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EUROPE 2020 CHALLENGES AND REGIONAL IMBALANCES. A SPATIAL ANALYSIS

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ABSTRACT

Europe 2020 is a 10-years EU key strategy, aimed at promoting EU smart, sustainable and inclusive growth. Despite its ambitious goals, Europe 2020 spatially blind approach might seriously threaten its success, as large territorial disparities still affect the EU. This paper tackles this issue by firstly assessing major differences in regional performances with regards to Europe 2020 main targets. A Principal Component Analysis is here applied to a list of input variables related to Europe 2020 Strategy's targets, by considering EU-27 NUTS 2 regions. In particular, two components are identified: i) smart and inclusive growth; ii) role of tertiary education. Then, a territorial analysis is performed by considering the presence of both rural and spatial effect in the allocation of components. Actually, both effects are correlated to extracted components. In particular, by computing global and local Moran's I statistics, a strong tendency to spatial autocorrelation in regional performances is verified. Thus, according to these results, large territorial imbalances characterise Europe 2020 regional performance. Nevertheless, the reduction of these disparities is a key issue in order to fully achieve Europe 2020 goals.

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1. Introduction

Major innovations have lately transformed EU political framework. Within EU policies, a key role is now played by Europe 2020 Strategy, a 10-years strategy that aims at promoting a smart, sustainable and inclusive growth by fostering the coordination of national and European policies. It has succeeded Lisbon Strategy and it focuses on a new socio-economic growth model, by paying a greater attention to both quality of life and economic and environmental sustainability. Despite its ambitious goals, Europe 2020 Strategy suffers from some major limits. In particular, it is a spatially blind policy: actually, the Strategy is implemented at European level, with just few adjustments at national level. Thus, territorial disparities throughout the EU are largely ignored, although they are wide at both national and sub-national level. Indeed, a wide heterogeneity still characterises EU regions, for example in terms of urban-rural differences, social capital endowment, economic growth, physical accessibility. All these differences in both urban and rural areas clearly affect the way each region will achieve the main goals of the strategy by 2020. Therefore, a spatially blind approach might seriously threaten Strategy's success.

According to this major issue, the paper aims to assess major differences in the way EU-27 NUTS 2 regions are approaching Europe 2020 targets. Regional performance is here analysed by applying Principal Component Analysis (PCA) to a list of inputs variables that refer to both specific targets of the Strategy (e.g., employment rate, share of R&D out of GDP, share of 30-34 year-olds completing third level education…) and other related variables (e.g., unemployment rate and share of NEETs aged 18-24). Data are collected for NUTS 2 regions throughout EU-27 (262 observations). Eventually, two components are extracted: a first component sums up the "smart and inclusive growth", thus representing a general indicator of regional performance; a second one specifically refers to "tertiary education".

Then, two elements that might be correlated to Europe 2020 regional performance are considered here: the extent of rurality at regional level (i.e., rural effect) and the role of geography and neighborhood (i.e., a generic spatial effect).

Firstly, existing links between rurality and the achievement of Europe 2020 targets are observed. Actually, rural areas still account for a large share of both EU area and total population. This is true even though great changes have lately affected them throughout the EU. Since the 80s, socio-demographic transformations, stagnation of the economic growth, the development of both physical infrastructure and the ICT have deeply altered EU rural space. Here, rurality is analysed at NUTS 2 level by alternatively considering population density and a Fuzzy Rural Indicator (FRI), i.e. a continuous and comprehensive indicator obtained by applying fuzzy logic technique to six variables related to population settlement, role of agricultural sector, land use characteristics. Eventually, Europe 2020 Strategy is found

to be a rather urban strategy: rural regions still incur in large difficulties when achieving a smart and inclusive growth, despite the major transformations they are facing.

Nevertheless, even geography is found to play a key role in the achievement of Europe 2020 main goals. In the second part of the paper the existence of such a generic spatial effect is tested. In particular, an exploratory spatial data analysis (ESDA) is carried out on the whole set of EU-27 NUTS 2 regions in order to detect major territorial patterns. Firstly, by performing global Moran's I statistics, a strong tendency to spatial autocorrelation in regional performances is verified. Then, by computing local Moran's I statistics, it is also possible to detect hot and cold spots, i.e., groups of spatially-contiguous regions that respectively show either good or bad performances in approaching Europe 2020 targets. Results confirm that both geography and neighbourhood matter in defining regional performance. Once again, more central and more accessible regions show best performances at EU level. Conversely, two typologies of regions show particularly poor performances referring to the main goals of Europe 2020 Strategy: i) rural regions and ii) peripheral and remote regions. Cold spots represent critical areas within the EU-27, thus both EU and national policymakers should concentrate their efforts in order to improve the general performance of those lagging-behind regions. Indeed, Europe 2020 Strategy could achieve its ambitious goals only if it is able to gradually reduce disparities within the EU.

2. Theoretical Background: Lisbon Strategy and Europe 2020 Strategy

2.1. From Lisbon Strategy to Europe 2020 Strategy

Within EU institutional framework, Lisbon Strategy and Europe 2020 Strategy have been playing a key role since 2000, at least in terms of promoting common goals at EU level. Not surprisingly, economic literature has widely focused on both of them. Lisbon Strategy was a 10-years strategy that had been firstly set out in 2000 (European Council, 2000). Its launch followed major socio-economic trends that had affected the EU since the 80s. Low productivity, stagnation of economic growth, low R&D expenditures as well as globalization trends have largely penalized the EU compared to the US (Sapir, 2004; Rodrigues, 2002, Zeitlin, 2008, Natali, 2010). Thus, Lisbon Strategy was characterised by a broad agenda, aimed at committing EU governments to concentrate their efforts on a single and specific goal, i.e. EU economic, social and environmental renewal. In particular, its ambitious goal was to make the EU "the most competitive and dynamic knowledge-based economy in the world capable of sustainable economic growth with more and better jobs and greater social cohesion" by 2010 (European Council, 2000). Lisbon Strategy was also aimed at innovating EU governance, by enhancing different forms of interactions between national governments and the EU. Actually, this strategy represented a major effort to transform the overall EU

project (Natali, 2010). According to these general objectives, Lisbon Strategy was then fashioned using a three-pillar structure:

- A social pillar comprised policies aimed at modernising the EU social model, through more investments in education and training as well as promotion of employment. In particular a greater social cohesion would be assured by fostering knowledge-based economy;
- An economic pillar was directly devoted to prepare the ground for the transition to a more competitive, dynamic and knowledge-based economy. In particular, the pillar included specific policies targeted to economic growth, such as increasing integration among EU national markets and promoting EU competitiveness;
- An environmental pillar (added at the Göteborg European Council in 2001) was aimed at drawing larger attention to the impact of the economic growth on the use of natural resources.

A set of more specific targets was set out as well: they represented a first effort to measure and quantify above-mentioned general objectives. Common target indicators (for instance, an overall employment rate of 70%; increasing the R&D spending to 3% of GDP by 2010 and so on) were jointly defined by Member States. In particular, Lisbon Strategy adopted the Open Method of Coordination (OMC) to provide a common framework for coordinating actions to be taken at national level (European Council, 2000; European Council, 2001).

