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A composite policy tool to measure territorial resilience capacity

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Abstract

The recent global recession and consequent slow recovery have revealed considerable heterogeneity in economic performance across countries and regions. This study aims at constructing a simple 'handy' composite Regional Resilience Indicator to measure and monitor economic system resilience at regional level in order to facilitate a common easily understanding of this complex and dynamic process. Our approach extends the existing theoretical framework and attributes to resilience a well-defined life cycle. The composite indicator weights have been attributed through weight elicitation techniques built upon principal component analysis.

1 Introduction

In the last years the European Union (EU) has been probably hit by the worst crisis in its history. The roots of this crisis are the combination of a loss of competitiveness and high indebtedness[1] especially of periphery countries in the European Monetary Union (EMU) (EC, 2010; Crescenzi *et al.*, 2016). The consequent instability, which has led to unprecedented turbulence on financial markets, has put a great challenge to the EU and to the rest of the world.

In response to the crisis, EU has agreed upon a common strategy within the 2008 European Economic Recovery Plan (EERP) (EC, 2008) that essentially proposes a number of measures to direct short-term actions to reinforce Europe's competitiveness[2] in the long term, i.e., smart investment for capacity building in order to promote efficiency and innovation. These measures have been included in the EU2020 framework with respect to which Cohesion Policy has been shaped. In view of EU2020 strategy, the capacity of the European regions to react to external shocks is of particular interest because it has a direct implication on the outcomes of European Economic Policy (Milio et al., 2014).

The crisis spread asymmetrically in time, strength, and speed across EU regions (ECB, 2010). Not all regions experienced economic decline and the territorial impact of the crisis has varied greatly also within the same country (European Commission, 2013; Martin, 2010). Similarly, while some regions experienced a swift return to pre-crisis levels of employment and output, the process of recovery has proved much more protracted for many regions entering a period of sustained stagnation.

In this context, a composite policy tool is becoming key in order to identify resilience and design territorial development strategies (Martin, 2016). To the best of our knowledge, economic resilience has been conceptualized (Martin, 2012; Briguglio *et al.*, 2009) as a multidimensional complex concept, but it has not been translated into a synthetic regional indicator. In the frame of the activities of the LUISA[3] Territorial Modelling Platform, our research aims to: i) setup a simple indicator of regional economic resilience, ii) identify the resilience degree of EU regions, iii) suggest a potential instrument to draw policy implications.

The paper is structured as follows. The theoretical framework is introduced in Section 2. Section 3 discusses data and methodological issues concerning the weighting and aggregation procedures of the composite indicator. Our results are reported in Section 4 and, finally, Section 5 concludes.

[1] The government budget position, measured by debt-to-GDP ratio index, is the result of fiscal policy, which is, combined with monetary policy, one the main policy instruments. A healthy fiscal position would allow adjustments to taxation and expenditure policies to offset adverse shocks. High level of external indebtedness would also limit the ability to mobilize resources in the face of external shocks.

[2] Competitiveness is generally agreed as the capacity of countries or regions to produce goods and services that meet the test of foreign competition which can be reflected in a sustainable balance of payments, while simultaneously maintaining and expanding domestic real income and jobs creation. The most commonly used measure of competitiveness is productivity (Camagni, 2002; Kitson *et al.*, 2004).

[3] LUISA Territorial Modelling Platform is implemented by the Joint Research Centre for the evaluation of EC policies that have a direct or indirect territorial impact.

2 The resilience framework

Recently, much work has been done to identify the drivers of crisis recovery and investigate the structural characteristics of the regions and determinants of resilience.

Briguglio *et al.* (2009) distinguish between economic vulnerability and economic resilience. The former is defined as the exposure of an economy to exogenous shocks, which depends on permanent or quasi-permanent inherent structural characteristic over which policy makers can exercise limited control while the latter is defined as the policy-induced capacity of an economy to withstand or recover from the effects of such negative shocks.

Martin (2012) analyses the concept of resilience identifying four main dimensions: (i) resistance, which identifies the sensitivity of regional output and employment to exogenous shock and determine the demand for public policies; (ii) recovery, which measures how fast the region bounces back from a negative shock; (iii) reorientation, which concerns the extent to which a region changes after a shock by switching for example its economic sectoral composition; and (iv) renewal, which is the ability of a regional economy to renew its growth path.

More recent literature, among others e.g., Martin and Sunley (2014), Diodato and Weterings (2015) and Manca *et al.* (2017), following Martin (2012), defines resilience as the multidimensional capacity of regional and local economy to absorb shocks, adapt or transit to new sustainable development path.

2.1 The life cycle of resilience

Our approach extends the previous conceptualizations and characterizes resilience as a complex process with a well-defined life cycle. We borrowed the product life cycle theory that was first developed by Raymond Vernon in 1966 in order to conceptualize our framework.

This theory identified four stages, each with its own characteristics crucial for business that are trying to manage the life cycle of their particular products. In Figure 1, we identify and characterize the different steps of a resilience capacity building process following the product life cycle theory's four stages:

- *Introduction Stage* – This stage of the cycle is characterized by a process of learning-by-doing that entails increasing returns to scale for the economy: a proportionate increase in the usual production inputs (labour and capital) gives rise to more than proportionate gains in output (Arrow, 1962; Romer, 1986, 1993; Lucas, 1988). It requires an active participation of different actors to earn enough in terms of capital accumulation and capacity building to escape from the spiralling mechanism of the so-called poverty trap and accumulate resilience capacity. According to Sachs (2005), many factors can contribute to stagnate into a poverty trap, including a limited access to credit and capital markets, poor infrastructure, lack of public services and corrupt governance, extreme environmental degradation, etc. Public interventions can help to reverse the vicious cycle.
- *Growth Stage* – The growth stage is typically characterized by a strong growth that benefits from economies of scale. Innovation processes and spill-overs that increase over time, enhancing skill and productivity levels throughout the economy, determine the speed of the growth process and then the slope of our curve of the resilience capacity-building process (Krugman and Obstfeld, 1997). During this phase, catching up and falling behind mechanisms act leading to different levels of development and resilience.
- *Maturity Stage* – During the maturity stage, the growth and capacity building process is close to its steady-state value, and the aim for regional and local authorities is now to maintain the adaptive and coping capacities they have

contributed to build up. This stage potentially identifies specific regions with a competitive advantage over others.

- *Decline/Renewal Stage* – Eventually, if a shock hits the economy two opposite options might occur. The resilience capacity can start to shrink, and this is what we refer to as the decline stage. This shrinkage could be due to the saturation or inadequacy of that capacity. The alternative can concern the extent to which a regional economy reacts after a shock and renews its growth path leading to a renewal stage. The capacity to recover built over the first three stages can determine the decline, renewal or eventually a scalloped pattern.

