**Location matters: a spatial econometric analysis of post-crisis economic growth in EU regions**

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**Abstract**

The aim of this study is to empirically examine regional economic growth in two distinct spatial regimes across the European Union (EU) from 2009 to 2015. In an effort to consider the regions as interconnected economic areas and account for spillover effects, the modelling approach incorporates complex spatial effects by considering both spatial heterogeneity and spatial dependence.

The analysis follows a step-wise approach. First, spatial heterogeneity in the EU is assessed by employing Exploratory Spatial Data Analysis (ESDA) to identify two distinct groups of regions on the basis of their regional Gross Domestic Product per capita in 2008. The two regimes clearly divide the EU territory into a north-west core, of relatively high income regions, and a south-east periphery, of lower income regions. Next, a Spatial Durbin Model is employed to estimate the determinants of regional growth in both spatial regimes and shed light on the significance of spillover effects. Complementing more traditional explanatory variables, this study employs components of the Regional Competitiveness Index – RCI – to explain growth differentials across EU regions. The inclusion of RCI components allows us to gain a more nuanced understanding of the causes of recent economic growth within each group of regions, as well as determine the degree to which specific factors of growth have significant spillover effects.

Empirical results indicate that while both spatial regimes experience processes of economic convergence, recent determinants of growth, as well as spillover dynamics, differ across the two groups of regions. In the high-income regime, better institutions, higher share of investment, and an economy specialized in higher value-added sectors significantly spur domestic growth, with the latter two also inducing positive spillover effects to neighbouring regions. In the low-income regime, low shares of lower-secondary educational attainment and higher shares of tertiary educational attainment

have a significant positive effect on domestic growth, with higher shares of tertiary educational attainment also inducing positive spillover effects.

**1. Introduction**

Within the discipline of economics, an abundance of research has been devoted to the study of economic growth. Since Solow's seminal contribution in 1956, the examination of growth dynamics has been at the forefront of theoretical and empirical inquiry. Correspondingly, regional scholars have explored the causes and characteristics of regional growth processes and have studied in depth the dynamics of regional convergence. While a profusion of research on regional growth emerged, much of the early empirical analyses (among others, Barro and Sala-i-Martin 1991, Carlino and Mills 1993, Armstrong 1995, Cheshire and Carbonaro 1995, Cheshire and Magrini 2000) did not consider the spatial dimension in which economic relationships take place and in so doing treated geographic units as "isolated islands" (Lim 2016, Rey and Janikas 2005, Quah 1996). In consequence, these early studies were unable to determine whether slow or fast growing regions were arbitrarily distributed or tended to cluster together. Moreover, they did not address to what extent a regions growth trajectory depended on or affected neighboring ones, thereby failing to account for spatial forces in regional growth dynamics (Lim 2016).

As Ertur et al. (2006) point out, numerous new economic geography theories advocate that "the geographical distribution of areas characterized by high or low economic activities is spatially dependent and tends to exhibit persistence". Rey and Janikas (2005) cite evidence suggesting that physical location and geographical spillovers may actually contribute more significantly to growth than traditional macroeconomic factors. As such, it is encouraging to note that the regional growth literature has since then benefitted from a growing number of empirical studies that explicitly take into account spatial effects, both in regard to spatial heterogeneity (Barro, 1991; Armstrong, 1995; Bivand and Brunstand, 2002; Baumont et al., 2003; Easterly and Levine, 2003; Roberts, 2004) and spatial dependence (Lopez-Bazo et al., 1999; Rey and Montouri, 1999; Fingleton 1999, 2004; Le Gallo and Dall'Erba, 2003; Le Gallo et al., 2003; Fischer and Stirboeck, 2004). The literature strongly confirms that space indeed matters in shaping regional growth (Dall'Erba et al. 2008).[1] Considering the geographic concentration of European countries and the common socio-economic policy framework pursued by the European Union (EU), it is of particular significance to empirically incorporate spatial dynamics into European regional growth analysis, in order to better understand spillover patterns among regions and thereby inform future policy development.

Spatial effects are composed of two kinds: spatial heterogeneity and spatial dependence (Anselin 1988). Spatial heterogeneity refers to the variation of underlying factors in growth processes that are contingent on the location of the respective unit of observation. Spatial dependence takes place when

[1] For a comprehensive literature review on the spatial effects literature see Abreu et al. 2005.

phenomena in one area depend on the values of phenomena in other locations. Hence, spatial heterogeneity is associated to absolute location whereas spatial dependence refers to relative location (Abreu et al. 2005). Absolute location refers to the particular point in space the geographic unit is situated in, thus possibly varying in climate, latitude or some other preordained factor. Relative location refers to the effect of being closer or further from other places, implying that one’s geographic position relative to others is what is of significance. While early research in the field often failed to address spatial heterogeneity before assessing spatial dependence, recent studies (Ertur et al., 2006; Ramajo et al., 2008; Lim, 2016) as well as this one benefit from the complementarity of the two effects, as Anselin (1988) suggests one ought to do.

Lim (2016) and Ertur et al. (2006) theoretically inspired and empirically guided this study. In Lim's (2016) regional income convergence is analysed across 177 economic areas in the United States from 1969 – 2008 by first applying Exploratory Spatial Data Analysis (ESDA) techniques to distinguish spatial regimes and account for spatial heterogeneity. Thereupon, Lim employs a spatial switching regression to test for convergence within the two regimes, finding substantive yet significantly different forms of convergence across the two. While Lim's results did not infer a convergence process among the more prosperous regime, it did indicate convergence patterns in the less prosperous regime, highlighting the different growth dynamics across the two spatial clubs. In a European setting, Ertur et al. (2006) sought to determine the significance of both spatial heterogeneity and spatial dependence in the estimation of conditional convergence processes in Europe. Identifying two spatial regimes through ESDA across 138 European regions from 1980 to 1995, the authors, using a spatial error model, find no signs of convergence in northern regions and only weak indications among southern regions. In a complementary step, they find highly significant spatial spillover effects within the respective spatial regimes – inferring that a region's average growth rate of per capita GDP is positively affected by the average growth rate of neighboring regions.

Employing a similar methodological framework, yet covering a wider scope and employing more recent data, it is the aim of this study to empirically examine the regional growth process in two distinct spatial regimes within the EU, from 2009 – 2015. In so doing, the study intends to both discern the recent determinants of economic growth and statistically assess the significance of spatial effects within the respective regimes. This will allow us to both test for spillover effects and determine their differing degrees of intensity within the two regimes. The study will contribute to the existing regional empirical growth literature in the following ways.

First, the study classifies spatial regimes according to patterns of economic development through an exploratory spatial data analysis approach consisting of the following steps:

1. The variogram analysis, one of the most popular instruments in geostatistics (Cressie 1984; Haining 2003; Thompson 1992) is employed across all the EU regions to identify the cut-off

distance beyond which spatial correlation is not significant. The distance adopted is the travel time along the road network, a more pertinent measure when investigating economic relationships across regions. To our understanding, this study is the first one adopting both the travel time distance and the variogram analysis to statistically identify the cut-off distance.

2. Moran's I and Geary's C global indexes of spatial autocorrelation (Geary 1954; Moran 1950) are then computed on initial values of regional GDP per capita (2008) to identify clusters of high-high or low-low regions, representing our spatial regimes. These indexes are computed using the travel time distance and the cut-off distance identified in Step 1.