In 2010, Lisbon Strategy came to its natural end. Despite major EU and national efforts, it missed its most important socio-economic targets. To explain this failure, several issues have been pointed out over time. Some of them came to light just after Strategy's first launch: thus, mid-term reviews were set out in 2005 and 2008, trying promoting new and more effective reforms (Kok, 2004; Deroose *et al.*, 2008). Criticisms to Lisbon Strategy have become even stronger since the beginning of international economic crisis in 2008. Actually, employment rates started falling throughout the EU-27 and social cohesion indicators worsened.

Nevertheless, despite these major failures, in 2010 an even more ambitious EU strategy replaced Lisbon Strategy: Europe 2020 Strategy. It is characterised by new keywords and new initiatives: in particular, it stresses the role of a new socio-economic development model, by paying increasing attention to quality of life and environmental sustainability. New targets have been set out; new tools and more coordinated policies have been implemented, too. In particular, Europe 2020 Strategy is about addressing the shortcoming of the EU growth model by creating the conditions for a (European Council, 2010):

- Smart growth: developing an economy based on knowledge and innovation, by investing in education and training;
- Sustainable growth: promoting a more resource efficient, greener and more competitive economy;

- Inclusive growth: fostering a high-employment economy, delivering both social and territorial cohesion.

As in the case of the Lisbon Strategy, a set of specific targets was set out: all of them have to be achieved by 2020 (Table 1). These ambitious goals confirm strong desire of EU Member States in promoting a sustainable growth path in the following years; at the same time, they also pose some questions about the effectiveness of their achievement. Indeed, many Member States did not achieve Lisbon Strategy's goals, so it is unrealistic to think that they would achieve Europe 2020's ones. Much more doubts may arise, as the effects of international economic crisis are still affecting most EU economies (especially in peripheral areas). Actually, latest economic figures show that most EU Member States are still far apart from expected targets. For instance, in 2012, EU-27 overall employment rate was just 68.5%; the share of EU energy consumption produced from renewable resources was less than 13% and the share of population aged 20-34 having a tertiary degree was just 35.8%. Despite these results, good news come from the way Europe 2020 Strategy is currently funded. Whilst Lisbon Strategy was not financed at all by EU common funds[2], current strategy is financed through Structural Fund.

Table 1 - Smart, sustainable and inclusive growth: EU targets

		Quantitative targets
Smart growth	Employment R&D Education	• 75 % of the population aged 20-64 employed • 3% of the EU's GDP invested in R&D • Share of early school leavers under 10% • 40% of the population aged 20-34 having a tertiary degree
Sustainable growth	Climate changes and sustainability (20-20-20 targets)	• 20% reduction in EU greenhouse gas emissions from 1990 levels • Raising the share of EU energy consumption produced from renewable resources to 20% • 20% improvement in the EU's energy efficiency
Inclusive growth	Social cohesion	• 20 million less people being at risk of poverty

Source: own elaboration

2.2. Major Criticisms to Lisbon Strategy and Europe 2020 Strategy

The adoption of Europe 2020 Strategy has not fully calmed down previous criticisms to Lisbon Strategy. Actually, both strategies seem unable to achieve their major objectives as even Europe 2020 Strategy is affected by same limits. Natali (2010) grouped major criticisms to both strategies into two main analytical dimensions.

First group of criticisms directly refer to political and economic foundations of Lisbon and Europe 2020 Strategies. Indeed, they have been considered as wrong strategies for EU integration, as they have enhanced an impossible convergence among too different economies, thus increasing the risk for a clash of capitalisms and hindering the achievement

[2] The only common tools were represented by the Open Method of Coordination and the definition of a set of common indicators that were developed in order to monitor the Strategy itself.

of positive results at EU level (Hopner and Schafer, 2007). Political agenda itself has been partially wrong: both the excessive liberal mark and a progressive shift towards right-centred political approaches were stressed as critical issues (Amable, 2009; Rodrigues, 2002).

A second criticism is related to the Strategies' governance. Actually, the EU has never developed proper economic policy institutions to foster its own growth. Despite the important role of Structural Funds in promoting EU cohesion, ECB has not played a role as strong as that played by FED in sustaining and fostering domestic economy. Furthermore, even Member States' participation in both Strategies has been uneven. OMC, though emphasizing subsidiarity through new democratic experimentalisms (Smismans, 2008) and making national legislations more and more homogeneous (Tucker, 2003; Zeitlin, 2007; 2008), has suffered from major methodological ambiguity. Indeed, it has never committed national governments to really respect EU targets.

Nevertheless, when addressing Lisbon and Europe 2020 Strategies' main limits, economic literature has often neglected other important issues. In fact, both strategies have just referred to EU level, thus ignoring any lower territorial dimension and, in particular, deep differences that exist across EU-27 Member States. Such a spatially-blind approach (Barca *et al.*, 2012) represents one of the major limits in the application of Europe 2020 Strategy.

Actually, Sapir (2004; 2006) had already stressed the existence of wide differences among EU social models throughout the EU. By just focusing on EU-15 Member States, he described four different social models (i.e., Nordic, Anglo-Saxon, Continental and Mediterranean models), according to a different equity-efficiency mix. National differences suggested by Sapir are just part of the story. Sub-national and regional differences may play an even greater role throughout the EU-27. Rodriguez-Pose and Gill (2004) claimed that regional disparities within the EU are larger than disparities among States within the US. Natural resources, capital endowment, geographical features, accessibility all play a role in shaping EU regional performances. Thus, even the way each region achieves Europe 2020's goals is largely affected by territorial imbalances.

Nevertheless, despite being so important, regional dimension and territorial perspectives have always been neglected in defining the goals of both Lisbon Strategy and Europe 2020 Strategy. Territorial issues are even more important if considering that many other EU policies have been targeted at EU regions and that Structural Funds play a role in financing Europe 2020 targets. Thus, the paper just moves from this major lack, by focusing on regional differences in the achievement of Europe 2020 goals. In particular, a specific focus will be on EU rural regions. Indeed, it is clear that regional structural features, such as the degree of rurality, can play a role in defining overall regional performance when moving towards a smart, sustainable and inclusive growth. The existence of specific territorial patterns within the EU will also be assessed.

3. Data and Methodology: PCA and ESDA

3.1. PCA

Regional performance in achieving Europe 2020 goals is expected to show large heterogeneity throughout the EU-27. It also represents a typical multidimensional indicator as a large set of different variables may affect it. Thus, conventional Principal Component Analysis (PCA) is here adopted in order to reduce such a multidimensional set of features. PCA was developed (and named) by Hotelling (1933), whereas methodology was first introduced by Pearson (1901). It helps reducing the dimension of a given problem to be investigated, while preserving most of the original statistical information (Everitt and Hothorn, 2010). Then, after the extraction of some Principal Components (PCs), it is possible to obtain a standardised score for each statistical unit: in this case, EU-27 NUTS 2 regions are considered.

In regional studies, PCA has been widely adopted in order to solve classification problems (see, for instance, Fanfani and Mazzocchi, 1999; Ocana-Riola and Sánchez-Cantalejo, 2005; Vidal *et al.*, 2005; Bogdanov *et al.*, 2007; Monasterolo and Coppola, 2010). Among its major strengths, PCA does not require any *ex-ante* assumption: here, original data determine transformation vectors (Mazzocchi, 2008). According to these properties, PCA is here used as an exploratory analysis[3].

