Why are some Spanish regions more resilient than others?

Abstract

The main objective of this paper is to analyze what are the characteristics of a region that influence more in its resilience. We begin the analysis constructing a composite index of resilience for the 17 regions of Spain in the different periods of recession and recovery from 1977 to 2015. We use the Data Envelopment Analysis (DEA) approach to obtain the index of resilience. In a second stage, we will analyze the factors that could contribute to the regional resilience. In order to segment regions, multiple factor analysis was chosen due to its strength in defining homogeneous groups of objects, or regions in our case. We will choose variables linked with determining the capacity of recovery of regions. In concrete, we will use variables related to capital (human, social, public, productive) and productive structure of regions. Moreover, we analyze the differences between our index of resilience and the Martin (2012) index. The findings suggest that those regions with productive structure focus on market services show a higher index of resilience in periods of recovery and those focuses on industry are more resilient in periods of crisis.

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Palabras Clave: *Resilience, Multiple Factor Analysis, Cluster*

Clasificación JEL: R11, R58

1. Introduction

Resilience is a relative new term in economics. Although the idea of "resilience" has been used for some time in the physical, engineering and ecological sciences, it is only very recently that it has attracted attention from regional analysts, spatial economists and economic geographers and it has become more popular with the last economic crisis suffered at the international level. Reggiani et al. (2002) argued that the notion of "resilience" should be a key topic in the study of the dynamics of spatial economic systems, especially concerning how such systems respond to shocks, disturbances and perturbations. Resilience is a broad concept, derived from engineering and ecological sciences pertaining to the manner in which systems react to, and recover from shocks. Recently, a renewed interest in this topic has arisen, with specific emphasis on the analysis of economic growth, and regional growth in particular. In broad terms, the basic idea is that different resilience behaviors are the reason why regions within a country show different economic growth performance (Fingleton et al., 2012; Martin, 2012).

Although there is no universally shared definition of regional economic resilience, three main interpretations have been commonly adopted: engineering, ecological and adaptative resilience. Probably the most frequently invoked meaning or definition of the notion is that of so called "*engineering resilience*". This focuses on the resistance of a system to disturbances (shocks) and the speed of return to its pre-shock state. In many discussions, the system is assumed to be in "equilibrium" before the shock, so that resilience is defined in terms of the stability of a system near its "equilibrium" (or "steady") state (e.g. Holling, 1973; Pimm, 1984; Walker et al., 2004). So, the "engineering" resilience could be defined as the ability of a system to return to its assumed stable equilibrium state or configuration following a shock or disturbance. It focuses on the resistance to shocks and stability near equilibrium. In ecology there is, however, a second way that the notion of resilience is used—so called "*ecological resilience*." This focuses on the role of shocks or disturbances in pushing a system beyond its "elasticity threshold" to a new domain. In this case, resilience is measured by the magnitude of disturbance or shock that can be absorbed before the system changes form, function, or position (Holling, 1973). According to this definition, then, systems are characterized by multiple stability domains, and that if a shock pushes a system beyond its "elasticity threshold" associated with its existing domain or state, the system may move to a different domain or state. Finally, "adaptative resilience" is defined as the ability of a system to undergo anticipatory or reactionary reorganization of form and/or function so as to minimize impact of a destabilizing shock (Martin, 2012).

So, these different interpretations of resilience suggest that this concept includes four interrelated dimensions: resistance, recovery, re-orientation and renewal (Martin, 2012). Resistance is the vulnerability or sensitivity of a regional economy to disturbances and disruptions, such as recessions. The second is that of the speed and extent of recovery from such a disruption. The third aspect concerns the extent to which the regional economy undergoes structural re-orientation and what implications such re-orientation has for the region's output, jobs and incomes. The fourth dimension concerns the degree of renewal or resumption of the growth path that characterized the regional economy prior to the shock.

Therefore, these different aspects of regional economic resilience may interact in different ways, to produce different outcomes.

We are interested in analyze what are the characteristics of a region that could influence in its resilience. For this, first of all we will construct a composite index of resilience for the 17 regions of Spain in the period 1977 to 2015, using DEA approach. In addition to characterizing the regions according to their resilience, another objective of this work is to compare our resilience indicator with those formulated by Martin (2012) and which have been used in most of the studies on resilience (Sánchez, 2012; Di Caro, 2014, Lagravinese, 2014). That is, to see if our indicator works the same as Martin (2012) or if depending on the indicator that is taken, the position of the regions in relation to their resilience varies. We will perform a Multiple Factor Analysis (MFA) to characterize the regions according to their resilience. In this paper we propose the use of this new methodology that allows the simultaneous analysis of groups of different partial indicators measured at different moments of time.

We study the case of Spanish regions because we consider that it is an interesting example of differences between regions when a crisis occurs. In fact, with the last economic crisis we have seen that Spain has been one of the most affected countries in relation to increasing of unemployment.

The paper is structured as follows. Section two shows a review of literature about resilience. Section three describes the methodology and data employed for constructing a composite index of resilience and MFA. Section four provides the results and the final section shows the main conclusions.

2. Review of literature

2.1. Concept and measurement of resilience

The majority of papers that study the resilience of different regions use the GDP per capita or the employment to analyze it. It is the case of Cellini and Torrisi (2014) that make a long run analysis of regional resilience in Italy. So, their analysis uses a time-series of real GDP per capita for the Italian regions over the period 1890-2009. They considered data on income per capita rather than employment. There are good reasons for either choice. Fingleton et al. (2012) argue that much of the impact of a recession is borne by the labour market, and declines in employment, after recessionary shock, are larger than decline in output; thus, the issue of regional resilience assumes particular relevance in relation to how regional labour markets are affected by, and recovers from, shock. With respect to the Italian experience, where labor markets are more rigid as compared with the UK case, the focus on GDP appears to be more appropriate, precisely because the reaction of labor markets is deemed to be less variable across regions, due to institutional rigidities.

Fingleton et al. (2012) focus on British regions in their analysis of the resilience to employment shocks during the period 1971–2010, indicating that the two dominating types of resilience that have characterized British regions are either "engineering resilience", when economies have bounced back to their past equilibrium, generally after a brief shock and "ecological resilience", in which the crises have been associated with permanent transfers to different equilibrium. Fingleton et al. (2012) find that ecological resilience changes are more likely to be associated with diverse resistances to initial shocks, rather than with developments in the recovery phase. Hence, they argue that initial shocks often tend to leave permanent effects. Their analysis focuses on regional employment, rather than output, for a number of reasons. Examination of past recessions suggests that, in most cases, the proportionate decline in employment during a recessionary downturn tends to be significantly greater than in output. In this respect, the issue of regional resilience assumes particular significance in relation to how regional and local labor markets are affected by and recover from major recessionary shocks. Within a local or regional setting, much of the impact of a major recession is borne by the labor market. Redundancies and layoffs of workers are key forms of adjustment by which employers seek to reduce costs and the scale of production in response to major falls in output demand. How far local employment falls, and how fast and far it recovers, will shape and limit the outcomes for local workers. How local wage structures react may also influence the scale and duration of the fall in employment. And of course, employers may seek to increase output when recovery comes without resuming their pre-shock workforce levels. The response of regional or local employment to a major shock, such as deep recession, will thus be a complex outcome of variety of adjustment strategies, mechanism, possibilities, and constraints on local employers and local workers.