The first three stages (introduction, growth and maturity) are not individually observed, but they belong to the so-called slow burning process (Manca *et al.*, 2017), which measures the capacity built over time of a region to cope with a shock. During these phases, policy-induced changes can strengthen the resilience capacity of a region. The last stage, decline/renewal, referred to as shock wave or dynamic process, is based on the immediate exposure to an unexpected shock over which a region can exercise limited control.

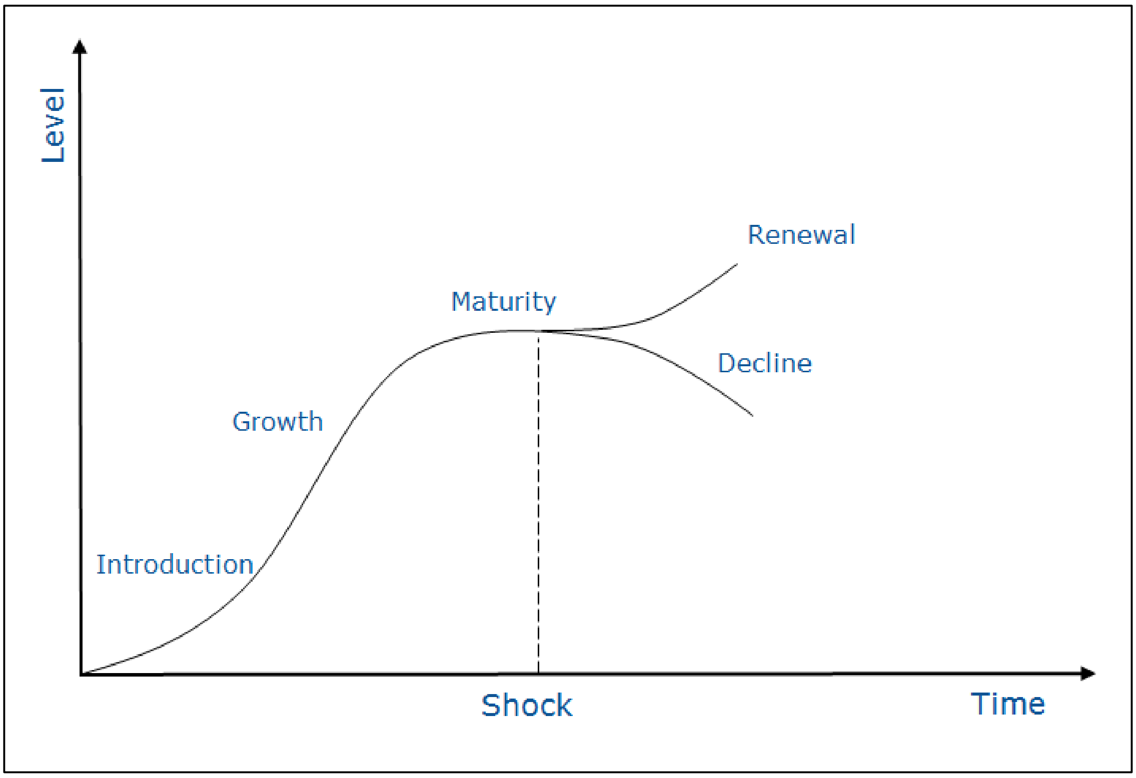

Figure 1 – The life cycle of Resilience

2.2 An exploratory investigation

A recent empirical exercise proposed by Crescenzi *et al.* (2016), split the time period analysis in pre-2008 crisis (slow burning process) and post-2008 crisis (shock wave) and apply a regression approach to explore the relation between post-2008 crisis regional performance indicators and pre-2008 national macroeconomic conditions and regional resistance factors.

In order to get a first understanding of the EU NUTS2 regions' pre and post-crisis performance, we explored the linkage between the growth trend before and after the crisis of some key economic variables i.e., GDP per capita, employment rate and productivity, defined as GDP per employee. [4] We borrowed the methodology of Gutierrez *et al.* (2007) and the World Bank stepwise decomposition approach using the Shapley decomposition method (World Bank, 2010) to decompose GDP per capita into output per worker and employment. These variables have been also chosen because i) they are the best indicator able to synthetize economic conditions at regional level, and ii) they quickly react to shocks. A lasting GDP per capita growth is sustained by productivity growth. At the reverse, a rising employment rate might hamper GDP per capita growth if not followed by productivity growth.

We classify the 271 NUTS2 regions according if they placed above or below the EU average for the three variables. [5] Thus, each of the points in Figure 2 represents a combination of performances' value measured before (x-axis) and after the crisis (y-axis). The x- and y-axes divide the scatterplot into four quadrants (anticlockwise from top right): in the first and third (high-high, HH, and low-low, LL, respectively) a region exhibits a high (low) value of both pre and post-crisis indicators. In the second and fourth quadrants (low-high, LH, and high-low, HL, respectively) a region reveals a low (high) value of the variable before the crisis and a high (low) value of the post-crisis variable.

In order to derive a classification of EU NUTS2 regions with respect to their economic behaviour before and after the 2008 financial and economic crises and the consequent potential for resilience, four different clusters of regions were identified. These quadrants, in anticlockwise, correspond to:

- Winners (top right) – Regions belonging to this group performed better than the European average before and after the crisis. The crisis hits them but the economic stability and resilience capacity reached before the shock occurred helped them to recover fast.
- Inefficient process (top left) – The group classifies regions that were not able to recover even if they were experienced a pre-crisis growth trend above the EU average. Many factors can contribute to negatively change the growth trend e.g., among others inefficient policies, lack of public services, etc. The growth and resilience capacity building process has not reached in the pre-crisis period such a critical mass necessary to recover from a negative shock.
- Falling behind (bottom left) – Starting from a position below the European average, these regions have been strongly affected by the negative shock and failed to recover.
- Inherent features (bottom right) – Regions in this quadrant were below the European average before the crises while they were able to efficiently react to the crisis revealing a post-crisis trend above the European average. We attribute this capacity to recover to some inherent structural characteristics that contributed to change past trend.

[4] The time period of the analysis is 2000-2015. We consider the 2000-2008 interval to compute the trend before the crisis while the 2009-2015 interval is chosen for the trend after the crisis.

[5] We choose the arithmetic mean as a threshold to split the sample of regions and not the median because outliers were not strongly affecting the distribution so that the arithmetic mean can be used as an adequate position index.