PCA is here applied to a list of indicators measuring regional performance with regard to Europe 2020 main targets. Firstly, specific Europe 2020 targets are taken into account[4]; then, other additional indicators are considered as well. Indeed, other variables may be useful in order to define regional performance when measuring smart, green and inclusive growth. Table 2 shows the full list of adopted variables. All data have been collected at NUTS 2 level.

NUTS 2 regions throughout the EU-27 are 271. Nevertheless, following regions have been dropped out from the original dataset, due to lack of territorial contiguity with the European continent:

- 4 French *Departements d'outre-Mer*: Guadeloupe, Martinique, Guyane and Réunion;
- Azores and Madeira, i.e., two archipelagos in the Atlantic Ocean belonging to Portugal;
- Spanish Canary Islands (Canarias – ES70) and Ceuta (ES63) and Melilla (ES64), i.e. two autonomous cities of Spain and exclaves located on the Northern coast of Africa.

[3] In many empirical works, PCA is often referred to as an exploratory factor analysis. This is a wrong interpretation: factor analysis is usually adopted to verify the existence of a given latent factor structure when just measuring observed variables. Thus, factor analysis requires the existence of a specified model, whose validity is tested through factors and error terms estimations.

[4] Those targets whose values are not available at sub-national level have been excluded from the analysis. In particular, this is the case of environmental targets.

Thus, 262 NUTS 2 regions compose the final set of observations. Some minor concerns refer to data availability: all missing values have been replaced with available data at either NUTS 1 or NUTS 0 (national) level. According to this set of observation, Table 3 shows main descriptive statistics for the whole sample of observations. In particular, average value and standard deviation as well as minimum value, 1st quartile, median value, 3rd quartile and maximum value are reported.

Table 2 - List of input variables by thematic area

	Label	**Variable**	**Source**	**Reference Year**
Europe 2020 targets	Empl.Rate_20_64	Employment rate for the population aged 20-64 years	Eurostat	2012
	Empl.Rate.M_20_64	Male employment rate (population aged 20-64 years)	Eurostat	2012
	Empl.Rate.F_20_64	Female employment rate (population aged 20-64 years)	Eurostat	2012
	R.D	Gross domestic expenditure on R&D as a percentage of GDP. All economic sectors (both public and private) are here considered	Eurostat	2009
	Tert.Edu_30_34	Population aged 30-34 with tertiary education attainment	Eurostat	2011
	Tert.Edu.M_30_34	Male population aged 30-34 with tertiary education attainment	Eurostat	2011
	Tert.Edu.F_30_34	Female population aged 30-34 with tertiary education attainment	Eurostat	2011
Related indicators	Unempl.Rate_15_24	Unemployment rate for the population aged 15-24 years	Eurostat	2011
	LT.Unempl.Rate	Long-term unemployment (12 months and more) rate.	Eurostat	2011
	LT.Unempl.Rate_%	Long-term unemployment (12 months and more) as a share of total unemployment rate.	Eurostat	2011
	Lower.Edu_25_64	Population aged 25-64 with lower secondary education attainment	Eurostat	2011
	Poverty	People at risk of poverty or social exclusion (% out of total population)	Eurostat (EU Silc)	2009
	NEET_18_24	Population aged 18-24 not in Education, Employment or Training	Eurostat	2011

Source: own elaboration

Table 3 - Input variables: descriptive statistics

	Mean	**Standard Deviation**	**Minimum**	**1st Qu.**	**Median**	**3rd Qu.**	**Maximum**
Empl.Rate_20_64	69.4	8.0	43.7	64.7	70.6	76.1	86.4
Empl.Rate.M_20_64	75.4	7.0	55.8	70.7	75.8	81.0	87.4
Empl.Rate.F_20_64	63.4	9.8	30.1	57.4	65.7	71.0	86.1
R.D	1.6	1.3	0.1	0.7	1.2	2.0	7.9
Tert.Edu_30_34	33.5	10.9	9.6	23.7	34.5	40.4	69.2
Tert.Edu.M_30_34	29.9	10.7	7.6	21.0	29.5	36.4	71.0
Tert.Edu.F_30_34	37.6	11.9	11.7	27.4	37.6	46.1	67.1
Unempl.Rate_15_24	22.4	11.5	4.3	12.8	21.6	28.5	54.4
LT.Unempl.Rate	3.8	2.6	0.1	1.9	3.1	5.0	13.3
LT.Unempl.Rate_%	39.7	11.7	4.0	32.3	40.5	47.4	71.1
Lower.Edu_25_64	25.6	13.6	3.3	15.1	23.9	31.9	69.5
Poverty	16.8	6.4	3.0	11.8	15.5	20.0	39.9
NEET_18_24	16.2	7.4	3.6	10.5	15.7	20.1	43.7

Number of observations: 262
Source: own elaboration

3.2. Measuring Rurality

After having extracted PCs, existing links between Europe 2020 regional performance and the extent of rurality of a given region are firstly considered. Nevertheless, it is not an easy task to define what a "rural" region is. Actually, univocal concepts still lack at international level, although since the 90s significant steps forward in providing homogeneous definitions have

been taken. To date, most well-known urban-rural typologies are those adopted by the OECD (1994; 1996a; 1996b; 2006) and the European Commission (Eurostat, 2010). These approaches are based on population density as a major criterion to define rural areas. Over time, other studies have tried overcoming them, for instance by adopting a multidimensional perspective (Copus *et al.*, 2008; Terluin *et al.*, 1995; Copus, 1996; Ballas *et al.*, 2003; Bollman *et al.*, 2005; Vidal *et al*., 2005; Camaioni *et al*., 2013).

Here, the Fuzzy Rurality Indicator (FRI) computed by Pagliacci (2014) is adopted. This is a comprehensive and continuous indicator of rurality that is obtained by applying Fuzzy Logic[5] to a set of six input variables that cover the role of agriculture, population settlement (i.e., population density) and land use features. By construction, the output (i.e., the FRI) ranges from 0 to 1, where 0 stands for minimum degree of rurality whereas 1 stands for maximum degree of rurality. In Pagliacci (2014), the FRI is computed at NUTS 3 level (1,288 observations), as that can be considered the proper level to deal with rurality throughout Europe. Nevertheless, all analyses in the present paper are performed at NUTS 2 level, due to the lack of data on Europe 2020 performance at a more disaggregated level (for instance, R&D expenditures, environmental data and indicators of social cohesion). Accordingly, even FRI values are here considered at NUTS 2 level, by taking average values from NUTS 3 data.

Eventually, in order to take into account different measures of rurality, in this work rural effect is expressed by both FRI (the greater the FRI, the more rural the region) and population density (the lower the density the more rural the region).

3.2. Exploratory Spatial Data Analysis (ESDA)

The existence of a rural effect is just part of the story when analysing Europe 2020 performance at regional level. Actually, territorial patterns and geographical spill-overs matters as well. In order to test for the presence of these effects, an exploratory spatial data analysis (ESDA) is performed, too.