Di Caro (2014) analyses regional resilience and local economic growth in Italy over the past four decades (1977-2013). Place-specific transient and permanent effects of aggregate employment shocks are studied. The importance of manufacturing activities for explaining economic resilience is assessed, finding out a positive relation between the resilience of the industrial sector and the overall local economic development. Employment series have been preferred to GDP or other economic measures for two main reasons: they are more articulated on a regional level and do not need to be deflated; they provide interesting insights into the evolution of a regional context, though they can be affected by issues related to place-specific frictions in labour markets.

Another author who focuses his attention in Italian regions is Lagravinese (2014) who investigates the economic crises that occurred in Italy between 1970 and 2011, referring in particular to the employment level and the different effects on the Italian regions. He refers to the “resilience” to describe the adaptive capacity of the regions to withstand the shock of economic recessions. Following the approach of Martin (2012) and Fingleton et al. (2012), the focus of analysis is the employment rather than income[1]. The employment experienced during an economic recession tends to return to pre-crisis levels with a much longer lag than output, which can lead to significant imbalances in the labour market, causing substantial inequality and social tension.

2.2. Factors that determine the resilience of regions

Most studies have focused on how different factors have impinged on the different levels of adaptability and resilience of regions in Europe. Martin (2012), for example, compares

[1] A recent paper by Cellini and Torrisi (2014), following the approach of Fingleton et al. (2012), used per capita income rather than the employment rate over a very long period of time (1890-2009) to analyse the Italian situation, finding few differences between Italian regions.

three British crises (1979-1983; 1990-1993; 2008-2010), underlining the importance of local economic structures for the resilience of regions. His analysis is confined to the movements in employment rather than output. Employment tends to take much longer than output to recover from recession, and is thus arguably the more critical variable, since a major decline in employment in a region or locality can have profound consequences for the local labour market. And mentioned earlier, a regional or local economy may resume output growth following a recession without a corresponding recovery in employment, thereby creating major problems of adjustment for local unemployment workers. How far and in what ways regional employment rebounds following recession is thus arguably a more insightful indicator of a regional economy's resilience.

And focusing in European regions, to level of NUTS II, Brakman et al. (2014) analyze the relevance of two possible determinants of a region's resilience to shocks, the degree of urbanization and specialization. They take the Great Recession, the economic and financial crisis that started in 2008, as their shock and analyze how the NUTS II EU regions differ in their resilience to the crisis in terms of unemployment and real per capita GDP.

In relation to the study of resilience in Spanish regions, Sánchez et al. (2014) try to identify the associated factors to regional resilience in rural areas of Andalusia in two time periods (2000-2008 and 2008-2012). They design a methodology applied in two periods of time allowed by a DEA to identify areas that have experienced resilient processes changes and determine the influence of a wide range of regional factors. As for the variables to consider, the most repeated in the literature on the characterization of territorial resilience in a context of change in the situation of "balance" as a result of an economic crisis are employment, income and the level of output of an economy (Davies, 2011; Hill et al, 2011;. Martin, 2012; Pendall et al., 2010). In fact, these three factors have been incorporated intrinsically in some of the definitions have been established on the concept of regional resilience (Martin, 2012).

Moreover, Rosell et al. (2011) seek to determine the impact of different factors on the degree of resilience of the territories of Catalonia (period 2007). The results indicate that business density, sectoral specialization, the percentage of foreign population, and the nature of rurality impact on the level of resilience of these territories. Finally, Marrades (2011) assesses regional resilience with a composite indicator. His point is that focus on employment changes may be the best choice to understand how regions are resilient to exogenous shocks. Concerning the two dimensions of resilience, resistance and recovery, the focus on employment is justified by the reason that it is less elastic than output when crisis occur. Employment tends to take longer than output to recover from recession, and reflects how the economy is able to allocate its main resource, hence human capital. On the other hand it is narrowly related to other critical issues as unemployment and labour market adjustment. Moreover, employment (and employment rate) is not biased by the participation rate and also can be a good instrument for welfare.

The resilience of regions to economic shocks is the result of the combination of two factors: regional shock-resistance and subsequent 'recovery' capabilities (Lagravinese, 2014; Martin, 2012). Depending on the characteristics of each region, its resilience will be different between each other. Specifically, some of the factors that can influence the resilience are following detailed. Martin and Sunley (2014) identify three main sets of factors: contextual, compositional and collective factors. Contextual factors refer to the way in which local and regional agents are situated within broader and multi-scale institutions, national policies, and even international networks and the global division of labor. Compositional factors make reference to the sectorial/industrial structure of local and regional economies. Collective factors include the characteristics and relationships between local economic agents within each regional economy.

The economic literature has identified numerous quantitative features of regional economies that shape their ability to resist and adapt to shocks and change (Crescenzi, 2009; Crescenzi and Rodríguez-Pose, 2011). In particular, two key sub dimensions are relevant with reference to regional resistance: the regional industrial mix, and a group of regional competitiveness/ innovation factors. The regional industrial mix, i.e. the sectorial structure of the regional economy, is a key factor determining regional crisis resistance. 'Conventionally, […] manufacturing and construction industries have been viewed as being more cyclically sensitive than private service industries, and the latter more sensitive than public sector services, which are often assumed to be largely immune to economic recessions' (Martin, 2012: 13). Regional sensitivity is the result of the combination of these sectorial sensitivities 'weighted' by the shares of these sectors in the regional economy, influencing the adjustment of the regional economy, its output and employment to cyclical shocks.

Another subset of regional factors likely to shape the ability to react to external shocks relates to the determinants of regional competitiveness. The accumulation of human capital and the allocation of (public and/or private) resources to R&D activities are long-term structural characteristics of the regional economy that adjust slowly over time and shape local growth trajectories through two key channels. First, both regional human capital and innovation efforts are crucially linked with the capability of the local economy not only to generate new knowledge but also to absorb externally generated new ideas and cognitions (Crescenzi, 2009; Crescenzi and Rodríguez-Pose, 2011). Regional human capital is positively and significantly associated to economic performance during the crisis. Conversely, R&D intensity is negatively linked to short-term economic performance. The existing evidence on long term growth and innovation dynamics of the EU regions (Crescenzi and Rodríguez-Pose, 2011; Rodríguez-Pose and Crescenzi, 2008) has shown that local R&D investments have a weak association with regional innovation and growth, while human capital is a stronger predictor of long term regional growth and innovation. It is the endowment of human capital that can provide the flexibility and the creativity to react to the negative shocks.

The different characteristics of regions, in our case, Spanish regions, determine the more or less resilience of them. In fact, regions where firms were more indebted have tended to suffer more from the crisis, as the supply of credit is not homogenous at national level (see, e.g. Bank of Italy, 2013). Regional specialization has also played a decisive part in how regions across Europe have weathered the crisis. Construction was possibly the most affected sector. Spanish coastal areas, which had thrived during the economic boom years thanks to the construction and sale of second homes, are a clear example of the construction-led bust. Construction was among the first and most severely hit sectors. Value-added in the construction sector fell between 6 and 20% -and employment between 10 and 20%-especially in those countries, such as Ireland, Latvia, Estonia, Portugal, Greece and Spain, that had developed construction bubbles in the pre-crisis period. Industry as a whole also declined by more than 2% for the whole of the EU between 2007 and 2011. But this average hides declines of more than 5% in the seven member states most affected by the crisis.