Next, a set of spatial econometric models are used to determine the spatial growth dynamics within the spatial regimes identified in Step 2. Both unconditional and conditional convergence is tested, using the components of the *Regional Competitiveness Index* (Annoni and Dijkstra, 2017) as explanatory variables. This allows us to gain a more nuanced understanding of the causes of economic growth within the spatial regime as well as the degree to which specific factors of growth have significant spillovers effects. Few spatial growth studies to date have gone beyond a general analysis of unconditional convergence, making this study a valuable source of insight for a more detailed and comprehensive understanding of the determinants of regional growth.

Furthermore, as Lim (2016) points out, the matter of what spatial units are most appropriate to use has received little attention so far. Among studies of European regions, the NUTS level-2 region is a prominent choice due to vast data availability. However, it remains uncertain whether such administratively defined regions are most suitable, since they sometimes are "neither economically homogeneous entities nor are they self-contained with respect to labor markets" (Lim, 2016) and thereby may cause nuisance spatial dependence.[2] Using functionally instead of administratively defined regions can help in reducing nuisance spatial dependence (Magrini, 2004). In a first step to address this issue, our study employs six Functional Urban Areas (FUA), as defined by Dijkstra and Poelman (2014), that would be particularly misrepresented if assessed strictly according to their NUTS-2 classification due to the significance of their commuting zones' impact on economic activity[3]. This contribution is an initial effort to better consider the suitability of spatial units in regional growth analyses.

Finally, the time period considered (2009 – 2015) purposefully sets the focus on growth dynamics in post-crisis Europe. While a long-term study of growth has its relevance, this analysis aims at investigating the recent growth patterns across and within different spatial regimes in the EU to offer

[2] Nuisance spatial dependence is defined by Lim (2016) as the result from a mismatch between geographic boundaries of the economic processes and the boundaries of the observational units.
[3] Defined by DG Regio of the European Commission, the FUAs are: Amsterdam, Berlin, Brussels, London, Prague, and Vienna.

insight into future growth dynamics and better inform European policy development for the regionally interconnected reality of the 21st century.

The remainder of the study is structured as follows. Section 2 presents the framework and data used in the analysis. Section 3 describes the exploratory spatial data analysis approach used to determine the spatial regimes, which includes a description of the variogram analysis, the ensuing spatial weight matrix and the Moran's I statistic. Section 4 outlines the empirical methodology of this study and presents the econometric results. Section 5 concludes and presents implications that can inform future regional growth policy.

## 2. Empirical Framework & Data Description

The empirical analysis is based on cross-sectional data from 2008 to 2015, the most recent year for which regional Gross Domestic Product (GDP) data was available across the EU. Please note that hereafter, the study refers to *regional* as synonymous with *NUTS 2 level*[4].

Our analysis is based on the theoretical growth framework pioneered by Solow, which controls for a regions initial GDP per capita as a proxy for its initial capital endowment (Solow 1956, Barro, Sala-i-Martin 1992). This basic model assumes that all regions feature the same structural characteristics, which is clearly an implausible assumption. As such, other explanatory factors are included in our model. In line with the literature , the regional factors included in our analysis range from human to physical capital, from levels of employment to the quality of institutions, from business sophistication to technological readiness. (Mankiw et al. 1992, Rodrik et al. 2004, Kwok, Tadesse 2006, Crescenzi, Rodriguez-Pose 2008, Mohl, Hagen 2010, Rodriguez-Pose 2013, Rodriguez-Pose, Garcilazo 2013, Pescatori et al. 2014, Annoni and Catalina Rubianes, 2016).

The dependent variable is based on average growth rates of regional GDP per capita in constant prices (reference year 2010) in the period 2009 – 2015. The initial GDP per capita in 2008 is measured in Purchasing Power Standards (PPS). Regional GDP data is from Eurostat and when necessary is supplemented by DG Regional and Urban Policy of the European Commission[5].

[4] The NUTS classification (Nomenclature of Units for Territorial Statistics) is a hierarchical system the European Statistical Office - EUROSTAT - employs for dividing the economic territory of the EU for the collection, development and harmonization of European regional statistics. There are different levels of NUTS regions: NUTS 0 corresponds to the country level while levels 1, 2, and 3 correspond to sub-national levels of smaller and smaller territorial units in terms of population.

[5] In some countries, NUTS 2 level growth rates are not readily available and thus are internally estimated by European Commission DG Regional and Urban Policy. This is performed by regionalising national GVA at constant prices with regional GVA at current prices by sector. Combining the Eurostat real growth rates with those estimated internally, they are applied to the current GDP to obtain the GDP in constant prices at NUTS 2 level.

This study employs the components of the 2010 *Regional Competitiveness Index* (Annoni and Kozovska, 2010) as explanatory variables for economic growth and its determinants across European regions. The *Regional Competitiveness Index* (RCI), published in 2010, 2013 and 2016, is a composite indicator which provides a synthetic picture of territorial competitiveness for each of the NUTS 2 regions in the EU. It consists of eleven components, nine of which have been adopted in our analysis of regional economic growth. The 2010 edition of the RCI is used in this analysis since its indicators are measured close to the starting year of our analysis (2008). The included components of the RCI as well as any details of modifications performed for this study are briefly outlined below.

1. *Institutions*

The significance of institutions and good governance as a determinant of economic growth has gained increased attention and consequent validation over the last decade. This study employs the European Quality of Government Index (EQI) (Charron et al, 2014), the sole measure of institutional quality available at the regional level across the EU. The index is based on an ad-hoc survey that measures three different broad aspects of governance within countries: corruption, impartiality and quality. While the regional EQI values were not available at the time the RCI 2010 was published, they have since become available and are therefore included in this study.

2. *Infrastructure*

Modern and effective infrastructure contributes to both economic efficiency and territorial equity as it allows for the maximisation of the local economic potential and the optimal use of resources (Crescenzi and Rodriguez-Pose, 2008). High quality infrastructure guarantees easy access to other regions and countries, contributes to better integration of peripheral and lagging regions, and facilitates the movements of goods, people and services (Schwab and Porter, 2007). This has a strong impact on competitiveness as it increases the efficiency of regional economies. This study uses the infrastructure component employed by the RCI as of 2013 onwards, whose motorway and railway infrastructure is based on 'potential accessibility' indicators. Potential accessibility is a concept based on the assumption that the attraction of a destination increases with its population size, a proxy for the market size, and declines with travel time (Spiekermann and Wegener, 1996).

3. *Education*

High levels of basic skills and competencies increase the ability of individuals to subsequently perform well in their workplace and potentially continue to tertiary education. A number of studies have found a significant positive association between quantitative measures of schooling and economic growth (see Sianesi and Reenen, 2003 or Krueger and Lindahl, 2001, Hanushek, E. A., and Wößmann, 2007) for an overview). Moreover, knowledge-driven economies based on innovation require well-educated human capital; not merely for knowledge generation but also in order to be able to adopt technologies developed elsewhere. This study replaces the RCI component of basic education, measured at the national level, with a regional indicator from Eurostat. The *lower secondary education* indicator included in the analysis measures the share of population with at most lower secondary educational attainment (ISCED levels 0-2). The *higher education, training, and life-long learning* component is adopted directly from the RCI 2010 and encompasses indicators such as population shares of tertiary educational attainment, accessibility to universities and higher education expenditure.