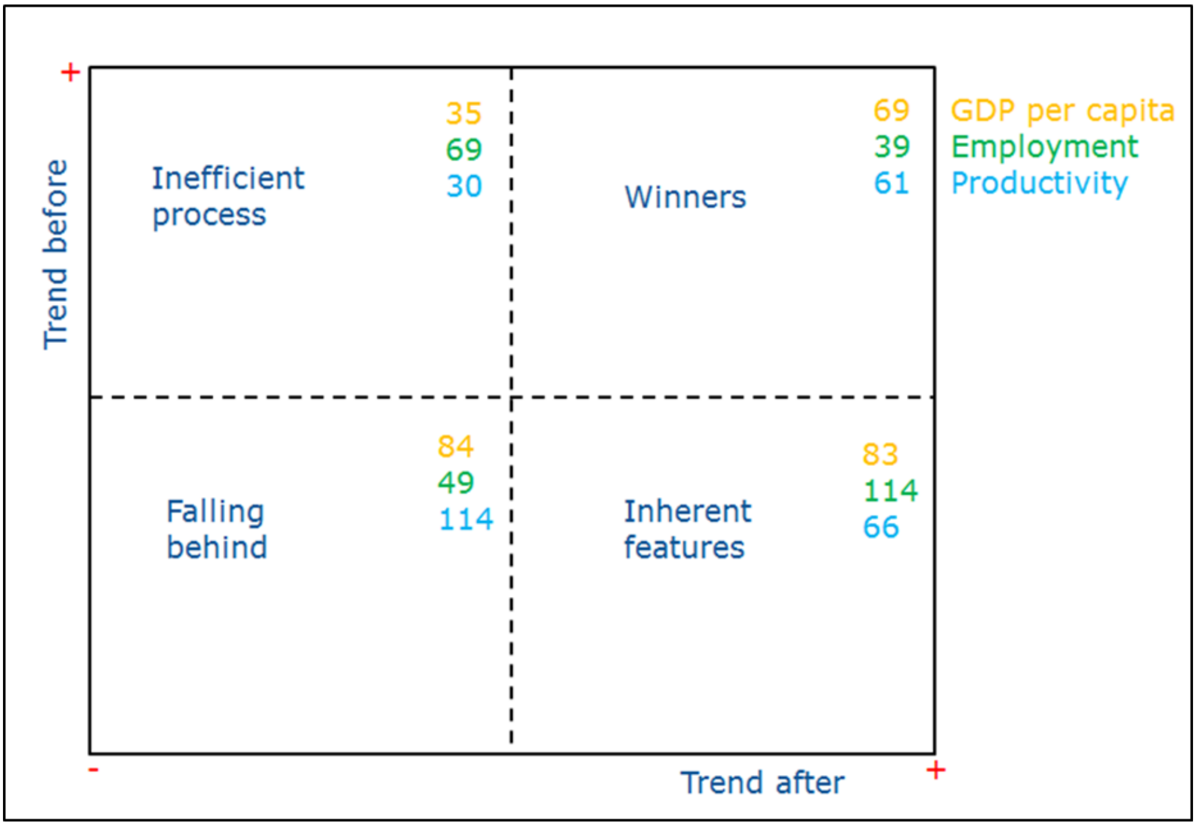

Figure 2 – Classification of EU NUTS2 over the period 2000-2015

In terms of GDP per capita, regions are equally distributed in the third and fourth quadrants, *falling behind* and *inherent features* regions, respectively. This means that, of the 167 regions that were declining before the crisis, half of them continued to decline, while half of them experienced a renewal process. Furthermore, 25% of regions well performing before the crisis continued to positively perform after. The pattern of employment rate shows that around 42% of regions are placed in the fourth quadrant, showing that the employment trend after the crisis is above the average, while it was below before the crisis. Furthermore, 25% of regions show that the rise of employment before the crisis was not sustainable. Finally, regarding productivity it can be observed that 42% of regions fall in the third quadrant, highlighting strong issues related to their business structure. Anyway, around 25% of regions improve the productivity, and 22% of them continue to have a trend above the average.

3 Methodology

Since the resilience of EU regions is a multidimensional complex concept, we propose a composite synthetic regional economic resilience indicator that considers the three variables above described.

To the best of our knowledge, this approach to resilience capacity is innovative since it assesses in a unique indicator all the phases of the resilience life cycle.

Weighting and aggregation approaches in composite index construction have been in detail surveyed by the OECD (2008). The regional resilience indicator is constructed through a normalization and weight elicitation based on principal component analysis that can be applied as a mean to reduce dimensionality by transforming the multiple dimensions into a set of few uncorrelated dimensions. For a robustness check, equal weighting has also been applied. This technique is the most commonly applied approach, mainly due to the simplicity of the concept, computation and interpretation of selected indicators.

The composite 'Regional Resilience Indicator' to external shocks is defined by two dimensions. The first measures the intrinsic capacity of a region registered over time along its resilient evolutionary path from a base line target point taken as a reference to the measurement period to cope with a crisis and figures out its so-called slow burning process. The second, to whom we refer as shock wave or dynamic process, allows us to analyse the immediate exposure and reaction capacity to an unexpected shock.

A three-step approach was followed for the identification of regional disparities in the resilience capacity to the crisis:

(i) data collection and indicators selection;

(ii) weighting and aggregation;

(iii) clustering and spatial analysis.

3.1 Data collection and indicators selection

This study employs annual data in 2005 constant price euros over the period 2000-2015 from Cambridge Econometrics' European Regional Database (GDP per capita, employment rate and productivity, defined as GDP per employee).

Then, our slow burning and shock wave indicators have been selected and built for each variable. The slow burning indicators are:

- mean over the period 2000-2008 indicates the level over a particular period of time or in the steady-state behaviour of the system;
- trend over the period before (2000-2008) and after (2009-2015) the crisis:[6] is the average sustainable rate of growth over a period of time. It is the slope of the line connecting the two points before and after the crisis and measures the steepness of that line and so the speed of the growth rate. The trend over the pre-crisis period is assumed to be the long run growth trend that a region would have had if the crisis did not occur. The trend over the post-crisis period is a proxy of the long run growth trend after the shock.

The shock dynamic indicators considered are:

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[6] The trend has been computed as follows: i) we regress the time period on the log of the selected variables, and ii) we keep the coefficient associated with the log of the selected variables. If it is positive (negative) and significant, it means that the slope rises up (falls). If the coefficient is zero or not significant, the trend is not statistically different from zero.

- the maximum hit of the crisis between 2009 and 2010 compared to 2008 pre-crisis year is conceived as the immediate reaction to an unexpected shock;
- the relative change between 2015 and 2008 pre-crisis year is assumed as the capacity to recover.

The following step consists in the aggregation of the measures created for each variable, GDP per capita, employment level and productivity.

3.2 Weighting and aggregation

Two different weighting and aggregation methodologies have been used. The first approach relies mainly on Goletsis and Chletsos, (2011), while the second proposed methodology is based on equally weighting and used, for example to construct the Regional Competitiveness Index (Annoni *et al.*, 2013). [7]

The first approach consists of two stages: (a) normalization and (b) weight elicitation.