Industrial variety in a region spreads risks and can better accommodate idiosyncratic sector-specific shocks (Dissart, 2003; Essletzbichler, 2007; Davies and Tonts, 2010; Desrochers and Leppala, 2011). Regional variety in skill-related industries is expected to speed up the recovery from sector-specific shocks, as the redundant employees can find more easily new jobs in a region with a local supply of skill-related industries in which their skills are still found relevant (Diodato and Weterings, 2014). This also prevents the destruction of human capital in a region as well as the outflow of high-skilled people to other regions. Specialized regions have few potential sources for renewal and diversification. What is more, their ability to diversify into new growth paths might be negatively affected by their specialized industrial structure (Boschma and Lambooy, 1999; Hassink, 2005; Martin and Sunley, 2006).

When an economic crisis occurs in a country, the flexibility, creativity and innovation are factors determining the behavior of regions; for example, the level of skills of the workforce. A better educated workforce facilitates the generation, assimilation and absorption of innovation, as well as the short-term adaptation and medium-term adaptability to new challenges (OECD, 2011).

Some regions provide better conditions for the growth of an industry, while other regions are not able to provide the industry with the needed environment (Boschma and Van Der Knaap, 1999). Some of these differences relate to differences in the regional stock of inputs, such as knowledge, skills and natural resources, while others stem from the initial structure of the industry (Henderson et al., 1995; Beardsell and Henderson, 1999; Feldman and Audretsch, 1999). Regions that have a more diverse industry structure might experience less growth, but they are also more resilient to external shocks.

Universities and other research organizations are located in the cities, which creates and attracts highly skilled workers and creative talented people (Florida, 2002), making such regions relatively adaptable. Firms in urban regions often have higher human capital intensity and are therefore more likely to be innovative, which can create localized knowledge spillovers (Audretsch and Feldman, 1996).

Another factor which governs the capacity of regions to adapt to sudden or prolonged shocks is the presence of “sheltered” or “protected” economies (Rodriguez-Pose and Fratesi, 2007; Trigilia, 1992). “Sheltered” or “protected” economies emerge when regions depend mainly on non-market oriented sectors. Sheltered regions have a tendency to have lower levels of employment and to rely on a swollen public sector. The idea is that there are structural conditions in sheltered regional economies which make them less exposed to market cycles, either because they have specialized in closed sectors that export less and whose demand is very stable, or because they are protected by economic policy conditions that dampen the immediate impact of a crisis, such as a high concentration of public employment. These regions are generally “more impervious to changes in the business cycle” (Rodriguez-Pose and Fratesi, 2007: 624); meaning that they are, in theory, more protected than open regions from downturns in the cycle, but are also less ready to benefit from economic recoveries.

More sheltered and less dynamic regions experience the worse overall performance. The best employment performances during the crisis are found among more open regions with good employment trajectories prior to the crisis but also in highly protected regions with good past trajectories.

3. Metodology and data employed in the analysis

3.1. Construction of a Composite Index of Resilience

Our first objective in this work is to elaborate a composite index of resilience. As in previous papers, we thought that the best factors to explain the capacity of recovery and reaction of a region are employment and GDP. These are two important variables associated to development, well being and quality of life of people measurement. Therefore, these will be used to construct the index.

We will focus on Spanish regions with data from INE (Instituto Nacional de Estadística) and BD.MORES (Base de datos regionales de la economía española, Ministerio de Hacienda y Administraciones Públicas). We take data of GDP with constant prices and employment for the period 1977-2015.

In next figures (figures 1 and 2) we can see the evolution of GDP and employment for Spain. They clearly show the economic crisis that Spain has suffered during the period analyzed (1977-2015). In concrete, international and internal factors (industry crisis) affected the Spanish economy between 1975 and 1985. The entry into the EEC opened a period of growth that lasted two decades. From 1985 to 2007 Spain lived a golden age of expansion almost unbroken; with the only exception of a crisis in 1992-1993, a short crisis that the government finished with a stabilization plan and traditional devaluations of the peseta. The crisis that erupted in 2007 still creeps up today and the result is still one of the deepest depressions of our history.

Figure 1. Evolution of GDP (thousands of €, 1977-2015)

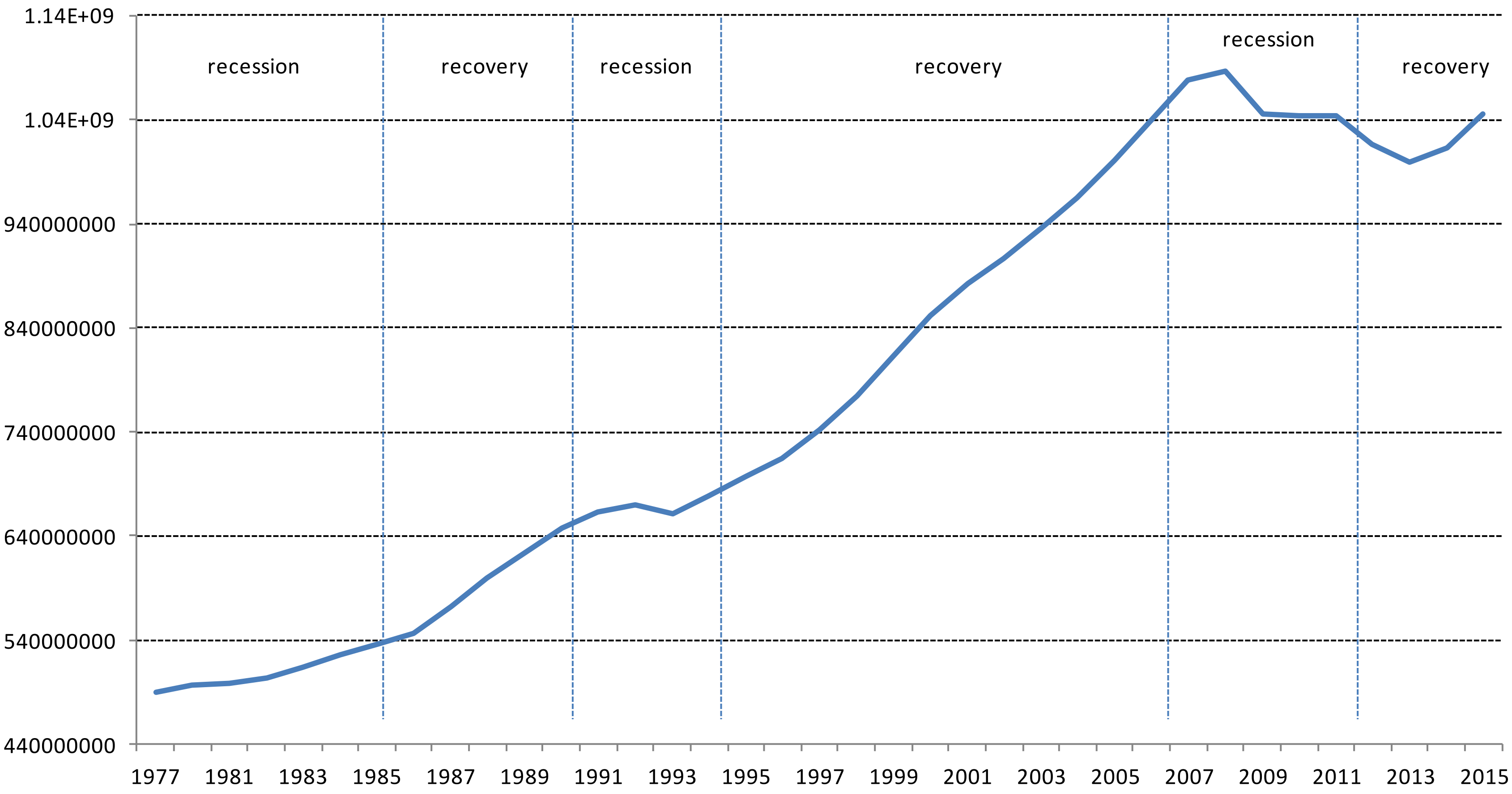
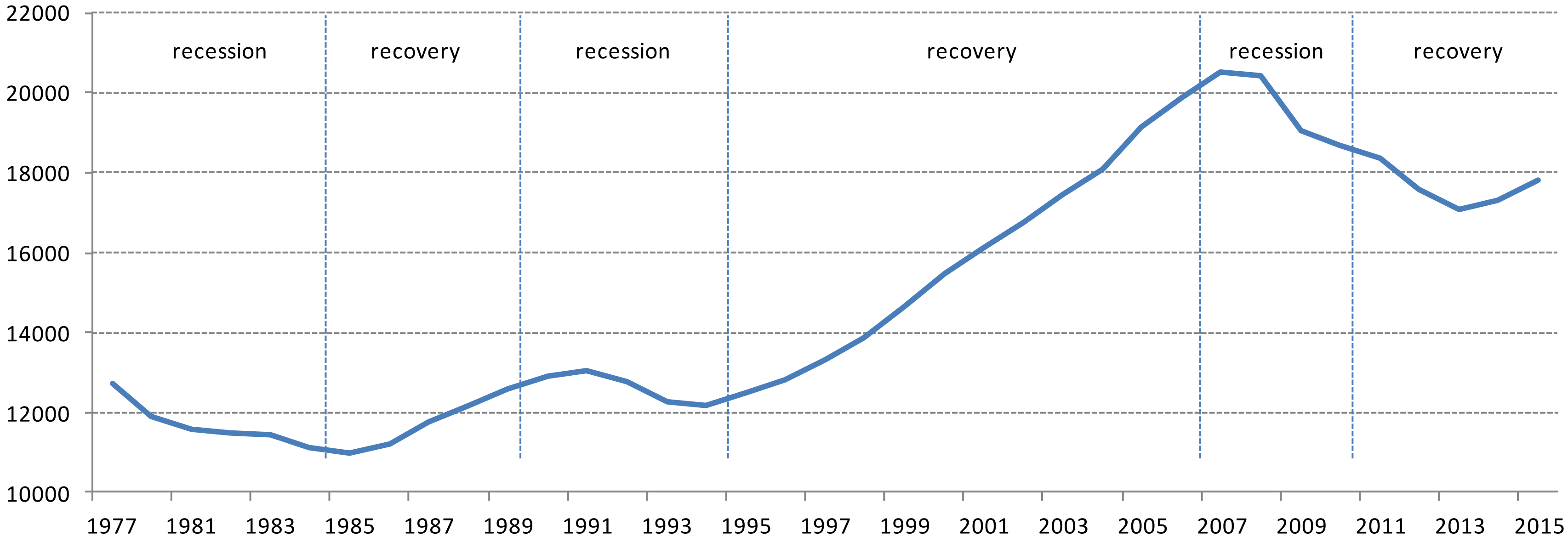