4. *Market Size*

This component describes the level of regional economic welfare and the size of the market available to firms. Larger markets allow firms to develop and benefit from economies of scale and encourage entrepreneurship and innovation. All the regions in the EU are part of the single market, which upholds the freedom of movement for goods, capital and people. As a result, one could argue that market size is the same for all EU regions. However, the access to the single market is likely to differ in terms of costs in time and money. For example, market accessibility is not the same for Northern Sweden compared to Bavaria, due to their geographic location. Therefore, in the RCI, the market size component includes measures of both potential access to GDP and to the population within and beyond its region (Annoni and Kozovska, 2010).

5. *Labour Market Efficiency*

Effective and flexible labour markets contribute to an efficient allocation of resources (Schwab and Porter, 2007) and are an important determinant of regional competitiveness. This component consists of both long and short-term unemployment rates, employment rates, labour productivity measures, as well as indicators of gender balance.

6. *Technological Readiness*

This component measures the degree to which households and enterprises use technology. Information and communication technologies (ICT) have profoundly changed the organisational structure of firms, facilitating the adoption of new and more efficient work practices and lifestyles, which improve productivity and speed-up commercial processes. Hence, the use of ICT has become an essential element of competitiveness. This component captures the use of ICT by households (private use) and by enterprises (business use).

7. *Business Sophistication*

The level of business sophistication provides an indication of the region's productivity and its responsiveness to competitive pressures. Specialisation in high value added sectors positively contributes to regional competitiveness. This component includes indicators related to employment and Gross Value Added (GVA) in sectors such as Information and Communication (NACE sector J) and Financial and Insurance activities (NACE sector K). Indicators for Foreign Direct Investment (FDI) and the strength of regional clusters are also included.

8. *Innovation*

As Schwab and Porter (2007) point out, innovation is especially relevant for developed economies. Maintaining their competitive advantage necessitates being at the forefront of new technologies, in order to be able to produce cutting-edge products and pioneer innovative processes. Research confirms that knowledge production is geographically concentrated. Feldman (1993) suggests that innovative firms tend to locate in areas with resources, which thereupon multiply due to a region's success with innovations. This component captures both the regional potential to innovate as well as its actual performance in innovative activities, by including indicators such as *employment in science and technology, patent applications, knowledge workers* and *R&D expenditures*.

The inclusion of RCI components allows us to gain a more nuanced understanding of the causes of recent economic growth within each spatial regime, as well as determine the degree to which specific factors of growth produce significant spillover effects.
Following Mankiw et al. (1992) we also control for other variables: population growth and regional investment. Population growth is measured as average population growth over the period 2008 – 2015. Investment is proxied by Gross Fixed Capital Formation at the NUTS2 level and is included in the regression as an average share of GDP from 2009-2015.

The spatial units of analysis in this study consist of both NUTS 2 regions and Functional Urban Areas (FUA). The majority of the spatial units of analysis employed in this study are at the NUTS 2 level. As discussed above, however, the study also incorporates six FUAs. As per the EU-OECD definition, FUAs consist of a city and its commuting zones (Eurostat Glossary). The FUAs defined in this study are: Amsterdam, Berlin, Brussels, London, Prague, and Vienna.

## 3. Identification of Spatial Regimes through Exploratory Spatial Data Analysis (ESDA)

Moran's *I* and Geary's *C* indexes are employed to test for global spatial autocorrelation (Geary 1954; Moran 1950). They both compare the value of the variable of interest, in our case the starting GDP per capita, in any one region with the value in all other neighbouring regions, within a pre-defined neighbouring area. If neighbouring regions over the entire area of observation have similar (dissimilar) values, then both statistics indicate a strong positive (negative) spatial autocorrelation.

The two indexes are related but not identical. Moran's I varies between -1 (perfect dispersion) and +1 (perfect spatial correlation). Perfect dispersion means that high values are always surrounded by low values and vice-versa. Perfect correlation indicates that there is always a concentration of above (below) average values spatially close to other above (below) average values (high-high or low-low). Under the null hypothesis of no spatial correlation, the expected value of the Moran's $I$ – $E[I]$ – depends solely on the number of regions ($n$). Values of $I$ larger than $E[I]$ indicate positive spatial autocorrelation, while values smaller than the expected indicate negative spatial autocorrelation. The value of Geary's $C$ lies between 0 and 2 with 1 meaning no spatial autocorrelation. Values lower than 1 demonstrate increasing positive spatial autocorrelation, whilst values higher than 1 illustrate increasing negative spatial autocorrelation. For both indexes, inference is based on the permutation approach, assuming that, under the null hypothesis, each observed value could have occurred at all locations with equal likelihood. A reference distribution can be empirically generated and significance values can be computed.

Both indexes depend on the definition of the neighbouring area of each region $k$ that, in turn, is defined on the basis of the spatial weight matrix $W(k)$. The specification of $W(k)$ is a much debated issue in the literature (Abreu et al, 2005) since the choice of spatial weights can profoundly impact the results. In cases where the spatial weight matrix is not a contiguity matrix, which is when neighbouring regions are simply defined as those sharing a boundary, two elements are of key importance in the specification of $W(k)$: the type of distance and the limit to the range of spatial dependence, the so-called cut-off distance. This paper offers innovative solutions on both fronts.

First, the distance employed in this study is the estimated travel time distance by road (ferry), which connects the regions along the actual road (ferry) network. Travel time distances are derived from the TRANSTOOLS road network tool, a European transport network model developed by the European Commission[6]. We consider this type of distance measurement a more realistic one than the classical Euclidean distance between regions' centroids, especially since urban areas in the EU are often located in highly congested networks.

[6] http://energy.jrc.ec.europa.eu/transtools/

Secondly, the cut-off distance, which is generally selected solely on the basis of theoretical consideration, is defined in our study by means of the Variogram Analysis, which is one of the most popular instruments in Geostatistics (Cressie 1984; Haining 2003; Thompson 1992).The variogram is a function estimated on georeferenced observed data, which describes their spatial dependencies. The shape of the estimated variogram function indicates the structure of spatial autocorrelation in the observed data. The variogram function is defined as the variance of the difference of the value of the variable of interest *y* at separate points (regions) across the area of interest:

$$2\gamma(h) = \mathrm{Var}[y_{i+h} - y_i] \tag{1}$$

where $y_i$ is the value of *y* at region *i* and $y_{i+h}$ is the value of *y* in a region separated from region *i* by the distance *h* . The function $\gamma(h)$ is called semi-variogram and describes the spatial dependence structure. In our case $y_i$ is the value of GDP per capita in region *i* at the beginning of the period under investigation (2008) and the distance is the travel time distance along the road network between regions.

With the assumption of 'second-order stationarity' (Cressie 1984), the semi-variogram is considered to be valid over the entire set of data and the relationship between the semi-variogram and the covariance of *y* is:

$$\begin{aligned} &\mathrm{Cov}[y_{i+h}, y_i] = \mathrm{E}[y_{i+h} \cdot y_i] - \mathrm{E}^2[y_i] = \mathrm{E}[y_{i+h} \cdot y_i] - \mu^2 \equiv C(h) \\ &\gamma(h) = \mathrm{Var}(y) - C(h) \end{aligned} \tag{2}$$

The estimated (semi-)variogram $\hat{\gamma}(h)$ is computed as:

$$2\hat{\gamma}(h) = \frac{1}{n(h)} \sum_i (y_{i+h} - y_i)^2 \tag{3}$$

where the summation is over all distinct pairs of regions that are *h* distance apart and $n(h)$ is the number of region pairs that are *h* distance apart. Values of $\hat{\gamma}(h)$ are close to zero if values in regions separated by distance *h* are highly correlated. Values of $\hat{\gamma}(h)$ increase as the correlation among neighbouring regions decreases. The variogram is therefore a measure of spatial dissimilarity.

