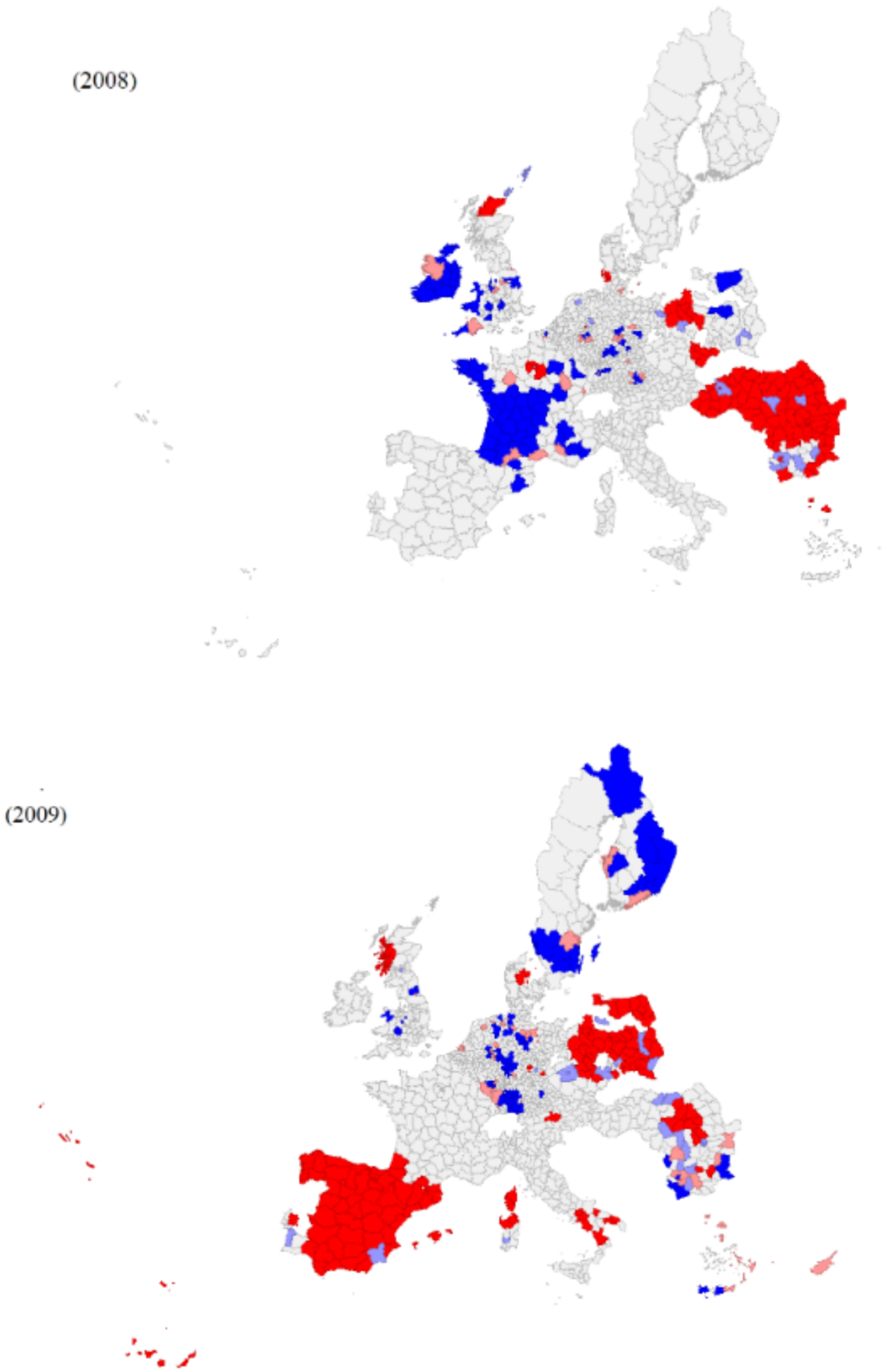
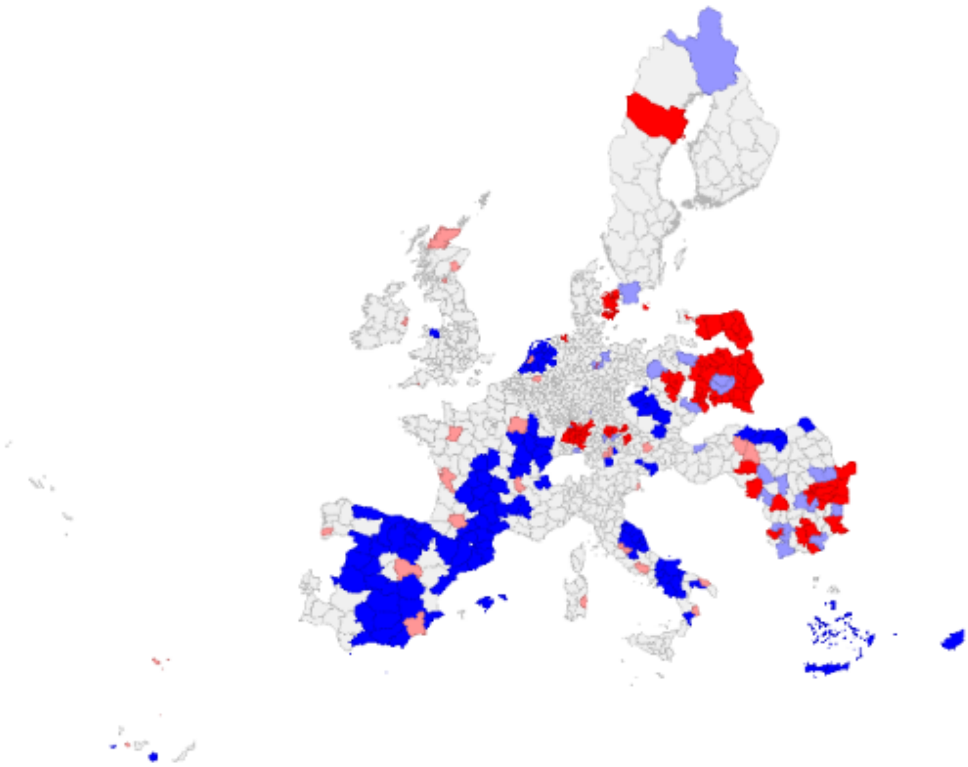