The interest on spatial data has largely increased since the development of Geographical Information System (GIS). Actually, ESDA uses spatially referenced data that show coordinate values as well as a system of reference (Bivand *et al.*, 2008). Accordingly, three different typologies of spatial analysis have lately developed: point process (i.e., a stochastic process in which the location of some events of interest is observed within a bounded region), geostatistics (the interest here is in inference of aspects of the variable that have not been measured) and areal data (data are observed on polygon entities with defined boundaries and spatial autocorrelation is mostly tested). ESDA refers to the latter case: it includes a set of techniques aimed at describing spatial distributions of data, at identifying spatial outliers, at

[5] Fuzzy Logic approach is similar to human logic: no clear cut-offs, strictly classifying observations in well defined values, are provided. Conversely, each observation is linked to its probability of belonging to a given class or set (Zadeh, 1965; 1968).

detecting patterns of spatial association, such as spatial clusters or hot spots (Anselin 1998)[6]. Referring to Europe 2020 regional performance, above-mentioned techniques are applied to the extracted PCs, in order to test the existence of spatial patterns. In particular, both global and local spatial autocorrelation are tested.

Firstly, the presence of possible spatial dependence is taken into account by computing global Moran's I statistics. This is a synthetic measure of global spatial autocorrelation, assessing the coincidence of value similarity with locational similarity (Anselin, 2000). Moran's I statistics can be computed as follows (Moran, 1950; Cliff and Ord, 1981):

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(y_i - \bar{y}\right)\left(y_j - \bar{y}\right)}{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2}, \forall i, j \in N \qquad (1)$$

where w_{ij} is the generic element of a row-standardized spatial weights matrix (**W**) that is defined as follows:

$$w_{ij} = \frac{w_{ij}^*}{\sum_{j=1}^{n} w_{ij}^*} \qquad (2)$$

The generic element w_{ij}^* can take two different values:

- $w_{ij}^* = 1$ when $i \neq j$ and $j \in N(i)$;
- $w_{ij}^* = 0$ when $i = j$ or $i \neq j$ and $j \notin N(i)$,

where $N(i)$ is the set of neighbours of the i-th region, according to a *first-order queen contiguity matrix*. According to this approach, two regions are considered as neighbours only if they share a common boundary or vertex (Anselin, 1988). The queen contiguity matrix is preferred to other possible spatial matrices (e.g., those based on the nearest neighbours or those based on a critical cut-off distance) because it better suits the case under study here. Actually, EU-27 NUTS 2 regions show great heterogeneity in terms of size, inevitably affecting distances among centroids. Nevertheless, when adopting a contiguity matrix, a major issue is represented by islands, not showing any contiguous region by definition. In this sample, there are 11 islands that have been considered as contiguous to the closest regions in terms of geographical proximity[7]. Furthermore, additional contiguity links have been added in case of those regions sharing some specific artificial infrastructures[8]. Eventually, NUTS 2 regions in the sample on average show 4.53 neighbouring regions (i.e. links). Nevertheless, 15

[6] Spatial association and spatial autocorrelation mostly derive from the First Law of Geography, according to Tobler (1970) definition. Indeed, they formally measure the degree of dependency among observations within a given geographic space.

[7] Here, no distinction has been made between trans-national neighbours and national neighbours, although national borders represent "institutional" obstacles deeply affecting regional connectivity. The same is true, however, even for "natural" obstacles between two regions (e.g., mountains chains). All these aspects could be considered in more sophisticated constructions of **W**.

[8] For instance, British NUTS 2 region of Kent and French NUTS 2 region of Nord-Pas-de-Calais are considered as neighbours, due to the presence of the Chunnel Tunnel.

regions just show a single neighbour, whilst just a single NUTS 2 region shows 11 neighbours. This row-standardized spatial weights matrix (**W**) is used to compute the global Moran's I statistic on the extracted PCs.

Global Moran's I statistic gives a formal indication on the degree of linear association between a vector of observed values and the vector of spatially weighted averages of neighbouring values (i.e., a spatially lagged vector). Nevertheless, it does not allow to detect the regional structure of spatial autocorrelation, such as the existence of either spatial cluster or spatial outliers. Local approaches for analysing spatial association just attempt to identify whether there are spatial patterns in the distribution of PCs. Among several local indicators of spatial association, the Local Indicator of Spatial Association – LISA (Anselin 1995; Anselin *et al.*, 1996) is used here. It is analogous to global Moran's I statistic, but it is region-specific. Indeed, it tests the hypothesis of random distribution by comparing values in specific localization with the values in neighbouring ones, as defined according to the spatial weights matrix (**W**). According to Anselin (1995), local Moran's statistics can be used as indicators of local spatial clusters, which can be identified as those locations or sets of neighbouring locations for which LISA values are significant. When a given significance level is set (here 1% significance level is mostly adopted), five different scenarios for each location may emerge (Oliveau and Guilmoto, 2005):

- *Hot spots*: those locations with high values with similar neighbours (high-high case);
- *Cold spots*: those locations with low values with similar neighbours (low-low case);
- *Spatial outliers*: those locations with high values but with low-value neighbours (high-low case);
- *Spatial outliers* those locations with low values but with high-value neighbours (low-high case);
- Locations with no significant local autocorrelation.

4. Main Results

4.1. Europe 2020 Strategy's main components

Table 4 (upper part) shows the results of the extraction of the Principal Components (PCs)[9]. Following both the criterion of eigenvalues (i.e., choosing PCs with eigenvalues greater than

[9] The Kaiser-Meyer-Olkin (KMO) test is preliminary applied on the original selected variables, in order to test whether they are suitable for PC extraction. This is a test of sampling adequacy calculated as the ratio between the sum of squares of all correlations of the variables and the same sum plus the sum of all bivariate partial correlations. If this ratio is low all variables do not share much variance and the PC extraction becomes less meaningful. The KMO test ranges from 0.0 to 1.0 (Kaiser, 1974). Here, the KMO test on the variables under study is fully satisfactory (.727).

1) and Guttman-Kaiser criterion[10], two PCs should be extracted: they account for more than 72% out of total variance. Then, factor loadings are reported in the lower part of Table 3. They provide an economic interpretation of PCs. Factor loadings just represent correlation coefficients between original input variables and PCs. Here, factor loadings that are smaller than |.20| are regarded as not significant and their coefficients are not shown in Table 3. In particular, the analysis of both sign and magnitude of factor loadings allows an economic interpretation to be attributed to the extracted PCs. According to it, it is then possible to properly label them.

Table 4 - PC extraction (eigenvalues and variance explained for the first 5 PCs) and factor loadings (only significant values, ≥ |.20|, are reported)

	Variable	PC1	PC2	PC3	PC4	PC5
	PC extraction					
Eigenvalues		6.79	2.59	0.92	0.72	0.70
% of variance		52.25	19.95	7.05	5.53	5.41
Cumulative % of variance		52.25	72.20	79.25	84.78	90.19
	PC factor loadings					
Europe 202 targets	Empl.Rate_20_64	0.361				
	Empl.Rate.M_20_64	0.339				
	Empl.Rate.F_20_64	0.353				
	R.D	0.212				
	Tert.Edu_30_34		0.531			
	Tert.Edu.M_30_34	0.208	0.484			
	Tert.Edu.F_30_34		0.530			
Other Related indicators	Unempl.Rate_15_24	-0.317	0.263			
	LT.Unempl.Rate	-0.328				
	LT.Unempl.Rate_%	-0.246				
	Lower.Edu_25_64	-0.223				
	Poverty	-0.234				
	NEET_18_24	-0.325				

Source: own elaboration

According to above-mentioned results, two extracted PCs might be defined as follows.