The variogram function is generally estimated by fitting the best curve to the observed data. The shape of $\hat{\gamma}(h)$ provides a graphical description of the structure of the spatial dependence at different distances. The shape generally shows a strong spatial dependence at short distances that decreases as *h* increases up to a certain distance, called the range, beyond which the level of spatial dependence levels off to nearly zero. The range of the empirical variogram specifies the maximum distance beyond which spatial correlation can be considered null, indicating the cut-off distance of the spatial weight matrix $W(k)$.

Initial GDP per capita levels (2008) across all EU regions and travel time distances across the road network are used to estimate the empirical variogram (Figure 1). The shape we find is typical, with the level of spatial correlation gradually decreasing as distances increase. The empirical cut-off distance is approximately 500 minutes, at which point the function levels off.

The weights that are used in the spatial weight matrix in the rest of the analysis are defined as the inverse of travel time distances with a cut-off of 500 minutes.

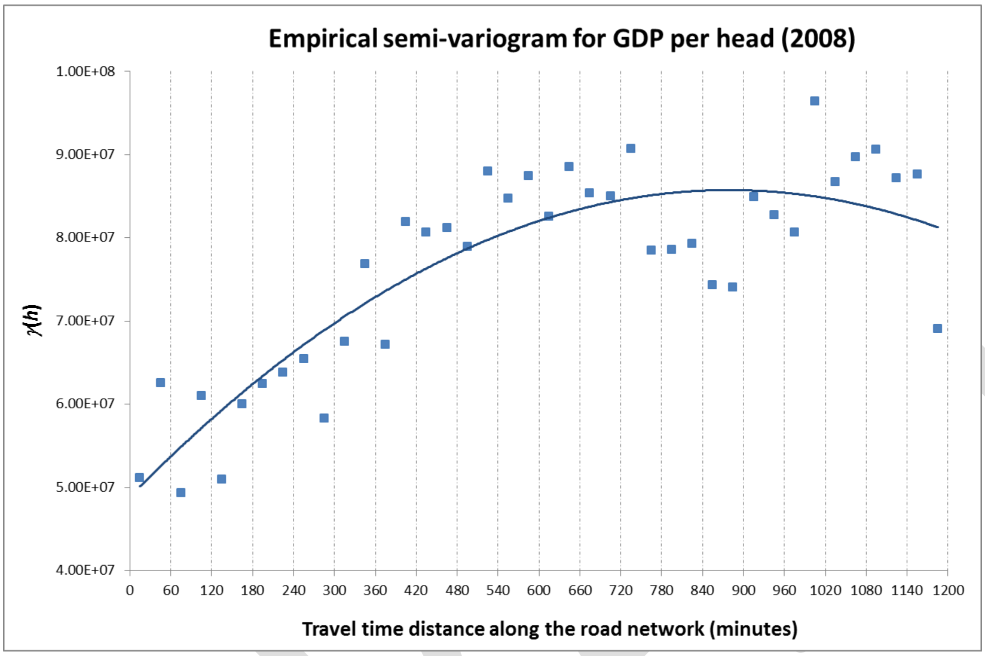


**Figure 1: Empirical semi-variogram based on GDP per capita (2008) for all the EU regions**

The global spatial autocorrelation indexes, Moran's *I* and Geary's *C*, are computed for the whole EU for the initial GDP per capita across all the years of the analysis with a spatial weight matrix based on the inverse of travel time distance with a cut-off of 500 minutes (Table 1). The values of both indexes and their p-value, always less than 0.0001, indicate a significant spatial autocorrelation pattern across the EU for the entire time period (2008-2015).

**Table 1: values of Moran's *I* and Geary's *c* for the whole EU in the years 2008-2015**

| Moran's *I* on GDP per capita | | | | | |
|---|---|---|---|---|---|
| Year | I | E(I) | sd(I) | z | p-value* |
| 2008 | 0.31 | 0.00 | 0.02 | 17.05 | 0.000 |
| 2009 | 0.31 | 0.00 | 0.02 | 16.83 | 0.000 |
| 2010 | 0.31 | 0.00 | 0.02 | 17.08 | 0.000 |
| 2011 | 0.33 | 0.00 | 0.02 | 17.92 | 0.000 |
| 2012 | 0.33 | 0.00 | 0.02 | 18.11 | 0.000 |
| 2013 | 0.33 | 0.00 | 0.02 | 17.88 | 0.000 |
| 2014 | 0.32 | 0.00 | 0.02 | 17.68 | 0.000 |
| 2015 | 0.31 | 0.00 | 0.02 | 17.04 | 0.000 |
| *1-tail test | | | | | |

| Geary's *c* on GDP per capita | | | | | |
|---|---|---|---|---|---|
| Year | c | E(c) | sd(c) | z | p-value* |
| 2008 | 0.71 | 1.00 | 0.03 | -11.36 | 0.000 |
| 2009 | 0.71 | 1.00 | 0.03 | -11.23 | 0.000 |
| 2010 | 0.71 | 1.00 | 0.03 | -11.32 | 0.000 |
| 2011 | 0.70 | 1.00 | 0.03 | -11.73 | 0.000 |
| 2012 | 0.69 | 1.00 | 0.03 | -12.10 | 0.000 |
| 2013 | 0.70 | 1.00 | 0.03 | -11.71 | 0.000 |
| 2014 | 0.70 | 1.00 | 0.03 | -11.33 | 0.000 |
| 2015 | 0.71 | 1.00 | 0.03 | -11.13 | 0.000 |
| *1-tail test | | | | | |


**Figure 2: Moran's I scatterplot on GDP per capita (2008).**

Moran's *I* scatterplot (Figure 2) visualizes the spatially weighted average GDP of all of region *i*'s neighbours on the GDP of region *i* (Anselin 1995; Ertur & Koch 2006). The different quadrants correspond to four types of local spatial association: High-High (HH), Low-Low (LL), Low-High (LH) and High-Low (HL). HH regions are those with GDP per capita above the EU average surrounded by neighbouring regions with a spatially-weighted average GDP above the EU average as well. Similar logic follows for the other categories. The most represented category of regions is the LL one, which includes 93 regions, closely followed by the HH category, which includes 89 regions. The LH category and the HL category include 56 and 16 regions respectively. Most of the regions in the HL category are either FUAs (Section 2) or capital regions: Vienna and Prague, with their respective communing belts, in addition to Madrid, Lisbon, Athens, Helsinki, Budapest, Bucharest and Bratislava. These regions can be considered as *ivory towers*, representing anomalies rather than the mainstream pattern of spatial dependence across the EU.

This study does not pursue a spatial econometric analysis with the four categories identified by the Moran's *I* scatterplot for several reasons. Primarily, the number of regions in two of the categories, HL and LH, is not high enough to generate reliable model estimates. Furthermore, Moran's *I* scatterplot relies solely on GDP per capita and does not take into account all the other explanatory variables that we seek to include in the model. Finally, most of the region i's in the LH quadrant have a GDP per capita very close to the EU average (see in Figure 2 how they are clustered towards the centre of the scatterplot, which represents the EU average of GDP per capita).