(a) The normalisation of the data helps to i) remove the different scale of each variable, and ii) identify indicators may be positively correlated with the phenomenon to be measured, whereas others may be negatively correlated with it. [8] There are different methods of normalization, such as ranking, re-scaling (or min-max transformation), standardization (or z-scores) and indicization. As suggested by Goletsis and Chletsos, (2011), we made use of the min-max transformation. Consider the *i-th* indicator for region j, $I_{ij}$is transformed to I_{ij}^{adj} taking values within the interval [0,1] according to the following equation:

$$I_{ij}^{adj} = \frac{I_{ij-}min_j(I_{ij})}{max_j(I_{ij}) - min_j(I_{ij})} \quad (1)$$

(b) A multivariate method usually applied for space reduction, namely the Principal Component Analysis (PCA) has been used for weight elicitation.

PCA aggregates sub-indicators that are collinear into new ones named components, which are able to capture as much of common information of those sub-indicators as possible. PCA determines the set of weights, which explains the largest variation in the original data. Different criteria can be applied on the selection of number of components in order to keep the maximum of information. We keep the components cumulatively contribute to the explanation of the total variance of the data by more than 70%. The selected components are then used for the aggregating procedure to ensure that the variables used are not correlated.

Weights are estimated as normalized squared loadings (implying the portion of variance of each component explained by each variable). We apply the approach, which uses highest loading per variable weighted according to the relative contribution of the respective component to the explanation of the overall variance. The indicator is aggregated through the following weighted additive function:

$$CRI_j = \sum_i w_i \, I_{ij}^{adj} \quad (2)$$

where CRI_j is the Composite Resilience Index for region j, w_i is the weight of indicator *i* and I_{ij}^{adj} is the adjusted value of indicator I_i for region j.

[7] The weighting scheme of the EU Regional Competitiveness Index (RCI) is more complex because it is based on z-scores normalization procedure and weighted arithmetic mean where the weights are the region’s stages of development.

[8] This step is required in order to ensure that an increase in the normalized indicators corresponds to increase in the composite index

The second approach shares with the first above explained the normalization procedure while differs for the weight elicitation since it is based on weighting equally the selected indicators through arithmetic mean.

3.3 Clustering and spatial analysis

The overall objective of clustering is to identify regions sharing common resilience features and, therefore, strategic geographical and thematic areas of intervention for policy makers.

Hierarchical clustering is applied to a distance matrix computed by using an Euclidean criterion in order to group together regions that share similar resilience capacity. The cluster analysis was done following a modification of the Ward method proposed by (Murtagh and Legendre 2014), the Ward^2, to identify the clusters of regions that share similar pattern. The Ward2method is hierarchical agglomerative and begins the analysis with as many groups as the units are. Groups are then formed ascendingly from these initial units. At each stage, the two clusters for which there is the smallest increment in the total value of the sum of the squares of the differences within each cluster are grouped. The goal of Ward^2'smethod is to create homogeneous groups with as uniform and little as possible within variability. This hierarchical agglomerative method can be drawn as a dendrogram, a visual tool that help to identify the groups that best represent the data structure. A general rule of thumb is that clustering is performed where significant gaps exist in the dendrogram.

The second step was to analyze the global and local spatial dependence.

Global spatial dependence was identified through the Moran's I (MI) (Moran, 1950). This statistics has been widely used in the literature to describe economic phenomena whose distribution in the space is not random (Le Gallo and Ertur, 2003; Ertur *et al.*, 2006; Dall'Erba, 2005; Gregory and Patuelli, 2015).

The MI relates the value of a selected variable with the values of the same variable in the neighbor areas, namely its spatial lag. The intuition behind is that socio-economic phenomena might be not isolated in space and what is happening in a certain location might be correlated to what is happening in the neighbor locations. The formal definition of this relation is as follows:

$$MI = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i w_{ij}(x_i - \bar{x})} \quad (3)$$

where N is the number of regions indexed by i and j, x is the variable of interest; $\bar{x}$ is its mean, and w_{ij} is an element of the spatial weights matrix **W**, which is defined as a queen contiguity matrix, i.e. regions are considered as neighbor if they touch themselves for at least a point. [9] Then, as customary, the matrix is standardized by row.

The calculated MI for global autocorrelation, in the case of **W** standardized by row, varies between -1 and 1. A positive coefficient points to positive spatial autocorrelation, i.e., clusters of similar values can be identified. The reverse represents regimes of negative association, i.e., dissimilar values clustered together in a map. A value close to zero indicates a random spatial pattern.

A precise evaluation and spatial identification of the levels of local spatial autocorrelation are achieved by Local Moran. The Local Moran allows identifying the clusters of "spatial outlier regions", i.e., the statistical hotspots and coldspots, the areas with a concentration of regions with high levels and low levels of turnout, respectively. This is possible because the Local Moran is able to identify for each region an indication of

[9] The islands have been connected to the nearest region.

significant spatial clustering of similar values around that observation. Furthermore, the sum of the Local Moran for all observations corresponds to the global indicator of spatial association, the Moran's I (Cochrane and Poot, 2008, p. 71; Le Gallo and Kamarianakis, 2011, p. 129).

The local version of Moran's I statistic is a LISA and expressed as follows:

$$I_i = (x_i - \bar{x}) \sum_j w_{ij} (x_j - \bar{x}) \sum_i \sum_j w_{ij} \quad (4)$$

Finally, given that the local Moran I_i is not approximately normally distributed, a conditional randomisation or permutation approach is used to yield empirical pseudo significance levels.

4 Results

4.1 The Regional Resilience Indicator

The composite index for resilience for 271 NUTS-2 regions has been constructed considering the two different aggregation procedures above illustrated. Since the correlation between the two approaches is very high, we only reported the results based on the first approach. PCA estimated the weight values for the 15 selected indices. PCA variable loadings and weights are reported in Table 1A in Appendix. Three components were extracted. The identified components account for approximately 77.2% of total variance. The weight associated to the slow burning process is equal to 0.53against 0.47 of the shock wave. Employment has a weight of 0.57 and it has the highest values in the pre-crisis and maximum hit axis. GDP per capita has a weight of 0.26, followed by productivity with a weight of 0.17.

Figure 3 shows the spatial distribution of the Regional Resilience Indicator by decile. The Regional Resilience indicator has been normalized and varies between 0 and 1, where the smaller values (lighter) represent the less resilient regions, and the higher (darker) the most resilient.

As expected, the consequences of the crisis were not uniform among EU regions.