Figure 2. Evolution of employment (thousands of people, 1977-2015)



Specifically, if we focus on GDP (figure 1), it shows that from 1985 GDP begins to grow until 1992 where GDP declines. From there, GDP starts to grow up to the current crisis that began between 2007 and 2008 with a decline in all regions. In the figure of employment rate (figure 2) we see with more precision the incidence of economic crisis and their influence. From 1977 to 1985 we observe a decline in employment rate that recovers from 1986 to 1993 where again unemployment increases. It is from 1995-96 when the economy recovers and with it the employment with a substantial rise. With current crisis, the employment suffers a sharp decline that seems to go recovering little by little in the last years.

Based on data on GDP and employment, we will use the methodology used by Martin (2012) to develop an indicator of resistance to a crisis, for employment and for GDP.The index is the ratio of change in employment or output in a region to the respective change in the country as a whole.

$$\text{Crisis index } C_{employr} = (\Delta E_r/E_r) / (\Delta E_N/E_N),$$

where $\Delta E_r/E_r$ is the change in employment for region r and $\Delta E_N/E_N$ is the change in employment for the whole country.

$$\text{Crisis index } C_{GDPr} = (\Delta GDP_r/GDP_r) / (\Delta GDP_N/GDP_N),$$

where $\Delta GDP_r/GDP_r$ is the change in GDP for region r and $\Delta GDP_N/GDP_N$ is the change in GDP for the whole country.

Moreover, we construct an index for recovery stages:

$$\text{Recovery index } R_{employr} = (\Delta E_r/E_r) / (\Delta E_N/E_N),$$

where $\Delta E_r/E_r$ is the change in employment for region r and $\Delta E_N/E_N$ is the change in employment for the whole country.

$$\text{Recovery index } R_{GDPr} = (\Delta GDP_r/GDP_r) / (\Delta GDP_N/GDP_N),$$

where $\Delta E_r/E_r$ is the change in employment for region r and $\Delta E_N/E_N$ is the change in employment for the whole country.

First, we calculate the growth rates of each region, both GDP and employment, for each subperiod considered (Tables 2 and 3). And from the growth rates we calculate the indicators of resistance to the economic crisis and for recovery stages.

As the indicators are quotients, depending on whether the quotient is positive or negative the interpretation of the same changes. Therefore, we have to normalize them so that the interpretation is the same in all the cases. When the country's growth rate is positive we normalize as follows:

Example: $C^{*}_{GD\,\mathrm{Pr}}(1977-85) = \dfrac{C_{GD\,\mathrm{Pr}} - Min(C_{GD\,\mathrm{Pr}(1977-85)})}{Max(C_{GD\,\mathrm{Pr}(1977-85)}) - Min(C_{GD\,\mathrm{Pr}(1977-85)})}$

But if the country's growth rate is negative we normalize in this other way:

Example: $C^{*}_{employ\,r}(1977-85) = 1-\left(\frac{C_{employ\,r} - Min(C_{employ\,r(1977-85)})}{Max(C_{employ\,r(1977-85)}) - Min(C_{employ\,r(1977-85)})}\right)$

Table 1. Growth rates in recession periods

	RECESSION					
	1977-85		1991-94		2007-11	
	GDP growth rate	**Employment growth rate**	**GDP growth rate**	**Employment growth rate**	**GDP growth rate**	**Employment growth rate**
Andalucía	1.397	-13.302	-0.709	-7.999	-3.653	-13.607
Aragón	1.354	-15.121	1.301	-5.877	-1.164	-11.703
Asturias	1.630	-18.299	1.335	-8.615	-4.308	-8.049
Baleares	4.027	-4.626	4.642	-3.428	-2.940	-8.760
Canarias	1.896	-2.337	7.412	0.598	-3.612	-13.743
Cantabria	0.160	-9.816	2.843	-5.578	-3.670	-8.172
Castilla y León	1.532	-16.834	2.894	-8.119	-1.585	-8.072
Castilla La Mancha	1.080	-12.018	-0.021	-6.525	-1.287	-9.182
Cataluña	0.361	-16.077	2.831	-7.091	-4.214	-10.339
Valencia	1.256	-11.872	1.469	-6.823	-5.212	-15.242
Extremadura	3.841	-22.723	4.115	-10.489	-2.894	-9.929
Galicia	0.720	-12.940	3.102	-8.867	-2.936	-8.713
Madrid	0.784	-10.239	3.324	-4.918	-2.308	-7.548
Murcia	1.603	-10.718	1.001	-3.269	-2.020	-14.661
Navarra	0.245	-9.358	1.517	-3.175	-0.101	-5.559
País Vasco	-0.489	-16.893	1.331	-4.904	-2.379	-4.480
La Rioja	2.006	-19.589	7.302	-7.743	-0.551	-9.008
MEAN	**9.491**	**-13.511**	**2.207**	**-6.539**	**-3.145**	**-10.535**