These observations led us to instead define two regimes out of the four identified by the Moran's *I* scatterplot. To this aim, an analysis of variance – ANOVA (Morrison, 2005) – on all the explanatory variables is carried out with all possible combinations of the four regimes. The ANOVA results (see Appendix) show that the highest polarisation of the explanatory variables is obtained by keeping the LL regime as a regime by itself while grouping the other categories into a single regime {HH,LH,HL}.

The two regimes, referred to from now on as *Low* for the LL regions and *High* for the HH, HL, and LH regions, clearly divide the EU into a north-centre core and a south-east periphery (Figure 3).

Descriptive statistics of all the variables included in the analysis is provided in the Appendix separately for the two spatial regimes.

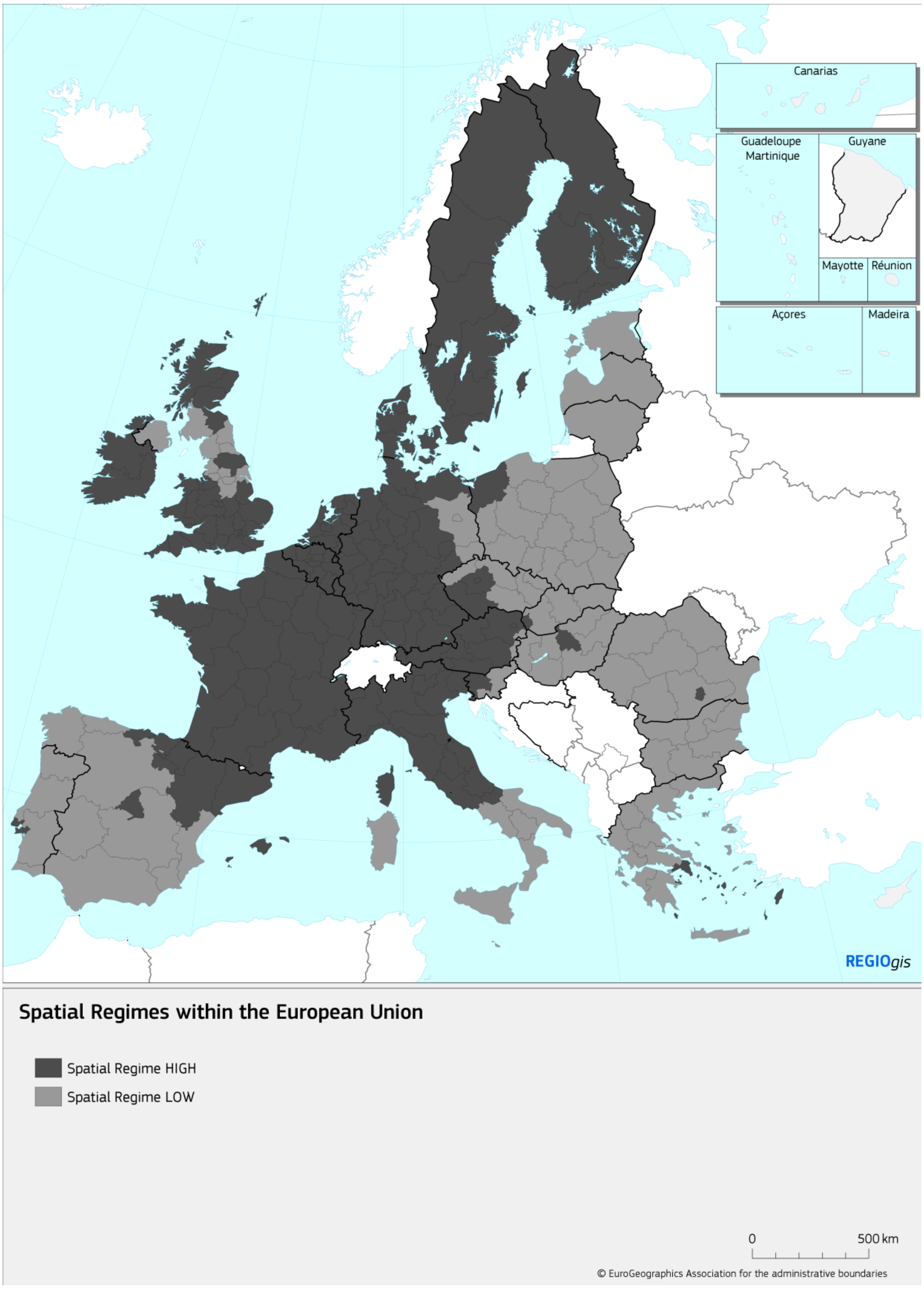


**Figure 3: The two spatial regimes identified by Moran's I scatterplot and ANOVA analysis**

## 4. Empirical model and estimations

Conventional growth regressions assume that variables observed at the regional level are independent, but there is an established consensus that regional economic growth rates exhibit spatial dependence (Abreu et al., 2005, Ertur et al., 2006, and de Dominicis, 2014, among others). Spatial regression models allow us to account for such dependence between observations, which are likely to occur when observations are collected at the level of territorial units (i.e. EU regions).

LeSage and Fisher (2008) argue that the conjunction of two specific circumstances in applied spatial growth regression modelling make the Spatial Durbin Model (SDM) specification a natural choice over competing alternatives. First, the presence of spatial dependence in the error terms of the OLS regression model. Second, the existence of an omitted spatially dependent variable (or variables) that is correlated with an included variable. The SDM (Anselin, 1988) includes the spatial lag of the dependent variable as well as spatial lags of all explanatory variables. The model we estimate is the following:

$$g = \beta_0 + \rho W g + \beta_1 X + \beta_2 W X + \epsilon \qquad (4)$$

where:

$g$ = growth rate of GDP per head in the period of interest, 2009-2015

$W$ = the spatial weight matrix $W$ (based on inverse travel time distance, with cut-off at 500 minutes)

$X$ = set of explanatory variables

$\epsilon$ = normally distributed error term

The terms $Wg$ and $WX$ are labelled spatial lag of the dependent and of the explanatory variables, respectively. $Wg$ represents a spatially weighted linear combination of the initial growth rate in neighbouring regions; while $WX$ represents a spatially weighted combination of characteristics in neighbouring regions.

Results of the OLS estimations of the specification in equation (4) are first discussed, without considering the spatially lagged variables in the right hand side (that is, we assume that parameters $\rho$ and $\beta_2$ are equal to zero). This approach is similar to the 'specific to general' coefficients search approach as suggested by Florax et al. (2003). The result of the spatial Chow test in Table 2 clearly confirms the rejection of the null hypothesis, suggesting significantly different coefficients in each of the two regimes. We therefore present results only for columns 2 and 3 of Table 2, looking at the different impact of the explanatory variables in the two groups of EU regions.