PC1 – Smart and inclusive growth: it provides a synthetic measurement of Europe 2020 performance. It is related to almost all input variables: it is positively related to employment rates, share of R&D expenditures out of GDP and share of population aged 30-34 with tertiary education. Furthermore, it is negatively related to unemployment rates and share of long-term unemployment out of total unemployment. Even the presence of NEET population is negatively related to it. Thus, this PC provides a good proxy of smart and inclusive growth at regional level.

PC2 – Tertiary education: this PC mainly refers to education variables. Actually, it is positively related to the share of population aged 30-34 with tertiary education. Nevertheless, it is also positively related to unemployment rate for the population aged 15-24 years.

[10] The Guttman-Kaiser criterion suggests choosing those principal components which are able to explain at least 70-80% of the cumulative variance.

According to these results, this PC provides a good proxy for tertiary education that actually represents one of the most important Europe 2020 targets (i.e., smart growth).

On the basis of selected PCs, a standardized score is then assigned to each EU-27 NUTS 2 region. A new EU geography emerges from this analysis. In particular, PC1 shows particularly high values throughout central Europe, Scandinavia and the UK. Conversely, poorest regional performances affect Eastern Member States regions, with the only exception of those regions hosting capital cities. Low PC1 values are found across Mediterranean regions as well. PC2 follows a rather different territorial pattern. It shows high values across the UK, the Baltic Countries and Scandinavia. Conversely, most Eastern and Southern regions as well as German and Austrian ones show very low values. Data about Austria and Germany are partially unexpected, even though those countries have been traditionally characterised by a wide presence of manufacturing activities as well as outstanding vocational schools.

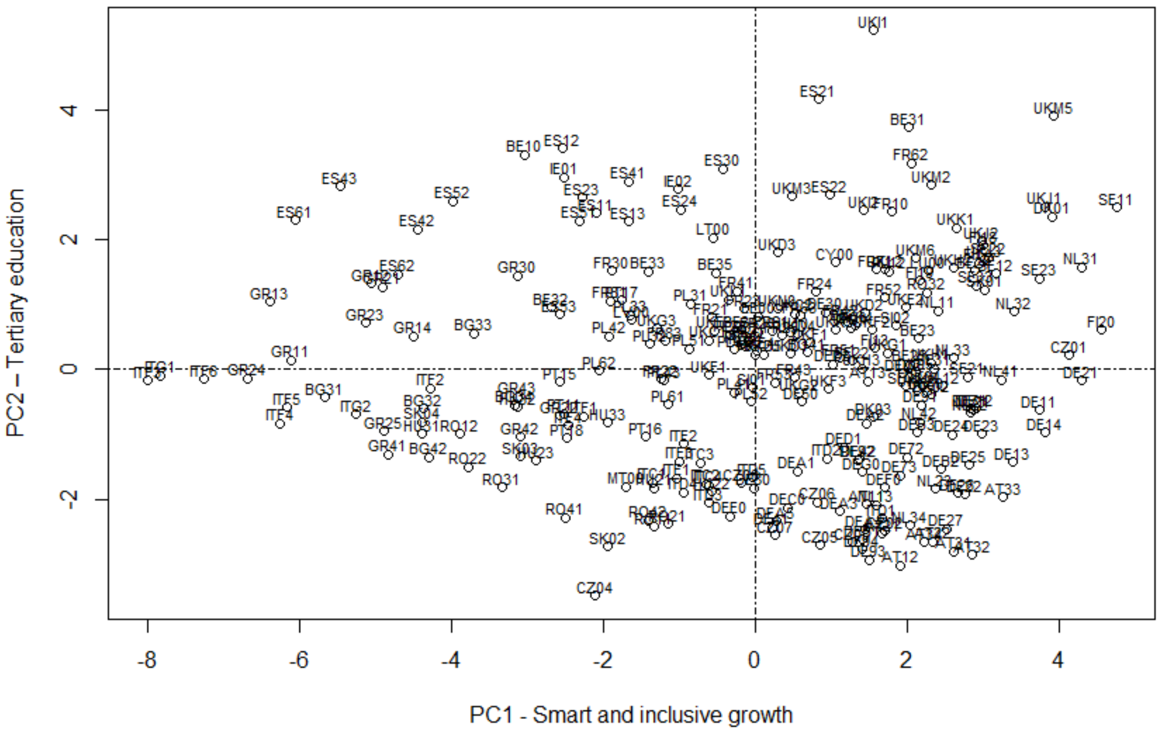
From a joint analysis on the spatial allocation of two PCs, it is possible to point out some major trends at EU scale. At first, smart growth seems to be correlated to inclusive one. Although nothing can be said about sustainable growth (due to lack of available data), other components of the Strategy (i.e., economic competitiveness and labour market, education and social inclusion) are found to be strictly linked to each others. Most indicators show similar values throughout the EU-27 at regional level, and this is the reason why a single PC (PC1) actually sums up most of the total variance that is associated to regional performances referring to Europe 2020 Strategy's targets. Eventually, PC2 shows a deeper focus on tertiary education that is characterised by different territorial patterns. In particular, it is possible to jointly represent PCs' distribution through a scatterplot[11] (Figure 1): each region is positioned on a Cartesian plane where the *x*-axis refers to PC1 and the *y*-axis to PC2. The origin of the plane (0,0) is positioned in the respective average PC values: taking these average values as a benchmark, it is possible to split EU-27 NUTS 2 regions into four different groups:

- High-High cases (NUTS 3 regions where both PCs are above the EU-27 average): *EU2020 best performers*;
- High-Low cases (NUTS 3 regions where PC1 is above the EU-27 average, while PC2 is below it): *good performers but under educated*;
- Low-High cases (NUTS 3 regions where PC1 is below the EU-27 average, while PC2 is above it): *bad performers but over educated*.
- Low-Low cases (NUTS 3 regions where both PCs are below the EU-27 average): *lagging behind regions*;

According to the above-mentioned classification, "EU2020 best performers" surprisingly represent the most important group at EU scale, including 77 NUTS 2 regions, with more than 146 million inhabitants, and covering about 1.4 million km^2. Nevertheless, lagging behind areas represent 62 NUTS 2 regions with about 124 million inhabitants (Table 5).

[11] By construction, PC1 shows a larger variance than PC2.

Figure 1 - Distribution of PC1 and PC2 (NUTS 2 code are reported)



Source: own elaboration

Table 5 - Europe 2020 groups: number of regions, total population and total area

	No. of regions	Population (000 inhabitants)	Area (000 km^2)
EU2020 best performers	77	146.731,3	1.396,1
Good performers but under educated	70	109.641,1	713,4
Bad performers but over educated	53	116.421,0	1.136,8
Lagging behind regions	62	124.383,4	1.059,2
Total	262	497.176,8	4.305.5

Source: own elaboration

Nevertheless, overall results, as shown in Table 5, partially hide a great complexity at a more local level. In order to explain such a puzzling performance at national and sub-national level, following sections will focus on some specific issues. In particular, both the role of rurality and the role of geographical spill-overs will be assessed in defining regional performances referring to Europe 2020 goals.