Well-identified territorial patterns can be observed:

- Generally, national common trends are observable. Mediterranean countries were characterized by slow growth of the selected indicators before and after the crisis, while Germany and Northern countries experienced strong growth and resilience capacities. Baltic countries were experiencing fast growth in the pre-crisis period and, in spite of the economic collapse, they were able to recover;
- Italy, Spain and Belgium show a north-south regional divide that often depends on historical origins;
- In the countries where NUTS2 regions have a more fine resolution, i.e., Germany,

  Great Britain, Belgium, Hungary and Austria, cities show a higher resilience than the surrounding regions. At the contrary, Dijkstra *et al.* (2015), conclude that capital metro regions under-performed compared with the national economy as a consequence of the crisis. The different results can be imputed to the analysis technique, but also to time period sample. Dijkstra *et al.* (2015), in particular, stop the analysis by 2011.

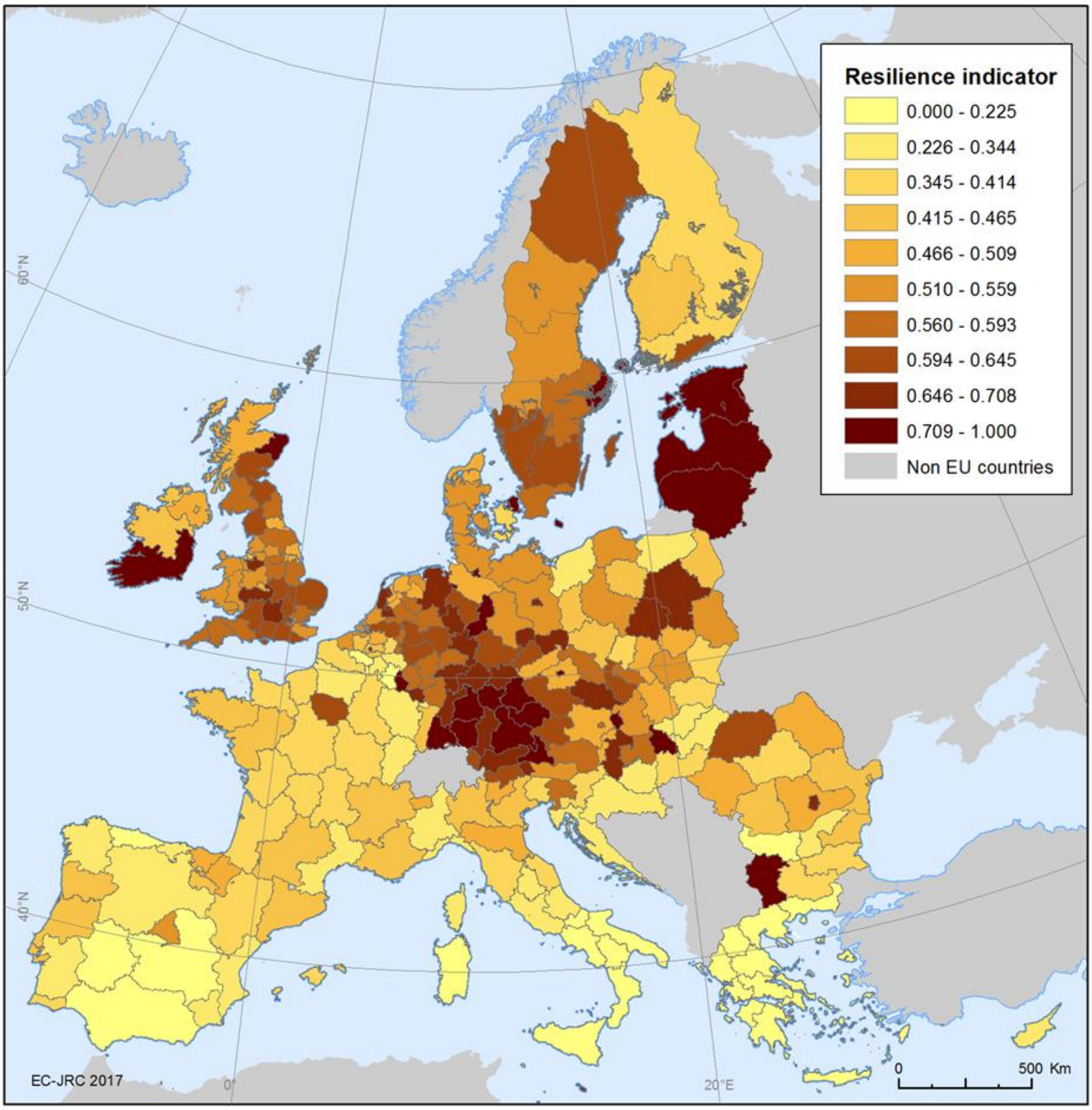

Figure 3 – Regional Resilience Indicator over the period 2000-2015 by NUTS2

Table 1 reports average and standard deviation values of the Regional Resilience Indicator. Countries are grouped into the EU-15 and EU-13, i.e., Member States that joined before and after 2004, respectively, and are ranked decreasingly according to their resilience average value. EU-15 countries were relatively less resilient to the crises and exhibited stronger variability from the group average than EU-13.

Regions tend to be centered on national averages in EU-15, with the exception of Italy, Spain and Ireland, while in the EU-13, all countries except Croatia have a quite high variability.

Table 1 – Regional Resilience Indicator by country

Country	Average	Std. Dev.	Country	Average	Std. Dev.

EU-15	*0.47683*	*0.19241*	*EU-13*	*0.50702*	*0.1667*
LU	0.874352		LT	0.78902	
DE	0.658265	0.088771	EE	0.735109	
SE	0.612089	0.08177	LV	0.710249	
IE	0.594767	0.204512	MT	0.652429	
UK	0.590866	0.078214	CZ	0.610226	0.134074
AT	0.585011	0.083818	SK	0.603422	0.275026
NL	0.564434	0.066124	RO	0.506934	0.101945
DK	0.534309	0.127734	SI	0.487645	0.10759
FI	0.527805	0.16034	HU	0.47958	0.211336
BE	0.392534	0.145969	PL	0.475467	0.107617
FR	0.38119	0.080456	BG	0.403235	0.179513
PT	0.36769	0.061551	CY	0.280693	
IT	0.30729	0.157966	HR	0.264775	0.019191
ES	0.290047	0.130648			
EL	0.105061	0.07076			
EU-28	**0.48329**	**0.18761**			

Note: the standard deviation is calculated for countries with at least two NUTS2 regions

4.2 Clusters and spatial pattern analysis

Figure 4 shows the results of the cluster analysis and number of regions belonging to each cluster is reported in brackets. Table 2A in Appendix reports average values of the resilience indicator and sub-indexes for each cluster. According to the dendrogram analysis, four clusters can be easily distinguished:

1. 125 regions across Greece, Spain and South of Italy were the less resilient to the crisis (lighter blue). The group has been hit moderately by the crisis but was experienced the worst growth in the pre-period crisis which led to the worst recovery. In 2015, the cluster did not recover to pre-2008 levels.
2. 36 regions are characterised by a low ability to cope with the financial crisis. They belong to France, Finland and eastern countries. The cluster was the less affected by the shock but was still registering a low growth capacity before the crisis. GDP per capita restored to pre-crisis level mainly sustained by productivity growth. Regions belonging to this cluster demonstrated higher efficiency in recover and overcome pre-crisis productivity levels.
3. 90 regions, mainly belonging to Germany, Sweden, Great Britain and eastern countries demonstrated a moderate resilience capacity. The 2008 crisis severally hits the cluster but since it was reaching high level of growth before the shock, regions in that cluster recover to pre-crisis GDP per capita and productivity levels.
4. 20 regions ranked as the highest resilient (darker blue). They belong mainly to Germany and the Baltics. Despite the cluster was the hardest hit by the 2008 crisis, regions belonging to it were on average able to recover in each of the three examined components.