Figure 23 - LISA cluster map of annual GDP per worker in PPS growth rate. Connectivity matrix based on a $K = 7$ nearest neighbours, years 2008-2011. Source: Own elaboration on ERD-CE dataset.



(2010)



(2011)

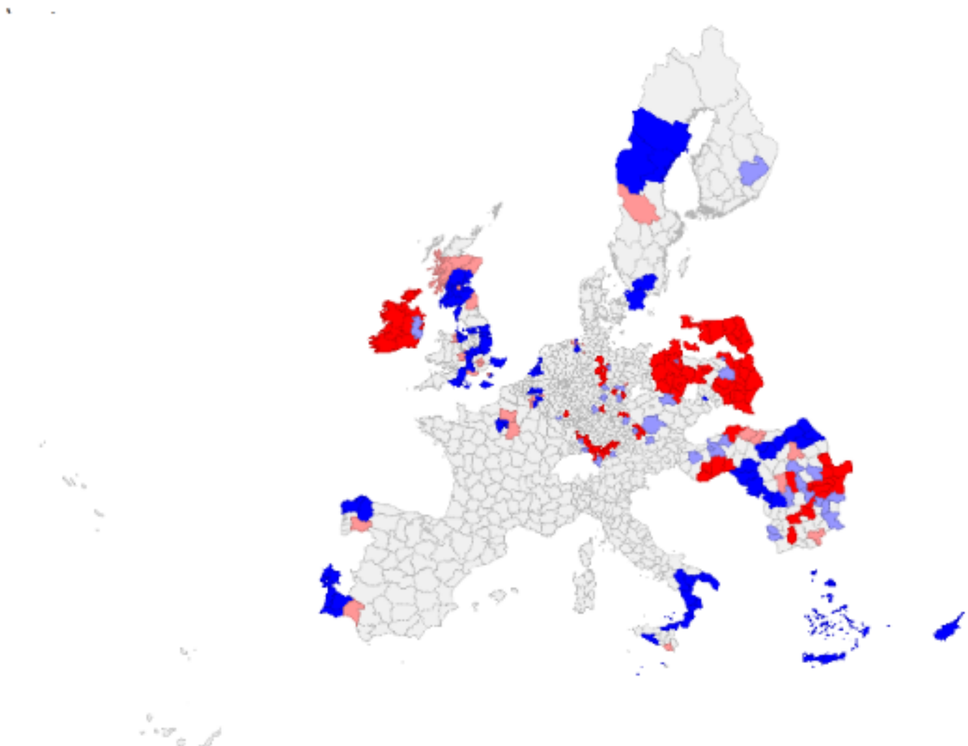
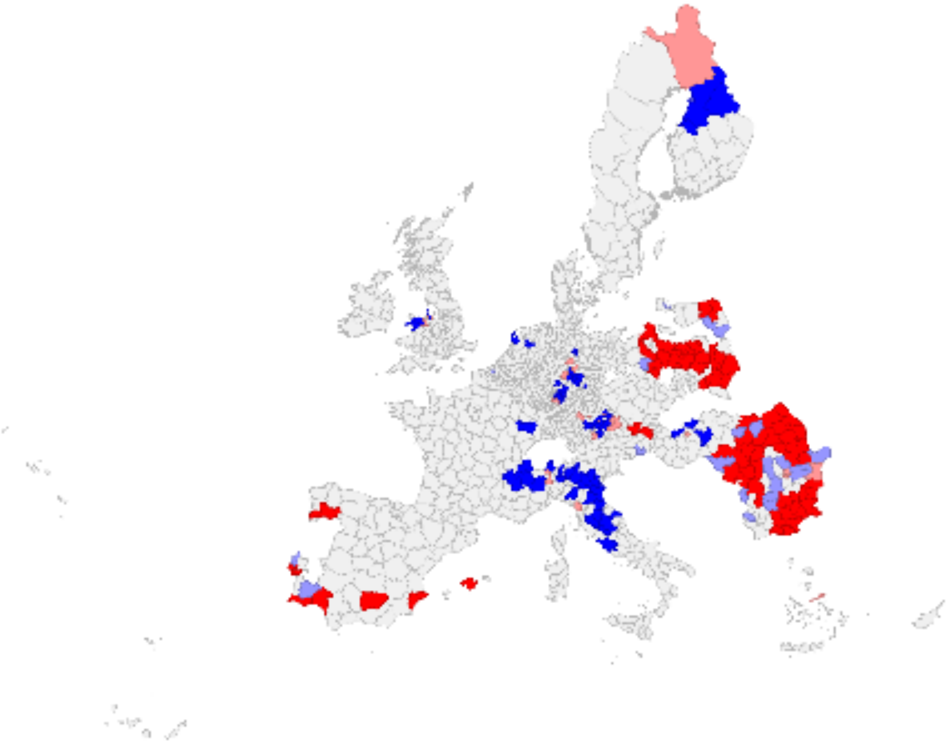
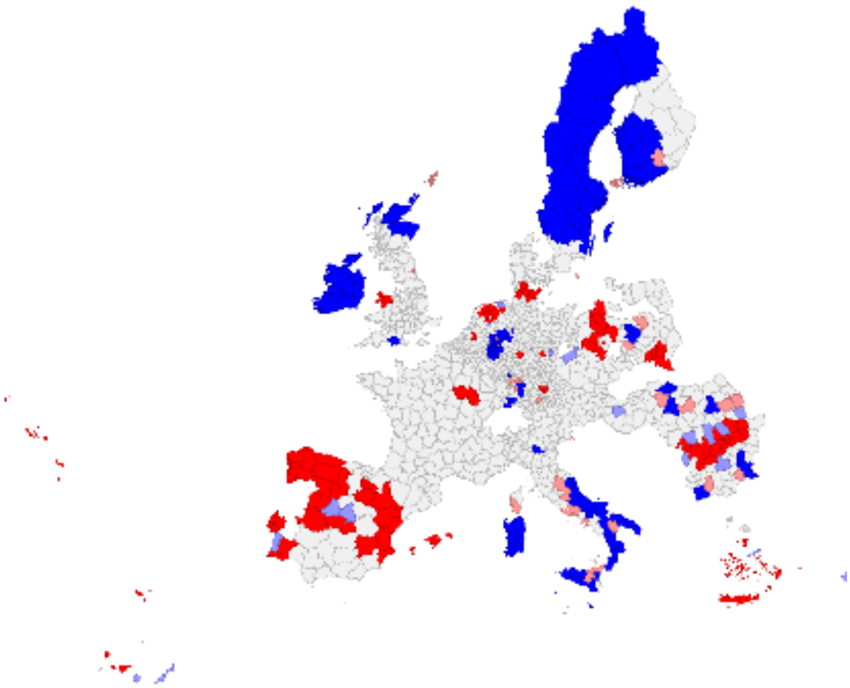