**Table 2. Estimation results of the OLS**

| | **(1) OLS No regimes** | **(2) OLS High income** | **(3) OLS Low income** |
|---|---|---|---|
| **Constant** | 27.55*** | 25.07*** | 34.18*** |
| | (3.11) | (4.71) | (5.60) |
| **Initial GDP per head (ln)** | –2.46*** | –2.19*** | –3.25*** |
| | (0.31) | (0.47) | (0.58) |
| **Average INV/GDP (ln)** | 0.86** | 1.06* | 0.72 |
| | (0.43) | (0.60) | (0.64) |
| **Average population growth** | –0.01 | –0.00 | –0.01 |
| | (0.02) | (0.02) | (0.02) |
| **EQI (RCI component)** | 0.21 | 0.43** | –0.20 |
| | (0.15) | (0.19) | (0.25) |
| **Low secondary** | –0.03*** | –0.03*** | –0.01 |
| | (0.01) | (0.01) | (0.01) |
| **High educated (RCI component)** | -0.09* | 1.05*** | 0.84*** |
| | (0.17) | (0.37) | (0.32) |
| **Potential accessibility (RCI component)** | –0.31*** | –0.31** | –0.45 |
| | (0.12) | (0.14) | (0.36) |
| **Technological readiness (RCI component)** | 0.42*** | 0.16 | 1.19*** |
| | (0.16) | (0.20) | (0.28) |
| **Business sophistication (RCI component)** | 1.09*** | 1.25*** | 0.07 |
| | (0.19) | (0.27) | (0.33) |
| Adj R-squared | 0.49 | 0.52 | |
| Chow test | | Significant difference between the two regimes | |
| **Spatial diagnostics** | | | |
| Moran's *I* (residuals) | 0.21*** | 0.16*** | |
| LMerr | 118.9*** | 64.32*** | |
| RLMerr | 31.15*** | 10.27*** | |
| LMlag | 100.41*** | 69.38*** | |
| RLMlag | 12.61*** | 15.32*** | |
| Number of observations: | 254 | 254 | |

*Note:* the dependent variable is the average annual growth rate of GDP per head between 2008 and 2015. Standard errors are shown in parentheses, and statistical significance levels are labelled with ***, **, and * referring to the 1, 5 and 10 percent significance level, respectively.

The coefficient associated to the initial level of GDP is negative and highly significant, in agreement with the conventional empirical literature on convergence. This suggests that the "catching-up" hypothesis, in which poorer economies grow faster than the richer ones, is confirmed, with regions in the low-income group growing at a faster pace. Higher growth rates are related to higher shares of investment over the period, particularly in the high-income group of regions. The quality of institutions is found to be a strong determinant of economic growth especially for richer economies, as can be seen by comparing the estimated coefficient of EQI in the two regimes. The significance of the quality of institutions for economic development is in line with recent literature on the topic (Rodrik et al. 2004, Kwok and Tadesse 2006, Rodriguez-Pose 2013), as is the fact that it exhibits a stronger effect among more developed economies (Annoni and Rubianes, 2016). Higher shares of lowly educated workers is detrimental to growth, especially in less developed economies, as also observed in recent literature (OECD 2012; Annoni and Rubianes, 2016). High shares of highly skilled workforce are an important factor for growth as well. In addition we observe that technological readiness is a significant factor for growth in less developed economies. Meanwhile, in richer regions an economy specialised in high value-added sectors appears to be a significant driver of growth.

The results of the spatial model diagnostics, presented at the bottom of Table 2, clearly indicate a potential problem of spatial autocorrelation. The Moran's *I* statistic for spatial autocorrelation applied on the residuals of the OLS is positive and highly significant, indicated that the model is misspecified. While Moran's *I* statistic has great power in detecting misspecifications in the model (not only spatial autocorrelation), it is less helpful in suggesting which alternative specification should be used. To overcome this limitation, it is common practice in the empirical spatial econometric literature to use the results of the Lagrange Multiplier (LM) test on the estimated OLS residuals to determine whether the true data generating process is a spatial lag or a spatial error model (Anselin and Florax 1995).

The analysis of the results of the LM test suggests the use of the spatial error model in the case of one regime, and the spatial lag model for the situation in which different spatial regimes are included. We adopt a different approach, selecting the SDM on the basis of LeSage and Fisher's (2008) discussion on the suitability of the SDM to estimate spatial growth regression. In addition, as explained by LeSage and Pace (2009) and Elhorst (2010), the cost of ignoring spatial dependence in the dependent variable and/or the independent variables is relatively high, since the coefficients estimated for the remaining variables are biased and inconsistent (Greene, 2005). On the contrary, ignoring spatial dependence in the disturbance term, if present, will still produce unbiased coefficients, although with a loss in efficiency.

A Spatial Durbin Model is therefore estimated, with both one and two spatial regimes. The results of the spatial Chow test in Table 3 point again at significant differences between the coefficients estimated in each regime. The existence of spatial externalities is strongly supported for the case of the lagged value of the dependent variable, highlighting the presence of spatial dependence between regional growth rates, confirming that OLS is not the most suitable estimator for our model.

As opposed to an OLS model (and other spatial models such as the spatial error model), the coefficients presented in Table 3 cannot be directly interpreted as marginal effects since the SDM model includes the spatially lagged value of the dependent variable (LeSage and Pace 2009; Elhorst, 2010). In all spatial regression models that include the spatial lag of at least the dependent variable, explanatory variables have both direct and indirect effects on the dependent (growth). The direct effect shows how a change in the *r*th explanatory variable in a region affects, on average, the dependent (growth) in that region. Direct effects are not region-specific and are represented by the estimated coefficient $\beta_1$ (see equation 4). Indirect effects are spillovers of the direct effects and are local in nature: only the region where the *r*th explanatory variable changed and its neighbours are affected. In the SDM, which includes the spatial lag of both the dependent and the explanatory variables, indirect effects are also induced by first-order and higher-order neighbours of region *i* (the neighbours of the neighbours of *i*, that includes region *i* itself). In other words, in the SDM, the direct effect refers to the extent to which regional growth in one region is affected by a shock in the region's explanatory variables. The indirect effect measures the extent to which a change in the explanatory variables in neighboring regions affects regional growth in the region itself, but also how a change in the explanatory variables in the region affects the region itself through feedback effects from its neighbours (Abreu et al., 2005; LeSage and Pace, 2014).

Table 5 presents the computation of the direct and indirect impacts in the two spatial regimes. In high-income regions, we observe positive direct effects of investment, institutional quality and specialization in high value-added sectors on regional growth, and a negative direct impact of a lowly educated working-age population. Higher shares of investment as well as a more 'sophisticated' economy also appear to produce significant positive spillovers in neighboring regions, as indicated by the indirect effects. Given that most of the so-called middle-income regions fall into our high-income spatial regime, these results can inform the debate on middle-income regions and how the infamous "middle-income trap" can be avoided (Iammarino et al., 2017; European Commission, 2017). Our findings indicate that sustaining levels of investment and moving-up the value chain may offer a path out of or around the middle-income trap, in line with the smart specialization policy supported by the European Commission (European Commission, 2013).

Among low-income regions in the EU, investment in human capital appears as the main determinant of economic growth in the years during and after the economic and financial crisis. Indeed, we find that higher education has a significant and positive impact on growth (a variable that in our case also includes investment in higher education and accessibility to tertiary education). This effect is not limited within regional borders but has significant spillover effects into neighboring regions. In addition, and in line with the results found for the high-income regions, a high share of lowly educated workers is detrimental to growth.