4.2. Europe 2020 Strategy and Rurality

Moving from the aforementioned results about Europe 2020 performance, this section focuses on existing links between regional performances and rural features. Among structural features, the urban-rural continuum is expected to deeply affect the achievement of a large set of Europe 2020 Strategy's targets. As already pointed out, EU-27 regions sharply differ in

terms of urban/rural characteristics: actually, both large metropolitan areas and deep rural regions coexist within the EU-27 boundaries.

Table 6 shows Pearson correlation coefficients between extracted PCs and two alternative indicators of rurality: i) population density (data refer to year 2010) and ii) the FRI, i.e. a composite indicator, previously computed by Pagliacci (2014) and here applied at NUTS 2 level. By construction, the lower the population density, the more rural a region is; conversely, the greater the FRI, the more rural a region is.

According to main results, PC1 is statistically and negative correlated to the FRI: thus, the more rural a given region is, the worse the performance according to Europe 2020 targets (i.e., achieving a smart and inclusive growth). Conversely, PC2 does not show any significant correlation with the FRI. Different results emerge when considering population density: in particular, a positive correlation is observed between PC2 and population density (the more densely populated a given region is, the larger the tertiary education presence)[12]. Although these results are not univocal, obtained signs are largely expected. Actually, Europe 2020 Strategy is found to be a quite urban strategy, as both most densely populated areas and those regions sharing the lowest values of FRI show better performances than other EU regions. Accordingly, regions with large urbanized traits, thus being characterized by high population density and a lower presence of agricultural activities, show better employment rates, larger social cohesion and better educated people. Conversely, those regions that are affected by deeper rural features tend to show a less smart and less inclusive growth than urban regions, thus lagging behind them.

Table 6 - Pearson correlation coefficients between indicators of rurality (FRI and population density) and PCs (p-values in parentheses)

	FRI	Population Density
PC1 - *Smart and inclusive growth*	-0.492** (0.000)	0.085 (0.170)
PC2 - *Tertiary education*	-0.112 (0.071)	0.258** (0.000)

**, *: statistically significant at the 1%, 5%, respectively

Source: own elaboration

These findings seem to be robust. Actually, when computing average FRI values as well as the average population density per each group of regions (i.e., "EU2020 Best performers", "Good performers but under-educated", "Bad performers but over-educated", "Lagging behind regions") results are largely confirmed. Values are shown in Table 7: as expected, "EU2020 Best Performers" show more urban features (low FRI and high population density) than other groups and in particular than lagging behind regions. Differences in both FRI and

[12] Nevertheless, these results may be affected by the presence of some statistical outliers, such as the city regions of London and Brussels.

population density have been statistically tested through One-Way ANOVA (Analysis of Variance)[13] and they are found to be statistically significant at 5% (2-tailed).

Table 7 - Average FRI and Population Density by Europe 2020 goals' groups (p-values in parentheses)

	Avg. FRI	Avg. Population Density
EU2020 best performers	0.350	556.85
Good performers but under educated	0.416	307.24
Bad performers but over educated	0.603	361.18
Lagging behind regions	0.696	140.56
Levene's Test	6.988**	2.678*
	(0.000)	(0.048)
One-Way ANOVA	29.376**	4.953**
	(0.000)	(0.003)

**, *: statistically significant at the 1%, 5%, respectively
Source: own elaboration

Analyses on PCs have suggested that a large heterogeneity affects EU regions when focusing on Europe 2020 performance. Indeed, EU urban regions are better approaching Strategy's targets than rural areas. Deep rural regions are particularly affected by a poor performance in achieving a smart and inclusive growth. The same is true when considering tertiary education: the latter is definitely larger within urban areas than across EU rural areas.
Nevertheless, rurality just represents part of the story. Actually, even rural regions may show opposite characteristics, according to major differences in terms of either natural characteristics (for instance, mountain regions vs. Flatlands) or other infrastructural features (namely accessibility). Thus, even geography matters, as Tobler (1970) suggested. According to this key concept, next section will focus on geographical spill-overs that may play a role in the way EU regions are currently achieving Europe 2020 Strategy's targets.

4.3 Europe 2020 Strategy: A Spatial Approach

As pointed out in previous sections, performances of EU regions when focusing on the achievement of Europe 2020 targets are very different. Nevertheless, other structural characteristics but urban and rural features may affect such a territorially-imbalanced performance.
Firstly, rough but interesting results emerge by analysing regional performances by groups of EU Countries. Indeed, in order to get spatially-characterised results, EU-27 Member States

[13] One-Way ANOVA uses F statistics to test if all groups have the same mean or not. As a major assumption of One-Way ANOVA is that variances of populations are equal, the Levene's Test has been preliminary computed, testing the null hypothesis of homoschedasticity among groups variances. When group variances are equal simple F test for the equality of means in a one-way analysis of variance is performed. In the opposite case, the method of Welch (1951) is used.

can be grouped into 5 macro-areas: i) Nordic Countries; ii) The UK and Ireland; iii) Continental Western Europe; iv) Mediterranean Europe and v) Eastern Europe[14]. Table 8 shows the number of NUTS 2 regions per macro-area, falling within each above-mentioned class ("EU2020 best performers", "Good performers but under educated", "Bad performers but over educated", "Lagging behind regions"). Nordic and Anglo-Saxon Countries show a large number of regions falling within the best classes, with a negligible share of "Lagging behind regions" out of the total. Conversely, Continental Western Europe shows a more scattered picture, being represented all typologies of regions. On the opposite side, Mediterranean and Eastern Europe regions show poorest performance: indeed, more than 50% of total regions fall in the "Lagging behind regions" typology. These patterns largely confirm Sapir (2004; 2006) hypotheses, suggesting that different EU social models may affect general performances in achieving Europe 2020 goals as well. Furthermore, current economic crisis seems having strengthened these patterns. Indeed, Mediterranean Europe has not yet caught up the same path of sustainable and inclusive growth characterising Northern Europe. Furthermore, Eastern Countries show an even more peculiar path of growth. Indeed, they show dichotomous performances: their capital cities are among EU best performing regions when focusing on Europe 2020 Strategy, whereas rural areas are still lagging behind.

Table 8 - Regional performances by groups of Countries

Country	Best performers		Good performers but under educated		Bad performers but over educated		Lagging behind regions	
	#	%	#	%	#	%	#	%
Nordic Countries	12	66.7	6	33.3	0	0.0	0	0.0
The UK & Ireland	29	74.4	3	7.7	6	15.4	1	2.6
Continental Western EU	25	26.6	54	57.4	12	12.8	3	3.2
Mediterranean EU	3	5.3	2	3.5	22	38.6	30	52.6
Eastern EU	8	14.8	5	9.3	13	24.1	28	51.9

Source: own elaboration

Spatial and other territorial spill-overs may also play a role at sub-national level. Such effects are here assessed through Exploratory Spatial Data Analysis (ESDA), by analysing both global and local Moran's I. For the sake of comparison, global Moran tests are computed according to two different spatial weight matrices: i) the first-order queen contiguity matrix adjusted for islands, already described in section 3 and ii) a 5 nearest neighbours' matrix[15]. Moran's I is here computed on both extracted PCs, i.e. "smart and inclusive growth" and "tertiary education". In both cases, results suggest that spatial autocorrelation occurs

[14] Nordic Countries comprise Denmark, Finland, Sweden. Continental Europe includes France, Luxembourg, Belgium, the Netherlands, Germany and Austria: Mediterranean Europe includes Portugal, Spain, Italy, Greece, Malta and Cyprus. Eastern EU includes Estonia, Latvia, Lithuania, Poland, the Czech Republic, Slovakia, Slovenia, Hungary, Romania and Bulgaria.
[15] In this case, for each observation, average value of the five nearest regions is considered.

throughout the EU space (Table 9). Accordingly, achieving Europe 2020 Strategy's goals at regional level clearly shows a tendency to spatial clustering throughout EU-27.