Capital regions tend in general to be more resilient than the overall country they belong to. A U-shape spatial pattern can also be easily observed in the figure below. In Middle Europe, medium high resilient regions surround resilient regions from North-East while medium low ones form a corridor around non-resilient regions from the South-West side.

EU-13 is "leopard spotted" demonstrating a stronger heterogeneity in the resilience capacity. EU-15 presents a more rigid clustering between moderate and non-resilient regions which origins from systemic dynamics and historical well-rooted pattern.

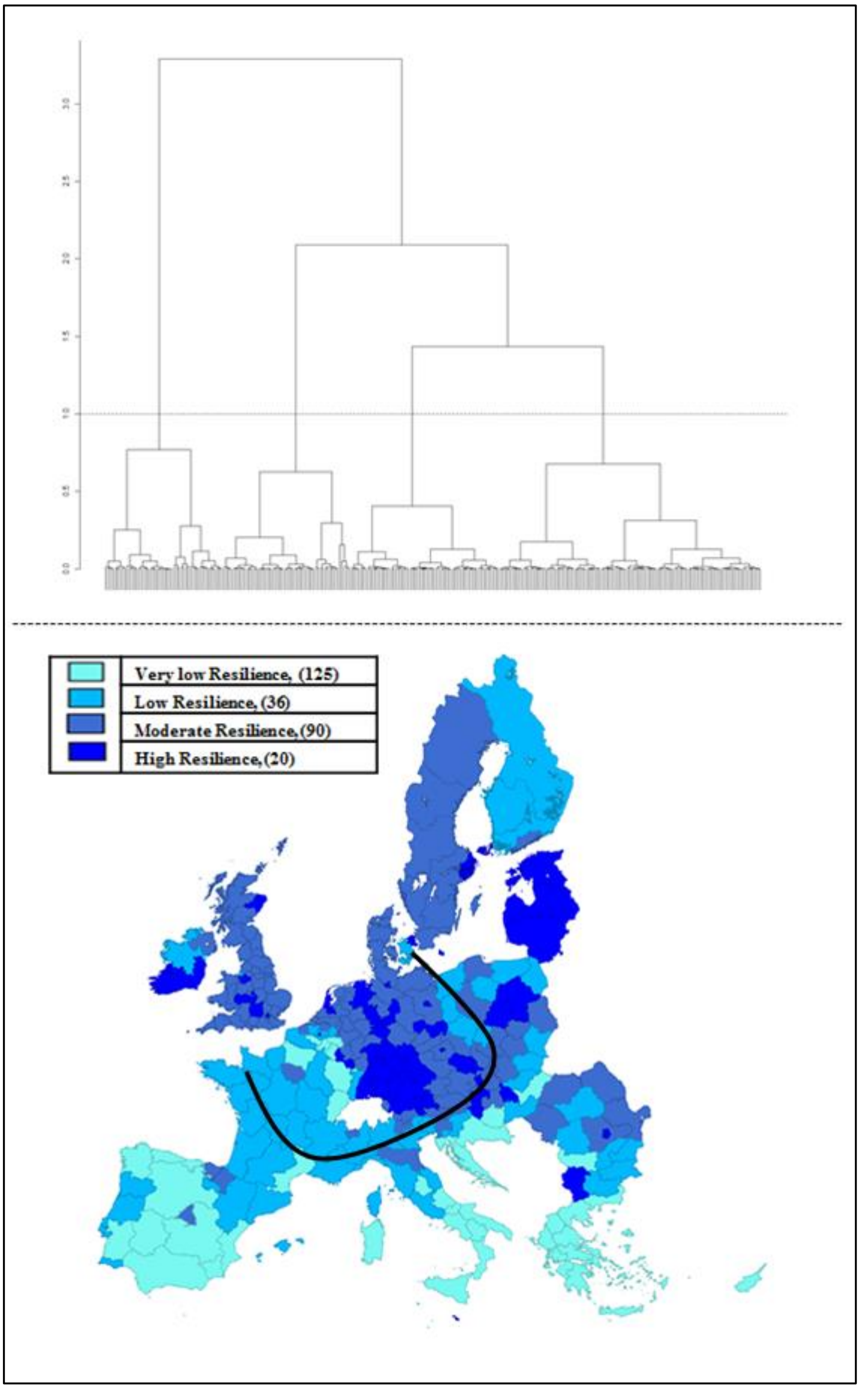

Figure 4 – A four cluster grouping of NUTS2 regions

Spatial pattern analysis is based on a 4 k-near neigh row standardized contiguity matrix. The results are robust to the specification of other contiguity matrix. Through the mean of the Anselin global Moran's I, which accounts for spatial autocorrelation, we measure of the presence of spatial clusters of regions sharing a similar value of resilience. It is due to externalities that consist in the influence that a region has on the neighbors as a consequence of different factors such as commuting, share of technology, trade, migration, and a set of intangible assets. A region can take advantage or disadvantage of the externality if i) it is surrounded by resilient or not resilient regions and ii) it has the capacity to be permeable to positive environment and impermeable to negative environment. It is worth mentioning that Moran's I is equal to 0.60. The Moran scatterplot map (Guillain *et al.*, 2010) in Figure 5 allows us to visualize well-defined and generally homogeneous regional patterns: around 82% of regions are high (low) resilient regions surrounded by high (low) resilient regions. High resilient regions surrounded by high resilient regions are present mainly in Germany, Great Britain, Sweden and the Baltics. Low resilient regions surrounded by low resilient regions belong to Greece, Spain, Portugal, France and Italy.