**Table 3. Estimation results of the spatial DURBIN model (SDM)**

| | Spatial DURBIN No regimes | Spatial DURBIN High income | Spatial DURBIN Low income |
|---|---|---|---|
| **Constant** | 7.19 | | |
| | (7.29) | | |
| **Initial GDP per head (ln)** | –1.36*** | –1.67*** | –1.82*** |
| | (0.32) | (0.43) | (0.52) |
| **Average INV/GDP (ln)** | 0.50 | 0.90* | 0.35 |
| | (0.37) | (0.49) | (0.55) |
| **Average population growth** | –0.01 | 0.01 | –0.01 |
| | (0.02) | (0.02) | (0.02) |
| **EQI (RCI component)** | 0.31** | 0.41** | –0.08 |
| | (0.15) | (0.19) | (0.21) |
| **Low secondary** | –0.02** | –0.03*** | –0.03*** |
| | (0.01) | (0.01) | (0.01) |
| **High educated (RCI component)** | 0.04 | –0.22 | 0.59** |
| | (0.16) | (0.18) | (0.27) |
| **Potential accessibility (RCI component)** | –0.41*** | –0.16 | 0.19 |
| | (0.14) | (0.15) | (0.34) |
| **Technological readiness (RCI component)** | 0.20 | 0.10 | 0.28 |
| | (0.16) | (0.18) | (0.27) |
| **Business sophistication (RCI component)** | 0.58*** | 0.79*** | –0.32 |
| | (0.18) | (0.23) | (0.29) |
| **GDP per head (ln), lag** | 1.26 | –5.53* | –5.17** |
| | (0.82) | (2.86) | (2.44) |
| **INV/GDP (ln), lag** | 3.20** | 5.61** | –6.28* |
| | (1.43) | (2.26) | (3.54) |
| **Population growth, lag** | –0.07 | –0.42*** | 0.06 |
| | (0.05) | (0.10) | (0.10) |
| **EQI, lag (RCI component)** | –1.52*** | –0.15 | –1.73*** |
| | (0.46) | (0.91) | (0.65) |

*Note:* the dependent variable is the average annual growth rate of GDP per head between 2008 and 2015. Standard errors are shown in parentheses, and statistical significance levels are labelled with ***, **, and * referring to the 1, 5 and 10 percent significance level, respectively.

**Table 3. Continued: Estimation results of the spatial DURBIN model**

| | Spatial DURBIN No regimes | Spatial DURBIN High income | Spatial DURBIN Low income |
|---|---|---|---|
| **Low secondary, lag** | 0.03* | 0.02 | 0.14*** |
| | (0.02) | (0.05) | (0.04) |
| **High educated, lag (RCI component)** | 0.13 | –1.68*** | 3.85** |
| | (0.44) | (0.65) | (1.56) |
| **Potential accessibility, lag (RCI component)** | 0.76** | –1.90*** | –0.27 |
| | (0.33) | (0.64) | (1.31) |
| **Technological readiness, lag (RCI component)** | 1.00* | 0.93 | 4.30*** |
| | (0.53) | (0.83) | (1.17) |
| **Business sophistication, lag (RCI component)** | –0.96 | 4.38*** | 5.99*** |
| | (0.62) | (1.17) | (1.38) |
| **Growth rate in neighbouring regions** | 0.78*** | 0.38*** | |

*Note:* the dependent variable is the average annual growth rate of GDP per head between 2008 and 2015. Standard errors are shown in parentheses, and statistical significance levels are labelled with ***, **, and * referring to the 1, 5 and 10 percent significance level, respectively.

**Table 5. Post estimations: Impacts for the spatial DURBIN model**

| | High Income | | | Low Income | | |
|---|---|---|---|---|---|---|
| | Direct effect | Indirect effect | Total effect | Direct effect | Indirect effect | Total effect |
| **Initial GDP per head (ln)** | –1.78*** | –9.82* | –11.61** | –1.92*** | –9.34** | –11.26** |
| **Average INV/GDP (ln)** | 1.01** | 9.49** | 10.50** | 0.24 | 9.80 | 9.56 |
| **Average population growth** | 0.00 | –0.66*** | -0.66*** | –0.01 | 0.08 | 0.08 |
| **EQI (RCI component)** | 0.41** | 0.01 | 0.42 | –0.11 | –2.82** | –2.94** |
| **Low secondary** | –0.03*** | 0.01 | –0.01 | –0.03*** | 0.20*** | 0.17** |
| **High educated (RCI component)** | –0.25 | –2.80** | –3.05** | 0.66** | 6.49** | 7.15** |
| **Potential accessibility** | –0.19 | –3.12** | –3.32*** | 0.18 | –0.32 | –0.14 |
| **Technological readiness (RCI component)** | 0.11 | 1.54 | 1.65 | 0.36 | 7.03*** | 7.40*** |
| **Business sophistication (RCI component)** | 0.88*** | 7.46*** | 8.34*** | –0.43 | –9.74** | –10.18** |

*Note:* The statistical significance levels are labelled with ***, **, and * referring to the 1, 5 and 10 percent significance level, respectively.

## 5. Conclusions

The aim of the study is to empirically examine recent regional economic growth in two distinct spatial regimes across the European Union. The focus is purposefully set on recent trends, from 2009 to 2015, in an effort to better understand growth dynamics in post-crisis Europe. While a long-term study of growth has its relevance, this analysis aims at investigating recent growth patterns across and within different spatial regimes in the EU to offer insight into future growth dynamics and better inform European policy development for the regionally interconnected reality of the 21st century.

The modelling approach adopted incorporates complex spatial effects and takes into account both spatial heterogeneity and spatial dependence. The incorporation of spatial effects in the model allows the regions to be treated as interconnected economic areas rather than "isolated islands".

The analysis follows a step-wise approach. First, spatial heterogeneity in the EU is assessed by employing Exploratory Spatial Data Analysis. We identify two distinct spatial regimes on the basis of the initial regional Gross Domestic Product per capita (starting year 2008). The two regimes clearly divide the EU territory into a north-west core, of relatively high income regions, and the south-east periphery, of lower income regions. Next, the Spatial Durbin Model is applied to examine growth processes in the two spatial regimes. Most of the components of the Regional Competitiveness Index, an aggregate measure of territorial competitiveness in the EU regions, are included at the regional NUTS2 level as explanatory variables. Each of these components consists of a composite index of basic indicators covering a wide range of issues including governance, human capital, physical infrastructure, labour market efficiency technological readiness, business sophistication and innovation. The inclusion of RCI components allows us to gain a more nuanced understanding of the causes of recent economic growth within each spatial regime, as well as determine the degree to which specific factors of growth have significant spillover effects. Regional population growth and regional investment are also added as prospective factors of growth.

Empirical results indicate that while both spatial regimes experience processes of economic convergence, recent determinants of growth, as well as spillover dynamics, differ across the two regimes. In the high-income regime (north-west core of the EU), greater investment as a share of GDP, higher quality of institutions and advanced levels of business sophistication significantly spur domestic growth, while high levels of investment and higher levels of business sophistication also induce positive spillover effects. High shares of poorly educated people are detrimental to growth in both regimes. The effect of human capital is particularly clear in the low-income regime (south-east periphery of the EU) where it has human capital have a significant positive effect on domestic growth, with higher shares of tertiary educational attainment also inducing positive spillover effects.