Table 2. Growth rates in recovery periods

	RECOVERY					
	1986-90		1995-2006		2012-15	
	GDP growth rate	**Employment growth rate**	**GDP growth rate**	**Employment growth rate**	**GDP growth rate**	**Employment growth rate**
Andalucía	23.587	21.942	52.584	74.630	2.224	4.216
Aragón	19.087	13.526	42.846	42.151	4.251	-0.943
Asturias	7.068	5.201	34.686	30.668	-0.167	-1.763
Baleares	13.770	16.426	42.651	82.709	2.822	8.006
Canarias	11.646	16.305	48.856	76.507	3.704	6.002
Cantabria	21.548	8.813	42.904	55.913	-0.229	-2.668
Castilla y León	10.484	10.657	31.516	33.327	1.185	-1.727
Castilla La Mancha	26.341	10.861	44.773	61.013	3.120	0.127
Cataluña	23.628	20.152	46.513	59.544	3.585	1.521
Valencia	18.508	17.976	55.640	68.133	4.183	3.848
Extremadura	18.562	15.727	42.635	40.408	3.515	5.134
Galicia	15.098	0.638	37.942	21.623	1.893	-2.858
Madrid	17.670	17.235	63.322	77.598	3.043	-0.257
Murcia	20.492	22.528	64.469	83.690	3.713	0.436
Navarra	20.371	12.419	51.089	50.677	3.127	-1.215
País Vasco	12.946	13.509	45.653	41.087	1.679	-2.930
La Rioja	12.193	12.449	45.691	65.312	2.004	3.204
MEAN	**18.577**	**15.286**	**49.418**	**59.411**	**2.870**	**1.325**

In this way, normalized indicators take values between 0 and 1 and their interpretation is: the greater the indicator, therefore, closer to 1, its resilience or recovery capacity is greater. Conversely, the smaller the indicator, therefore, the closer to zero, the less resistance or recovery capacity (Tables 4 and 5).

Table 3. Crisis indexes

	CRISIS					
	1977-85		1991-94		2007-11	
	C_{GDPr}	$Cemploy_r$	C_{GDPr}	$Cemploy_r$	C_{GDPr}	$Cemploy_r$
Andalucía	0.418	0.462	0.000	0.225	0.305	0.152
Aragón	0.408	0.373	0.248	0.416	0.792	0.329
Asturias	0.469	0.217	0.252	0.169	0.177	0.668
Baleares	1.000	0.888	0.659	0.637	0.445	0.602
Canarias	0.528	1.000	1.000	1.000	0.313	0.139
Cantabria	0.144	0.633	0.437	0.443	0.302	0.657
Castilla y León	0.448	0.289	0.444	0.214	0.710	0.666
Castilla La Mancha	0.347	0.525	0.085	0.358	0.768	0.563
Cataluña	0.188	0.326	0.436	0.306	0.195	0.456
Valencia	0.386	0.532	0.268	0.331	0.000	0.000
Extremadura	0.959	0.000	0.594	0.000	0.454	0.494
Galicia	0.268	0.480	0.469	0.146	0.445	0.607
Madrid	0.282	0.612	0.497	0.502	0.568	0.715
Murcia	0.463	0.589	0.211	0.651	0.625	0.054
Navarra	0.162	0.656	0.274	0.660	1.000	0.900
País Vasco	0.000	0.286	0.251	0.504	0.554	1.000
La Rioja	0.552	0.154	0.986	0.248	0.912	0.579