Figure 24- LISA cluster map of annual GDP per worker in PPS growth rate. Connectivity matrix based on a $K = 7$ nearest neighbours, years 2012-2014. Source: Own elaboration on ERD-CE dataset.

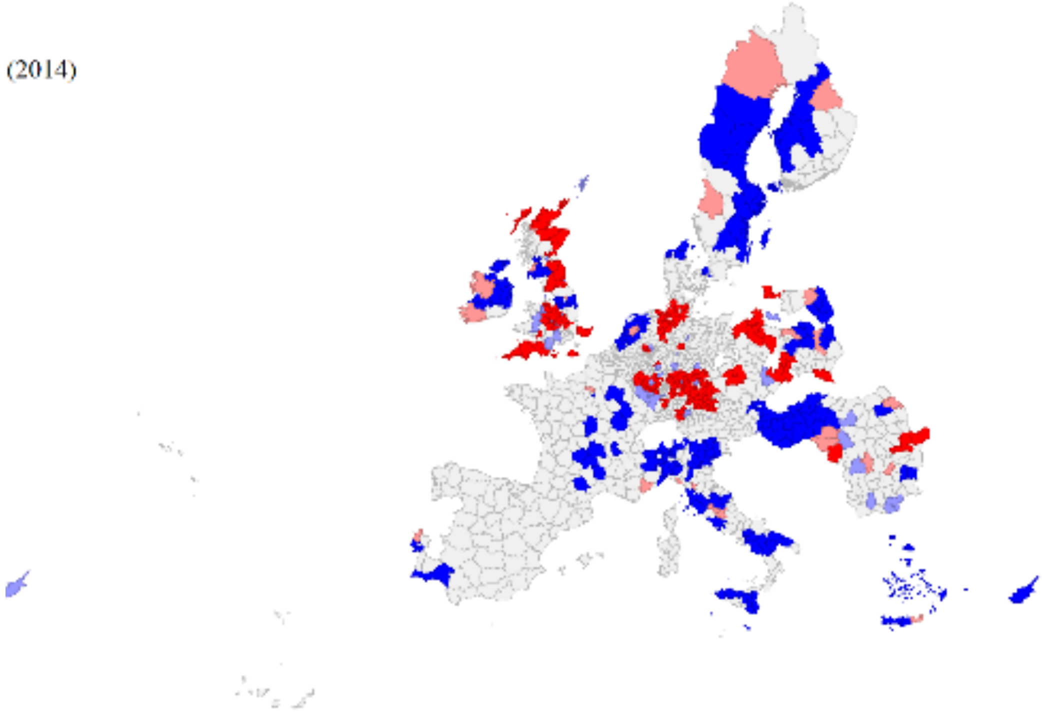
(2012)



(2013)



(2014)



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