Table 9 - Global Moran's I on extracted PCs

Country	First-order Queen Contiguity Matrix		5-nearest Neighbours Matrix	
	Moran's I	**p-value**	**Moran's I**	**p-value**
PC1 - *Smart and inclusive growth*	0.756	0.000	0.702	0.000
PC2 - *Tertiary education*	0.629	0.000	0.565	0.000

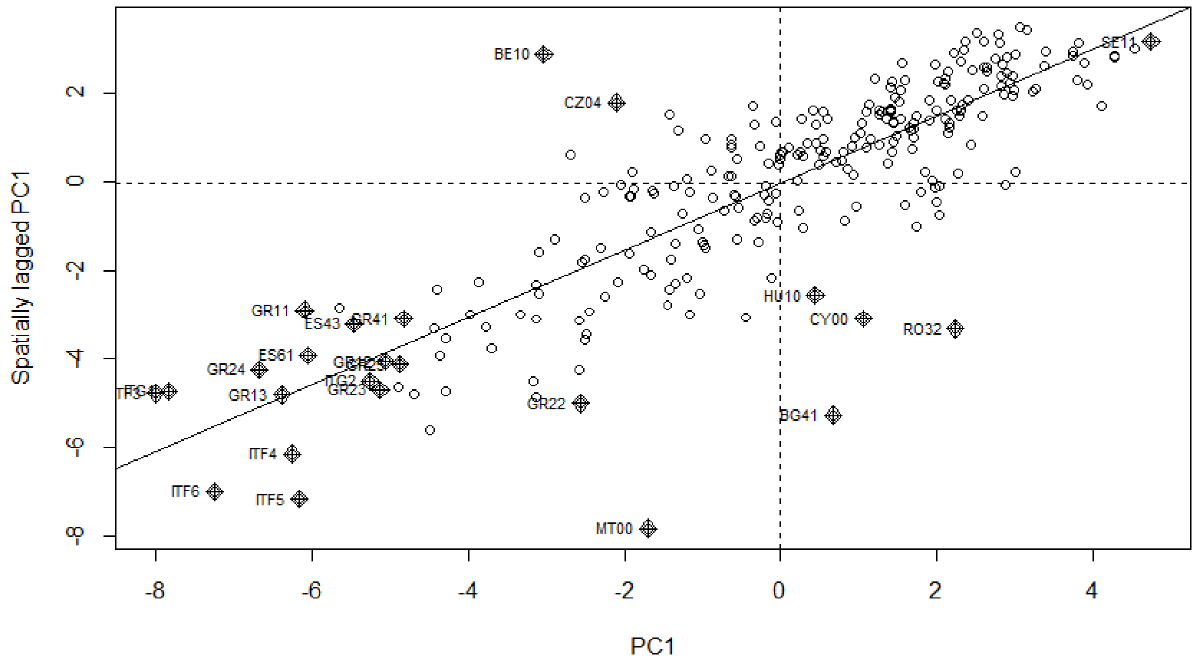
Source: own elaboration

A Moran scatter plot provides similar information: it enables to assess how similar each observed value is to its neighbouring observations. Observed values (i.e., each extracted PC, at regional level) are shown on horizontal axis whereas spatial lags of corresponding observations (i.e., the average values observed throughout neighbouring regions) are shown on vertical axis. Thus, points in the upper right (high-high) and lower left (or low-low) quadrants indicate positive spatial association of values that are higher and lower than the sample mean, respectively. The lower right (or high-low) and upper left (or low-high) quadrants include observations that exhibit negative spatial association; that is, those observed values carry little similarity to their neighbours.

Figure 2 shows Moran scatter plot for PC1; Figure 3 shows same plot for PC2[16]. In both cases, the slope of the line equals to the respective global Moran's I coefficients, as shown in Table 9. It is easy to notice that both PCs show positive spatial autocorrelation. Furthermore, some specific regions have been highlighted in both plots, as they show extreme values thus deeply affecting global Moran's I values. For instance, referring to PC1, some Eastern capital cities (for instance Bucarest – RO32 and Budapest – HU10) are highlighted in the lower right quadrant: they show very good performances, despite lagging behind neighbouring regions. Conversely, many Mediterranean regions show extreme values in the low-low quadrant (e.g., Campania – ITF1, Sicily – ITG1, Sterea Ellada – GR24, Andalucia – ES61).

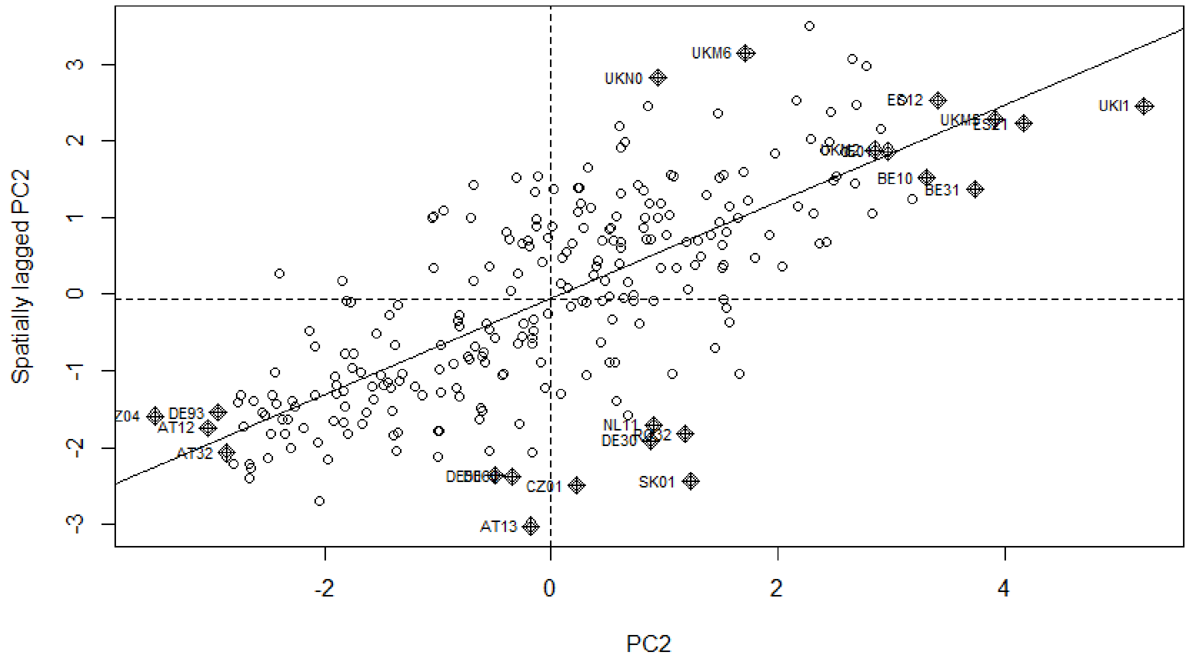
[16] In both cases, the first-order queen contiguity matrix adjusted for islands is used to define spatially lagged variables.