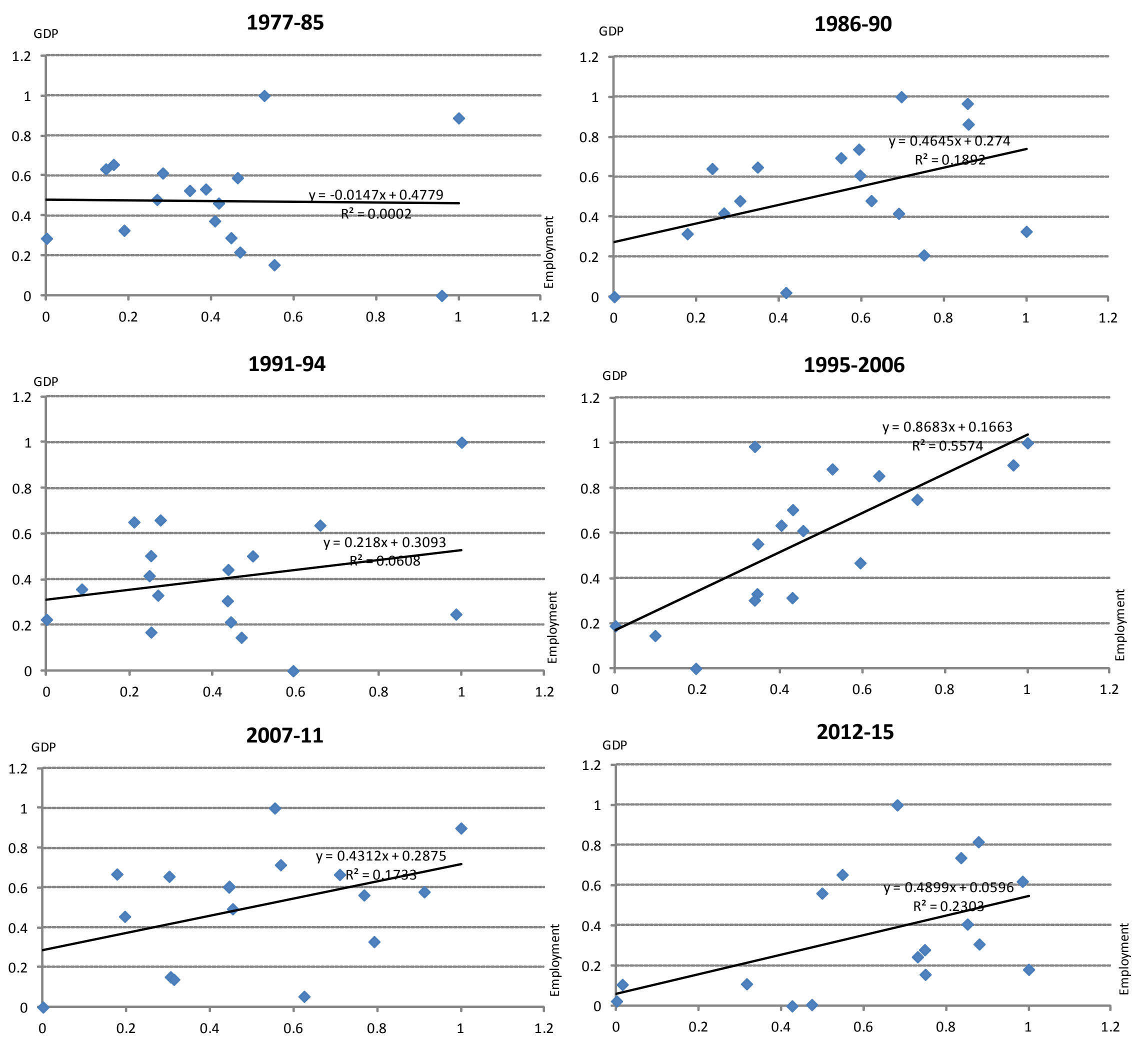
Table 4. Recovery indexes

	RECOVERY					
	1986-90		1995-2006		2012-15	
	R_{GDPr}	$R_{employr}$	R_{GDPr}	$R_{employr}$	R_{GDPr}	$R_{employr}$
Andalucía	0.857	0.966	0.639	0.854	0.548	0.653
Aragón	0.624	0.480	0.344	0.331	1.000	0.182
Asturias	0.000	0.000	0.096	0.146	0.014	0.107
Baleares	0.348	0.648	0.338	0.984	0.681	1.000
Canarias	0.238	0.641	0.526	0.884	0.878	0.817
Cantabria	0.751	0.208	0.346	0.552	0.000	0.024
Castilla y León	0.177	0.315	0.000	0.189	0.316	0.110
Castilla La Mancha	1.000	0.327	0.402	0.635	0.748	0.280
Cataluña	0.859	0.863	0.455	0.611	0.851	0.407
Valencia	0.594	0.737	0.732	0.749	0.985	0.620
Extremadura	0.596	0.608	0.337	0.303	0.836	0.737
Galicia	0.417	0.021	0.195	0.000	0.474	0.007
Madrid	0.550	0.695	0.965	0.902	0.730	0.244
Murcia	0.697	1.000	1.000	1.000	0.880	0.308
Navarra	0.690	0.417	0.594	0.468	0.749	0.157
País Vasco	0.305	0.479	0.429	0.314	0.426	0.000
La Rioja	0.266	0.418	0.430	0.704	0.498	0.561

From these indicators we could be setting for each region how its GDP and employment indicator behaves, but here we want to collect the information of those two indicators in a composite indicator of resilience in such a way that we value how it behaves a region in terms of resilience given GDP and employment.

Given the scatter plots obtained (figure 3), we consider that both variables are useful to explain the behavior of the regions, and also behave in the same direction.

Figure 3. Scatter graphics of GDP and employment



We will use the DEA approach to obtain the composite index of resilience. The DEA approach exhibits some advantages measuring resilience. First, it can deal with a variety of values and data. Second, it provides a method of data standardization, as "decisional units" are ranked from zero to one, according to their level of resilience, in our case. Using DEA we can order regions in function of their resilient behavior from the construction of a composite index. This approach allows for having an outline of weights for variables that define the territorial resilience without resorting to arbitrary allocation of weights and without using aggregation based on the personal views of various experts' methods. The literature has previously explored the usefulness of DEA for building composite indexes in similar contexts (Reig, 2010; Sánchez et al., 2014).

The DEA is a technique designed by Charnes et al. (1978) to calculate, through mathematical programming, different measures of efficiency in productive unites, or generally decision making unit (*DMU*). The basic theoretical framework underlying DEA is a production function, in which it is assumed that a set of $k = 1,...,K$ *DMU* make use of a vector of *inputs* $x = (x_1,...x_M)$ to produce a vector of *outputs* $y = (y_{1,...,}y_R)$. In a basic DEA model, the efficiency of *DMU₀* is defined by the maximum of a ratio that transforms *inputs* to *outputs* (Reig et al., 2011):

$$Max_{u_{r0}v_{m0}} \frac{\sum_{r=1}^{R} u_{r0} y_{r0}}{\sum_{m=1}^{M} v_{m0} x_{m0}}$$

subject to: (1)

$$\frac{\sum_{r=1}^{R} u_{r0} y_{rk}}{\sum_{m=1}^{M} v_{m0} x_{mk}} \leq 1 \qquad k = 1,...,k$$

$$u_{r0} \geq 0 \quad r = 1,...,R$$

$$v_{m0} \geq 0 \quad m = 1,...,M$$

The weights u_{r0} and v_{m0} , represent the no negative weights that are applied to *output* y_{r0} and to *input* x_{m0}, and are chosen in order to place *DMU*$_0$ under the most favorable light, meaning that they are computed by maximizing its efficiency ratio. In this regard, weights are specific for each DMU under evaluation, subject to the constraint that the efficiency ratios computed with those weights have an upper bound of one. Therefore the dominance of a *DMU*$_0$ over any other *DMU*$_k$ requires finding positive weights u_{r0} and v_{m0} such that

$$\sum_{r=1}^{R} u_{r0} y_{r0} - \sum_{m=1}^{M} v_{m0} x_{m0} \geq \sum_{r=1}^{R} u_{r0} y_{rk} - \sum_{m=1}^{M} v_{m0} x_{mk} \quad \text{For all other } DMU_k \qquad (2)$$

Expression (1) can be used as well to assess the relative performance of a decisional unit, that is, concerning resilience, after undertaking a suitable transformation to a linear form. It can be simplified by assuming a single input (equal to unity) for each unit. One input give rise to different intensities in several features that are relevant for the assessment of resilience. Thus for each DMU_0 the following model can be computed.

$$Max_{\mu_{r0}} h_0 = \sum_{r=1}^{R} \mu_{r0} I_{r0}$$

subject to: (3)

$$\sum_{r=1}^{R} \mu_{r0} I_{rk} \leq 1 \quad k = 1,\ldots,K$$

$$\mu_{r0} \geq 0 \qquad r = 1,\ldots,R$$

where h_0 is the technical efficiency (resilience in our study) for DMU_0; μ_{r0} is the weight attached to the indicator *r* in the assessment of resilience of DMU_0; I_{rk} represents the value of indicator *r* for DMU_k. The objective function involves achieving the maximum value of a composite index derived from a set of indicators corresponding to different stages of change processes of resilience.

DEA methods show some advantages in order to measure resilience. First, it is a proper approach dealing with a range of data, which is considerable important due to the multifaceted nature of resilience. Second, it provides a method of data standardization, ranking decisional units from zero to one, according to their efficiency level. And it does not precise *ex ante* exogenous information to determine weights, which are calculates by solving a linear program optimization.

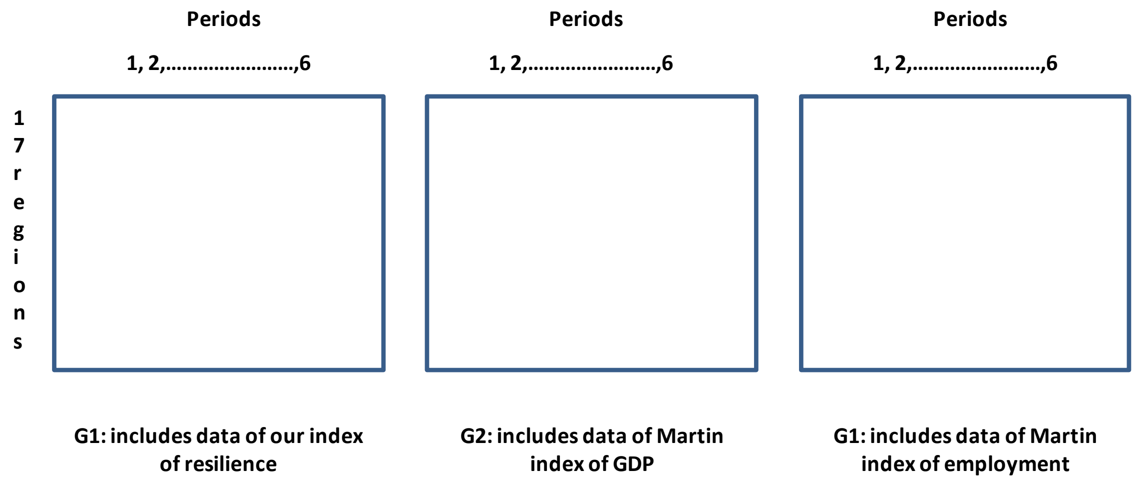
3.2. Multiple Factor Analysis

The method MFA has been applied to study the evolution of economic variables of a latent nature such as welfare, level of development or in our case resilience. This method allows analyzing groups of different indicators measured at different moments of time. It is possible, therefore, to include qualitative changes that occur in the latent variable by selecting the most suitable indicators for each moment of time. It is a multivariate exploratory method that allows us to study the resilience of the regions of Spain from an essentially graphic perspective. The choice of graphical representations for the study of numerical data is supported by the psychology of human information processing, which could be summarized in the following sentence: *the perception in graphics optimizes the capacity of our information processing system*, Batista and Martínez (1989). This method allows us to synthesize and analyze the large amount of information that we have.