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## Appendix

| Variable | F statistics (*p*-value) | | | |
|---|---|---|---|---|
| | {HH} contrasted to {HL, LH, LL} | {HL} contrasted to {HH, LH, LL} | {LH} contrasted to {HH,HL,LL} | {LL} contrasted to {HH,LH,HL} |
| eqi2010 | **50.32 (< 0.0001)** | 0.00 (0.95) | **13.69 (0.0003)** | **140.13 (< 0.0001)** |
| Investment | 1.32 (0.18) | 0.00 (0.97) | 1.91 (0.17) | 0.02 (0.89) |
| Population_growth | **21.32 (< 0.0001)** | 3.26 (0.07) | 3.25 (0.07) | **57.01 (< 0.0001)** |
| Infrastructure | **26.13 (< 0.0001)** | 2.56 (0.11) | **8.57 (0.004)** | **88.26 (< 0.0001)** |
| Health | **51.46 (< 0.0001)** | 0.47 (0.49) | 0.01 (0.92) | **55.14 (< 0.0001)** |
| Lower_Secondary_Ed | 2.38 (0.12) | 1.75 (0.19) | 0.37 (0.55) | **7.44 (0.0068)** |
| Higher_Education | **15.81 (< 0.0001)** | **15.68 (< 0.0001)** | 0.60 (0.44) | **48.78 (< 0.0001)** |
| Labor_Market_Efficiency | **88.42 (< 0.0001)** | **8.89 (0.003)** | 0.01 (0.93) | **143.31 (< 0.0001)** |
| Tech_Readiness | **72.04 (< 0.0001)** | 0.22 (0.64) | 5.01 (0.026) | **143.44 (< 0.0001)** |
| Market_Size | **57.34 (< 0.0001)** | 5.82 (0.02) | 0.45 (0.50) | **102.74 (< 0.0001)** |
| Business_Sophistication | **63.41 (< 0.0001)** | **9.12 (0.003)** | 0.05 (0.83) | **109.02 (< 0.0001)** |
| Innovation | **111.33 (< 0.0001)** | 7.01 (0.009) | 1.54 (0.22) | **240.66 (< 0.0001)** |
| GDP_head_PPS_2008 | **198.55 (< 0.0001)** | **14.49 (0.0002)** | 3.96 (0.05) | **202.10 (< 0.0001)** |
| GDP_growth_09_15 | 1.60 (0.21) | 0.08 (0.78) | 3.80 (0.052) | 0.07 (0.7926) |

Note: p-values < 0.01 in bold

| Variable | F statistics (*p*-value) | | |
|---|---|---|---|
| | {HH,HL} contrasted to {LH, LL} | {HH,LH} contrasted to {HL, LL} | {HH,LL} contrasted to {HL, LH} |
| eqi2010 | **46.34 (< 0.0001)** | **130.7 (< 0.0001)** | **11.25 (0.0009)** |
| Investment | 1.66 (0.20) | 0.02 (0.88) | 1.67 (0.20) |
| Population_growth | **29.99 (< 0.0001)** | **38.41 (< 0.0001)** | **6.98 (0.009)** |
| Infrastructure | **34.35 (< 0.0001)** | **63.08 (< 0.0001)** | **12.88 (0.0004)** |
| Health | **54.20 (< 0.0001)** | **45.75 (< 0.0001)** | 0.07 (0.79) |
| Lower_Secondary_Ed | 4.62 (0.033) | 4.00 (0.05) | 1.60 (0.21) |
| Higher_Education | **36.04 (< 0.0001)** | **20.63 (< 0.0001)** | **7.88 (0.005)** |
| Labor_Market_Efficiency | **131.37 (< 0.0001)** | **82.38 (< 0.0001)** | 2.74 (0.10) |
| Tech_Readiness | **72.23 (< 0.0001)** | **122.84 (< 0.0001)** | 5.35 (0.02) |
| Market_Size | **80.24 (< 0.0001)** | **64.38 (< 0.0001)** | 3.64 (0.058) |
| Business_Sophistication | **96.81 (< 0.0001)** | **61.98 (< 0.0001)** | 3.23 (0.073) |
| Innovation | **155.91 (< 0.0001)** | **141.78 (< 0.0001)** | 6.60 (0.011) |
| GDP_head_PPS_2008 | **344.29 (< 0.0001)** | **101.39 (< 0.0001)** | 0.03 (0.87) |
| GDP_growth_09_15 | 1.85 (0.175) | 0.15 (0.70) | 2.69 (0.10) |

Note: p-values < 0.01 in bold

**Low Income**

| Variable | n | Mean | S.D. | Quantiles | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | Min | 0.25 | Mdn | 0.75 | Max |
| Growth Rate | 94 | 1.00 | 0.02 | 0.95 | 0.99 | 1.01 | 1.02 | 1.04 |
| GDP per head | 94 | 16983.00 | 4977.00 | 7383.00 | 12466.00 | 17762.00 | 21347.00 | 25797.00 |
| Investments | 94 | 0.19 | 0.04 | 0.11 | 0.17 | 0.19 | 0.22 | 0.34 |
| Population Growth | 94 | -1.69 | 6.22 | -17.49 | -4.55 | -1.03 | 2.06 | 21.62 |
| Quality of Government | 94 | -0.65 | 0.91 | -2.65 | -1.19 | -0.88 | 0.00 | 1.31 |
| Potential Accessibility | 94 | -0.81 | 0.48 | -1.34 | -1.15 | -0.93 | -0.65 | 0.81 |
| Lower Secondary Education | 94 | 32.20 | 19.05 | 3.40 | 15.40 | 27.80 | 49.50 | 77.90 |
| Higher Education | 94 | -0.46 | 0.63 | -1.98 | -0.91 | -0.44 | 0.03 | 1.13 |
| Technological Readiness | 94 | -0.81 | 0.80 | -2.19 | -1.33 | -0.84 | -0.37 | 1.05 |
| Business Sophistication | 94 | -0.75 | 0.52 | -1.60 | -1.09 | -0.83 | -0.38 | 0.75 |

**High Income**

| Variable | n | Mean | S.D. | Quantiles | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | Min | 0.25 | Mdn | 0.75 | Max |
| Growth Rate | 160 | 1.00 | 0.01 | 0.96 | 1.00 | 1.00 | 1.01 | 1.04 |
| GDP per head | 160 | 29296.00 | 7310.00 | 12979.00 | 24003.00 | 28379.00 | 32789.00 | 67605.00 |
| Investments | 160 | 0.19 | 0.03 | 0.12 | 0.17 | 0.19 | 0.21 | 0.34 |
| Population Growth | 160 | 3.66 | 4.50 | -9.00 | 0.88 | 3.21 | 6.92 | 21.85 |
| Quality of Government | 160 | 0.57 | 0.68 | -2.84 | 0.32 | 0.73 | 0.97 | 1.76 |
| Potential Accessibility | 160 | 0.16 | 0.90 | -1.36 | -0.62 | 0.04 | 0.81 | 2.13 |
| Lower Secondary Education | 160 | 27.11 | 11.04 | 4.43 | 18.43 | 25.15 | 33.48 | 60.13 |
| Higher Education | 160 | 0.11 | 0.59 | -2.15 | -0.23 | 0.10 | 0.45 | 1.53 |
| Technological Readiness | 160 | 0.46 | 0.80 | -1.74 | -0.18 | 0.72 | 1.14 | 1.83 |
| Business Sophistication | 160 | 0.03 | 0.61 | -1.50 | -0.34 | -0.05 | 0.41 | 1.88 |