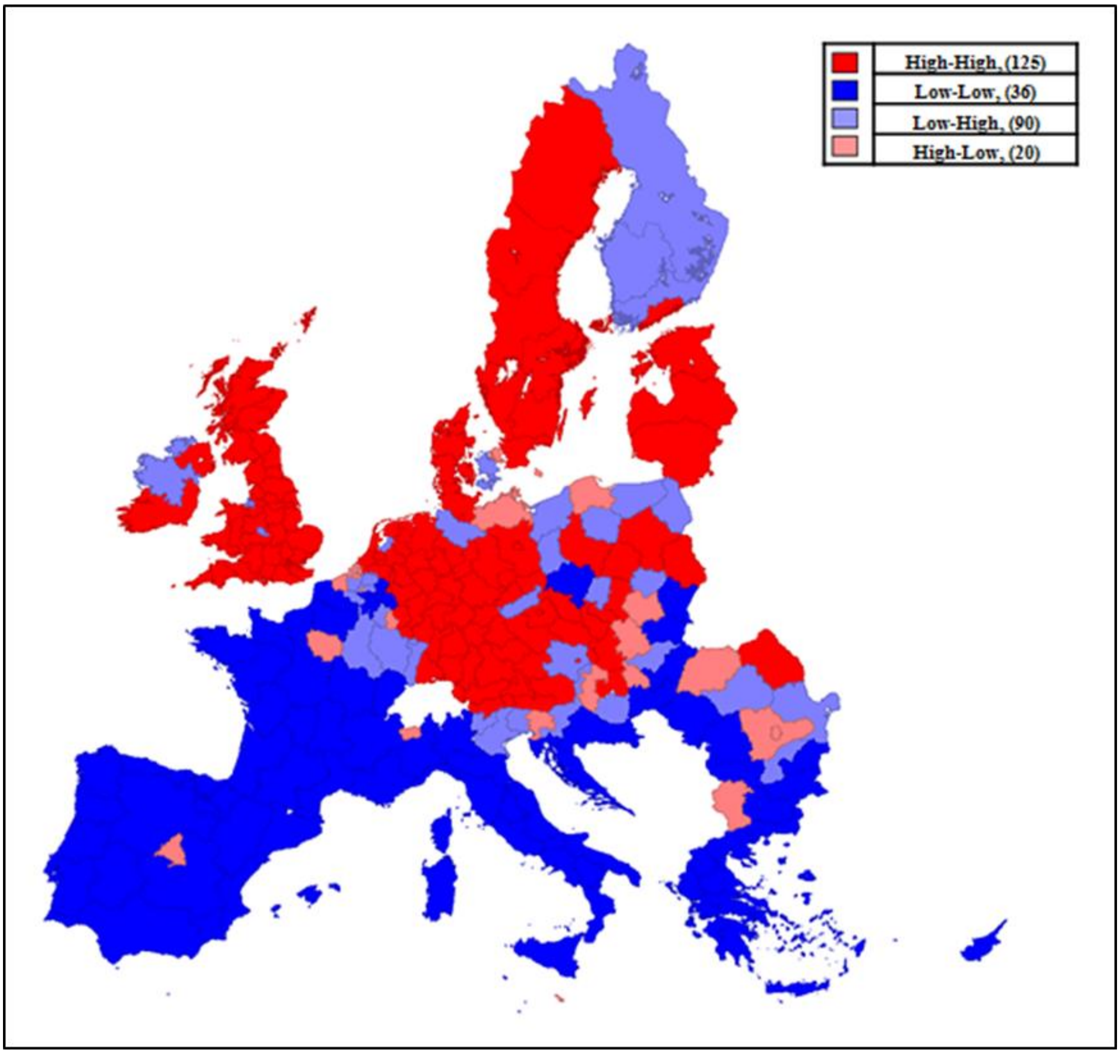

Figure 5 – Moran scatterplot map

The local Moran significance map in Figure 6 identifies the statistically significant spatial clusters of resilient and non-resilient regions. The divide within countries detected in Figure 3 is only partially confirmed, highlighting the importance of using statistical tools to identify clusters.

Southern regions of Italy, Spain and Portugal and Greece belong to group of 'cold-spot' regions. The statistically significant spatial cluster of resilient regions is located in Latvia, Southern Denmark, center and south Germany, the northern region of Sweden, and around London.