The MFA, developed by Escofier and Pagés (1992, 1994), is a factorial method adapted to treatment of data tables in which a same set of individuals is described through several groups of variables. The groups of variables can arise from the joint use of variables from different nature, quantitative or qualitative, from the use of tables that come from others of three dimensions or from the use of a same set of variables measured in different periods of time. The organization in variables groups of original data rewards their study because the followed goals do not limit to the obtaining of a typology of individuals defined by a set of variables, but are extended to the search for possible relationships between the structures obtained within each of the groups. The variables of a group measured on a set of individuals define a table of two dimensions.

In this paper we work with 3 tables, one for each considered index of resilience (our resilience index, Martin index of GDP and Martin index of employment) and each table contains 17 files, one for each region, and 6 columns, one for each period included in the analysis (3 periods of crisis and 3 periods of recovery). We build the global table juxtaposing these 3 tables (figure 4).

Figure 4. Tables used in the analysis



The aim of the analysis is to show the main factors of maximum variability, the latter being described, in a balanced manner, by the various groups of variables. The MFA technique is based on Principal Component Analysis (PCA) and consists of two phases. In the first one, it is analyzed each group of variables or table separately through a PCA. In the second phase, it is analyzed the global table, where each table has been weighted by the inverse of the first eigenvalue of their separated PCA done in the first phase. This weighing balances the importance of groups in the getting of first factor. As complete factorial analysis that it is, the MFA shows the classic results of PCA. In case of analyzing categorical tables, MFA shows the results of Multiple Correspondence Analysis (MCA).

The objective of MFA is examining the existence of common structures between groups of variables (tables). Moreover, the MFA gives the global measurements of relation between groups, based on RV coefficient of Y. Escofier (Escofier and Pagés, 1992; 1994). This coefficient is obtained from the coefficients of linear correlation between any two variables. Its value is between 0 (there is no relationship between variables of the two considered groups) and 1 (the clouds that represent to groups are homothetics). The RV coefficients allow quantifying the global similarity between groups of indicators.

Regarding the factorial scores of individuals (or cases); MFA provides two different results, called partial and global points (individuals).

When we speak of a **partial point**, it refers to the factorial score of an individual but considering only the values of one group of variables. That is, in our study we will have 3 partial individuals for each of the Spanish regions, the G1 that only collects the values of the indicator of resilience elaborated by us; the G2 collects the values of Martin indicator referred to the GDP; and the G3 collects the values of Martin indicator referred to employment.

Those individuals, which similar partial points, reflect a weak variability inside them and illustrate the common structure between tables which it has been previously detected. In the opposite, those individuals with different partial points reflect high variability inside them and constitute the exceptions to the common structure. In our case, a region with similar partial points indicates that their resilience position will be also similar with the three indexes. Conversely, a region with different partial points indicates that at least one of the three resilience indexes shows a different behavior.

The **global or mean points** of each region refer to the factorial score of an individual considering all the values of each one of the variables of all groups. A global point is the barycenter or mean of their respective partial points so it represents the greater synthesis for an individual. In our study, the global points reflect the resilience of the regions from the common point of view of the three indexes.

It has been shown that partial and global points can be represented simultaneously in the same factorial plane, giving rise to a powerful visual instrument for the comparison of resilience from multiple points of view. The complete presentation of this method can be read in Lebart et al. (1995) and Escofier and Pagés (1992). Different applications of MFA for time evolution are found in García Lautre and Abascal (2003); García Lautre (2001), Abascal, García Lautre and Landaluce (2004).

The MFA offers the possibility of including illustrative or supplementary elements (individuals or variables) as in any exploratory factor analysis. The supplementary variables are included in new groups or tables. These elements do not play an active role in making the factors but can be projected in the factorial planes improving the interpretation of factorial planes. The supplementary variables contain relevant information that is considered not to be a direct part of the problem studied. In our case, a set of such as, for example, the public capital or human capital that each region possesses in each period is considered.

The supplementary variables that will characterize the Spanish regions are those detailed below. A review of relevant literature was undertaken, to help the identification of such variables. These can be classified into 2 groups: value of capital and productive structure.

In the following table (table 5) we can see the descriptive statistics of employed variables.

Table 5. Descriptive statistics

	Units	N	Minimum	Maximum	Mean	Stand. Deviation	Source
GDP	Thousands of €	629	3,554,855.00	200,807,804.00	45,973,769.82	45,893,738.18	BD.Mores and INE
Employment	Thousands of people	629	78.20	3,581.35	872.79	796.33	BD.Mores and INE
Value of capital							
Social capital per capita	Index	510	37.48	1989.18	375.69	362.83	Fundación BBVA e Ivie
Public capital per capita	Thousands of €	510	2.88	19.00	9.29	3.84	Fundación BBVA e Ivie
Illiterates and without studies	%	527	19.09	80.16	47.60	14.89	INE
Bachelor	%	527	15.13	49.64	31.63	7.14	INE
Vocational training	%	527	0.58	24.74	9.51	5.13	INE
Superior studies	%	527	3.72	28.91	11.25	4.66	INE
Value of human capital	%	527	2.13	3.20	2.58	0.22	INE
Productive structure							
Agriculture	%	561	0.12	15.24	5.43	3.70	INE
Industry	%	561	5.31	34.82	20.22	7.31	INE
Construction	%	561	4.37	14.56	8.44	1.87	INE
Market services	%	561	36.84	73.27	50.27	8.31	INE
Non-market services	%	561	7.76	28.08	15.69	3.40	INE
Productive specializaton	%	561	0.24	0.56	0.34	0.07	INE

Value of capital

For assessing the capital we focus on three types of capital: social, public and human.

The value of **social capital** is given by the variable social capital per capita. These data are taken from the Fundación BBVA and Ivie (Instituto Valenciano de Investigaciones Económicas). A lot of papers consider social capital as an intangible asset which facilitates the achievement of personal and group results, both economic and social, thanks to generating positive externalities or potential benefits for members of a particular social group[2]. These benefits are derived from the effects of a shared trust, rules and values about expectations and behaviors of members of the group. Paxton (1999) highlights that a relevant characteristic of social capital – which makes that it is something more than only trust, rules and shared values – is that its positive effects are generated from a social network. Because of that, the amplitude of the network that makes up the group and benefits from these effects on its members is a key aspect of social capital. It should be noted that the size of the network can be very variable, sometimes limited to the closest people but reaching the whole of society and include all its members. To calculate the social capital requires to model the investment of it and to do assumptions about the determinants of individuals when they decide their optimal investment (Glaeser et al., 2002). Therefore, we must embody assumptions about future expected profitability and the costs associated with their investment. For this, two databases that provide time series of capital were built. The first includes most OECD countries and the second relates to Spain, its regions and provinces. Both cover extended periods of pre-crisis (Pérez et al., 2008a, 2008b) time and have been used in various analyzes (Pastor and Tortosa 2008; Peiró and Tortosa 2015; Salas and Sanchez 2012; Barrutia and Echebarria 2010; Boix and Galletto 2009; Gleave, Petrey and Carroll 2012; Manca 2011, 2012; Miguélez, Moreno and

[2] In Molina et al. (2008, 17-22) can be found a review of the concept of social capital.