Figure 2 - Moran scatter plot: PC1 - smart and inclusive growth



Source: own elaboration

Figure 3- Moran scatter plot: PC2 – tertiary education



Source: own elaboration

Furthermore, specific spatial clusters co-exist with this global tendency to spatial clustering, as pointed out by global Moran's I. In order to identify those more specific spatial patterns, local Moran statistic can be used. The indicator is analogous to global Moran's I statistics, being region-specific though.

Referring to PC1, 59 significant values (at 1% significance level) are identified: in particular, 22 hot spots (i.e., high-high cases) and 37 cold spots (low-low cases) can be detected.

According to general definition, hot spots represent spatially-clustered best performing regions. Conversely, cold spots represent bad performing regions that are surrounded by other bad performing areas. Hot spots are mostly located in Southern Germany, the Netherlands, Southern England and Southern Sweden; cold spots are mostly found throughout Mediterranean (Southern Spain, Southern Italy and Greece) and Eastern Europe (Bulgaria, Romania and Hungary).

Referring to PC2 (*tertiary education*), 27 hot spots and 35 cold spots are identified. Here a Eastern-Western divide seems emerging: hot spots are located throughout Spain, Ireland and Scotland, whereas cold spots are largely located throughout Germany, the Czech Republic, Austria, Northern Italy and Romania[17].

Besides the spatial allocation of both hot and cold spots in the achievement of Europe 2020 targets, it is also interesting to detect whether hot and cold spots show specific features in terms of rurality. Referring to Europe 2020 global performance (i.e., PC1), cold spots are much more rural and less densely populated than other regions, and in particular than hot spots. These differences among average FRI values are found to be statistically significant according to a One-Way ANOVA. Less straightforward results characterise PC2 (i.e., tertiary education). In the latter case, no significant differences in terms of urban-rural features affect hot and cold spots. Nevertheless, hot spots are characterised by a larger population density than both cold spots and other regions (Table 10).

Table 10 – Hot and cold spots features

		Avg. FRI	Avg. Population Density
PC1	Hot spots	.368	302.72
	Cold spots	.797	123.28
	Other regions	.461	399.11
	Levene’s Test	17.183**	1.357
		(.000)	(.259)
	One-Way ANOVA	58.037**	1.580
		(.000)	(.208)
PC2	Hot spots	.546	654.19
	Cold spots	.554	144.64
	Other regions	.485	347.58
	Levene’s Test	8.847**	2.98
		(.000)	(.053)
	One-Way ANOVA	1.586	2.593
		(.214)	(.077)

Source: own elaboration

Through global and local Moran statistics, some important findings have been pointed out. Firstly, regional performances referring to Europe 2020 Strategy show large territorial imbalances throughout the EU-27. Furthermore, regional results show clear tendencies to spatial clustering: as a consequence, EU cannot be considered as a homogeneous area with regard to that strategy. Geography definitely plays a key role in affecting the way EU regions react at new political challenges. Then, the analysis of local statistics has pointed out the

[17] It is interesting to notice that spatial outliers are found in neither case.

existence of cold spots, i.e. lagging behind regions surrounded by other lagging behind areas. According to these analyses, both rural and peripheral regions are found to be largely unable to catch up a path of growth that is smart and inclusive. On the contrary, more urban areas show a better performance referring to Europe 2020 Strategy's goals. Thus, a core-periphery pattern seems emerging at EU level, largely confirming Sapir (2004; 2006) major hypotheses. Although the current work has been developed moving from different perspectives (in terms of both geographical and temporal dimensions, as well as socio-economic objectives), results largely converge: Europe 2020 geography mostly follows the four social models already identified by Sapir. Furthermore, the outburst of the economic crisis has further delayed the process of convergence among different regions and Countries.

5. Conclusions and policy implications

The analysis has focused on major differences in the way NUTS 2 regions are approaching Europe 2020 Strategy's main targets. Through a Principal Component Analysis (PCA), two main components have been identified: first component sums up regional smart and inclusive growth, thus representing a general indicator of regional performance whilst second one refers to the importance of tertiary education. By jointly considering both PCs, four typologies of regions can be detected: "EU2020 best performers", "good performers but under educated", "bad performers but over educated", "lagging behind regions". Then, the presence of a rural effect in regional performance has been tested, too. According to major results, both PCs seem to be negatively correlated to rurality: thus, the more rural a given region is, the worse the performance according to Europe 2020 Strategy's targets. Signs are largely expected: actually Europe 2020 Strategy mostly is an urban strategy. Furthermore, a generic spatial effect has been considered as well, by performing an exploratory spatial data analysis. Accordingly, geography is found to play a key role in the achievement of Europe 2020 main goals. The analysis of global Moran's I statistics has confirmed a strong tendency to spatial autocorrelation in regional performances. Moreover, when computing local Moran's I statistics, hot and cold spots have been detected as well. According to these results, a special attention has to be devoted to cold spots, as they are groups of spatially-contiguous regions showing below the average performances in approaching Europe 2020 targets. In particular, two typologies of cold spots can be identified: i) deep rural regions and ii) peripheral/remote regions.

Territorial imbalances in the achievement of Europe 2020 Strategy's targets are large throughout Europe. Due to the presence of important spatial spill-overs, a need for more place-based policies, both at national and EU level, clearly emerges. In particular, such a place-based approach would make Europe 2020 Strategy more capable to respond to future challenges, by making it more effective and efficient than past interventions (Barca *et al.*,

2012). Actually, just devoting a specific focus on lagging behind regions, Europe 2020 Strategy could fully achieve its ambitious goals.

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SOMMARIO

La Strategia Europa 2020 rappresenta una strategia decennale che ha l’obiettivo di promuovere la crescita intelligente, sostenibile e inclusiva dell’Unione Europea. Nonostante un obiettivo tanto ambizioso, la Strategia soffre di alcuni limiti, tra i quali spicca l’assenza di una sua dimensione territoriale. La presenza di divari territoriali tanto ampi entro la UE potrebbe dunque minacciare il successo di questa Strategia entro il 2020. Il presente lavoro affronta questo tema, misurando in primo luogo la performance delle regioni europee rispetto agli obiettivi della Strategia Europa 2020. Un’analisi in componenti principali è applicata ad una lista di variabili di input, raccolte a livello territoriale NUTS 2 per i 27 Stati Membri. Sono così identificate due componenti principali: i) crescita intelligente e inclusiva; ii) ruolo dell’istruzione terziaria. Successivamente, la presenza di un effetto rurale e di un generico effetto spaziale sono presi in considerazione: entrambi risultano correlati alle componenti estratte. In particolare, attraverso il calcolo della I di Moran globale e locale, viene evidenziata una forte tendenza all’autocorrelazione spaziale delle performance regionali. I risultati dunque confermano la presenza di ampi divari regionali. Soltanto la riduzione di tali divari permetterà di raggiungere pienamente gli obiettivi previsti dalla Strategia Europa 2020 entro la fine del decennio.