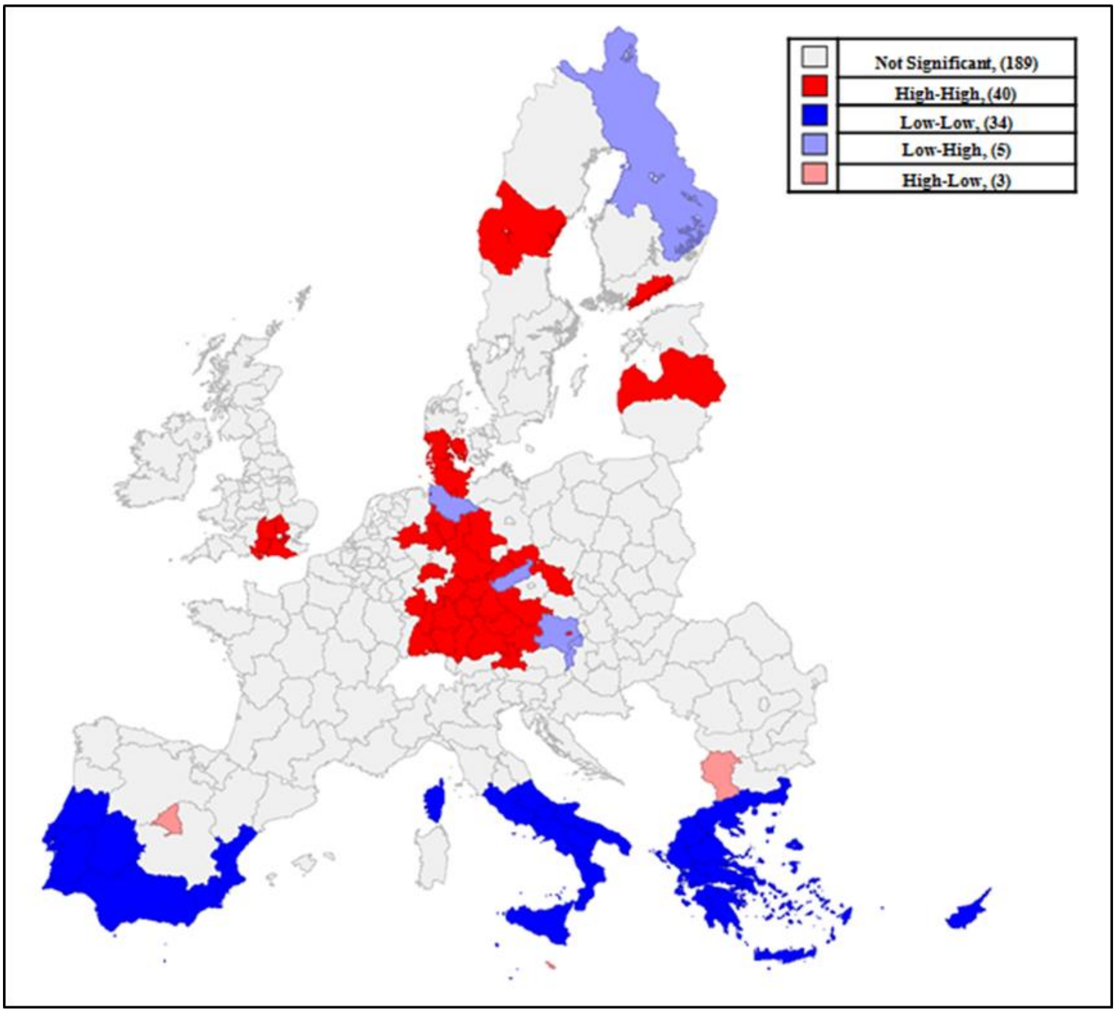

Figure 6 – Moran significance map

5 Conclusion

The Regional Resilience Indicator is a tool that accounts for several components of economy related resilient capacity and combines them into a comparable, synthetic and easily understandable measure. Compared with previously examined studies which aimed to provide a useful taxonomy of economic vulnerability and regional resilience and to test the relation between regional performance and crisis-resistance and national macroeconomic conditions, our Regional Resilience Indicator defines the resilience life-cycle and monitors the regional degree of resilience capacity.

Our main results show that resilience national trends dominate in the EU-15, while in the EU-13, a more heterogeneous spatial pattern is present. Capitals are generally more resilient than the surrounding regions. Finally, the analysis shows that the resilience capacity of a region is heavily co-related to that of the surrounding regions.

This confirms the limitations of national-level analyses in favor of a more territorial oriented debate.

However, our analysis shows that the national dimension still plays a strong role in shaping regional resilience, because regions tend to be affected by common institutional and legal frameworks, structural policies, etc. Lack of competitiveness, huge debt, heavily borrowing and large exposure to financial markets had plunged Greece into a recession deeper than in many other European countries. Similar factors affected with a more smoothed strength Italy, Portugal and Spain's economy but the effects were not uniform across regions, with some that have shown a much lower resilience. A combination of strong economic activity, more stable public finances and favourable political environment helped Germany to recover faster.

The identification of the regionally differentiated effects of the shocks requires an explanation of the results in terms of their determinants, including economic, institutional and social aspects (Martin and Sunley, 2015).

Martin (2011), Fingleton *et al.* (2012) and ESPON (2014), explain the different degrees of regional resilience through several economic common channels, among which the most important are: the sectoral composition of the economy, the export-oriented enterprises and their capacity to innovate and the skills of the workforce. The importance of a favorable business environment is attested by the strict relation with the EU Regional Competitiveness Index (RCI), which is equal to around 68%.

Institutional aspects, originally not considered a completely satisfactory explanation for the existence of regional disparities (Overman and Puga, 2002), recently turned into one of the key explanatory factors (Boschma, 2014). Our results, on the other hand, tend to support the position of Boschma for countries with historical well-grounded territorial development gaps such as Italy, Spain, Portugal and Germany.

Social aspects result to be less important factor to explain resilience. The relation with the social progress indicator which, as defined in the 7th Cohesion Report (European Commission, 2017), captures the society's capacity to meet the basic human needs, to establish the foundations of well-being and to create opportunity, is equal to 48%.

These findings, in light of the Cohesion policy that aims to a general integrated and inclusive territorial approach, suggest that policy response to enhance resilience capacity should consider the systemic structure of EU-15 countries where, despite well-targeted interventions in the past, historical gaps persist. In the EU-13 which is somehow likened to leopard spots, regionally targeted policies have to be adopted. Moreover, spatial spill overs originating from capital regions, which enhance the competitiveness of the neighbouring regions and whole countries, have to be promoted as potential driver of regional resilience (European Commission, 2017).

Appendix

Table 1A - PCA variable loadings and weights

		Axis 1	Axis 2	Axis 3	
	Standard deviation	0.353	0.295	0.223	*Weights*
	Proportion of variance	0.368	0.257	0.147	
	Cumulative proportion	0.368	0.625	0.772	
PCA variable loadings					
Slow burning indicators					
Pre-crisis 2000-08	mean GDP per capita 2000-08	0.019	0.036	0.019	0.0163
	mean Employment 2000-08	0.009	0.065	0.396	0.1798
	mean Productivity 2000-08	0.022	0.028	0.002	0.0129
	trend GDP per capita 2000-08	0.137	0.038	0.036	0.0625
	trend Employment 2000-08	0	0.021	0.013	0.0097
	trend Productivity 2000-08	0.107	0.005	0.008	0.0486
Post-crisis 2009-15	trend GDP per capita 2009-15	0.144	0.092	0	0.0655
	trend Employment 2009-15	0.032	0.233	0.039	0.1058
	trend Productivity 2009-15	0.07	0	0.019	0.0318
Shock wave indicators					
Maximum hit 2008-10	fall GDP per capita 2008-10	0.12	0.077	0	0.0546
	fall Employment 2008-10	0.004	0.035	0.363	0.1648
	fall Productivity 2008-10	0.11	0.067	0.006	0.0500
Post-to-pre crisis 2008-2015	recovery GDP per capita 2008-15	0.129	0.062	0	0.0585
	recovery Employment 2008-15	0.03	0.239	0.075	0.1087
	recovery Productivity 2008-15	0.067	0.001	0.025	0.0305

Table 2A – Clusters scores

Regional Resilience Indicator		**Very low Res.**	**Low Res.**	**Moderate Res.**	**High Res.**
		0.18835	0.394879	0.5551489	0.7274402
Slow burning indicators					
Pre-crisis 2000-08	mean GDP/pop	16696.2	19371.39	24839.37	32833.63
	mean empl.	0.3847	0.4171	0.4625	0.5213
	mean prod.	43.5522	45.9626	52.7679	61.5275
	trend GDP/pop	0.0184	0.0208	0.0232	0.0274
	trend empl.	0.0105	0.0049	0.0045	0.0069
	trend prod.	0.0079	0.0158	0.0187	0.0205
Post-crisis 2009-15	trend GDP/pop	-0.0159	0.0065	0.0096	0.0174
	trend empl.	-0.0147	-0.0052	0.0017	0.0055
	trend prod.	-0.0013	0.0118	0.0079	0.0118
Shock wave indicators					
Maximum hit 2008-10	Fall GDP/pop	-0.8373	-0.7916	-0.8670	-0.8958
	fall empl.	-0.2784	-0.3276	-0.3983	-0.4696
	fall prod.	-0.8555	-0.7992	-0.8630	-0.8769

Post-to-pre crisis 2008-15	recovery GDP/pop	-0.1142	0.0145	0.0170	0.0689
	recovery empl.	-0.0986	-0.0444	-0.0065	0.0155
	recovery prod.	-0.0168	0.0640	0.0249	0.0540

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