Artís 2008, among others) who study the relationship between social capital and economic performance, often with confirmatory results of its importance.

Public capital is given by the variable public capital per capita in thousands of euros valued in constant prizes of 2008. Data has been taken from the Fundación BBVA and Ivie (Instituto Valenciano de Investigaciones Económicas).

The investor public sector's role is crucial in the economic growth of all countries. The existence of certain infrastructure (transport, water supply and sanitation, urban, health, education, etc.) depends on investment activity in the public sector, which if not suitable or sufficient, can cause constrictions in private activities and public services supply. The share of public capital stock in the production processes of companies, as a factor of production makes these infrastructures to be a key factor in the economic growth of each country or region. Moreover, public investment also plays an important role in the economic cycle and, in particular, in the economic policy debate against the current recession because it can be used as a stabilization mechanism to compensate possible falls in private investment. However, the importance of long-term results is discussed and, in the short term, it can also be counterproductive, driving out private investment (crowding out effect). For these reasons, it is of great interest to study the evolution of public investment and the effects it has had on economic growth. Therefore, we include in our analysis the variable public capital in order to study whether it influences on the resilience of the regions.

Different variables are taken in relation to **human capital** (Crescenzi et al., 2015). In concrete, employed population by levels of education and region (expressed in %): illiterates and without studies, bachelor, vocational training and higher studies. These data are taken from the Labor Force Survey of INE. Moreover, we take another variable to determine the value of human capital: the value of human capital per capita. It is measured in function of the number of equivalent workers without human capital that would be necessary to get their productivity capacity. At the same time, the aggregated human capital of a region will be the number of equivalent workers without human capital that would be necessary to get the productivity capacity of the population. It is taken from the Fundación Bancaja e Ivie (Instituto Valenciano de Investigaciones Económicas)[3].

Qualifications can increase resilience and economic growth for some authors (Glaeser and Saiz, 2004), because "workers with college degrees and higher educational qualifications are more flexible and agile in an economic downturn" (Christopher et al., 2010). Overall, some authors (among others, Chapple and Lester, 2010; Sheffi, 2005) indicate that highly skilled workers strengthen regional resilience. Moreover, the quality of human capital affects the regional growth. Large differences in relation to human capital between regions have also repercussions in terms of infrastructure, services, and therefore income inequalities (Lagravinese, 2014).

Productive structure

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[3] Capital Humano en España y su distribución provincial. Enero de 2013. Database available in Internet: http://www.ivie.es/es/banco/caphum/series.php

The productive structure of a region is essential for explaining its capacity to recover of a crisis, that is, its resilience (Crescenzi et al., 2015). One possible explanation for resilience can be the performance of the industrial sector and particular industrial activities during and after a recessionary event. The importance of the manufacturing sector for explaining regional economic growth and convergence across areas is related to its ability of sustaining higher investments, capital accumulation and producing tradable goods (Porter, 2003; Rodrik, 2013). The business cycle literature has long studied the close relationship between shocks affecting industrial employment and aggregate employment fluctuations and the importance of industrial activities for analyzing national and regional economic growth during booms and busts (Garcia-Mila and McGuire, 1993).

Thus, besides including the productive structure of each region, we also include a variable which determines the productive specialization, *SI*. Specialisation is measured by a specialization index based on the Herfindahl concentration index:

$$SI = \sum_{i=1}^{N} s_i^{\,2}$$

where SI is the specialization index and s_i is the share of the i^{th} activity in total activities. The index is the sum of the squared market fraction of the n economic activities. In this paper we calculate the productive specialization index from the sharing supposing each activity (GDP of each activity) in the total of all productive activities (total GDP of economy). I.e., the i^{th} activities included in the index are agriculture, construction, industry, market services and non-market services.

The index varies between 0 and 1 with higher values indicating higher specialization. Very often the regional specialization in a specific sector is an advantage during the periods of economic growth, but at the same time it can become a disadvantage in time of crisis.

Moreover, certain economic sectors are known to be more subject to cyclical economic fluctuations than others and as such suffer the most from economic downturns (Conroy, 1975; Siegel et al., 1995; Ormerod, 2010). The manufacturing and construction industries typically appear to suffer to a greater extent than the services sector during an economic crisis. The latter is more flexible and can absorb and renew itself more rapidly than the former. Furthermore, the presence of a significant number of public employees enhances resilience to economic shocks, managing nearly completely absorb the effects of the recession. The geographical distribution of these activities across regions might then be expected to be relevant in explaining spatial differences in resistance to recessionary shocks (Martin, 2012).

4. Results

4.1. Composite Index of Resilience

In table 6 we can see the resilience index for 17 regions of Spain for the different considered periods of time, crisis and recoveries. We can observe that in the first crisis, the most resilient regions are Baleares and Canarias, situation that also occurs in the last recovery. In the crisis of 90's, Canarias is still the most resilient followed by La Rioja; and in the last crisis, the regions that appear as more resistant are País Vasco and Navarra. In the recovery stages Andalucía, Castilla La-Mancha and Murcia are the most resilient between 1986 and 1990, and Murcia also remains in the next recovery period. In the last stage, 2012-15, Aragón, the islands and Valencia are the leading positions in resilience.

Table 6. Resilience index (1977-2015)

	Crisis			**Recovery**		
	1977-85	**1991-94**	**2007-11**	**1986-90**	**1995-2006**	**2012-15**
Andalucía	0.499	0.225	0.305	**1.000**	0.854	0.712
Aragón	0.418	0.416	0.792	0.682	0.344	**1.000**
Asturias	0.469	0.252	0.668	0.000	0.146	0.107
Baleares	**1.000**	0.659	0.624	0.648	0.984	**1.000**
Canarias	**1.000**	**1.000**	0.313	0.641	0.884	**1.000**
Cantabria	0.633	0.443	0.657	0.751	0.552	0.024
Castilla y León	0.448	0.444	0.734	0.315	0.189	0.318
Castilla La Mancha	0.540	0.358	0.768	**1.000**	0.635	0.753
Cataluña	0.329	0.436	0.456	0.980	0.611	0.860
Valencia	0.554	0.331	0.000	0.752	0.749	**1.000**
Extremadura	0.959	0.594	0.530	0.682	0.337	0.935
Galicia	0.483	0.469	0.629	0.417	0.195	0.474
Madrid	0.612	0.502	0.749	0.707	0.965	0.734
Murcia	0.621	0.651	0.625	**1.000**	**1.000**	0.885
Navarra	0.656	0.660	**1.000**	0.730	0.594	0.750
País Vasco	0.286	0.504	**1.000**	0.479	0.429	0.426
La Rioja	0.552	0.986	0.912	0.418	0.704	0.627

Figures 5 and 6 show the index of resilience during crisis and recovery periods. Figure 5 shows that the trajectory of the regions is very similar during the first and second crises. However, the last crisis follows a trajectory opposite to the previous ones. This crisis has been the most severe since GDP growth rates are negative for all regions, unlike previous crises that only show negative employment growth rates. In the recovery periods the trajectory followed by the regions is very similar as shown in figure 6.

Figure 5. Resilience during recession periods

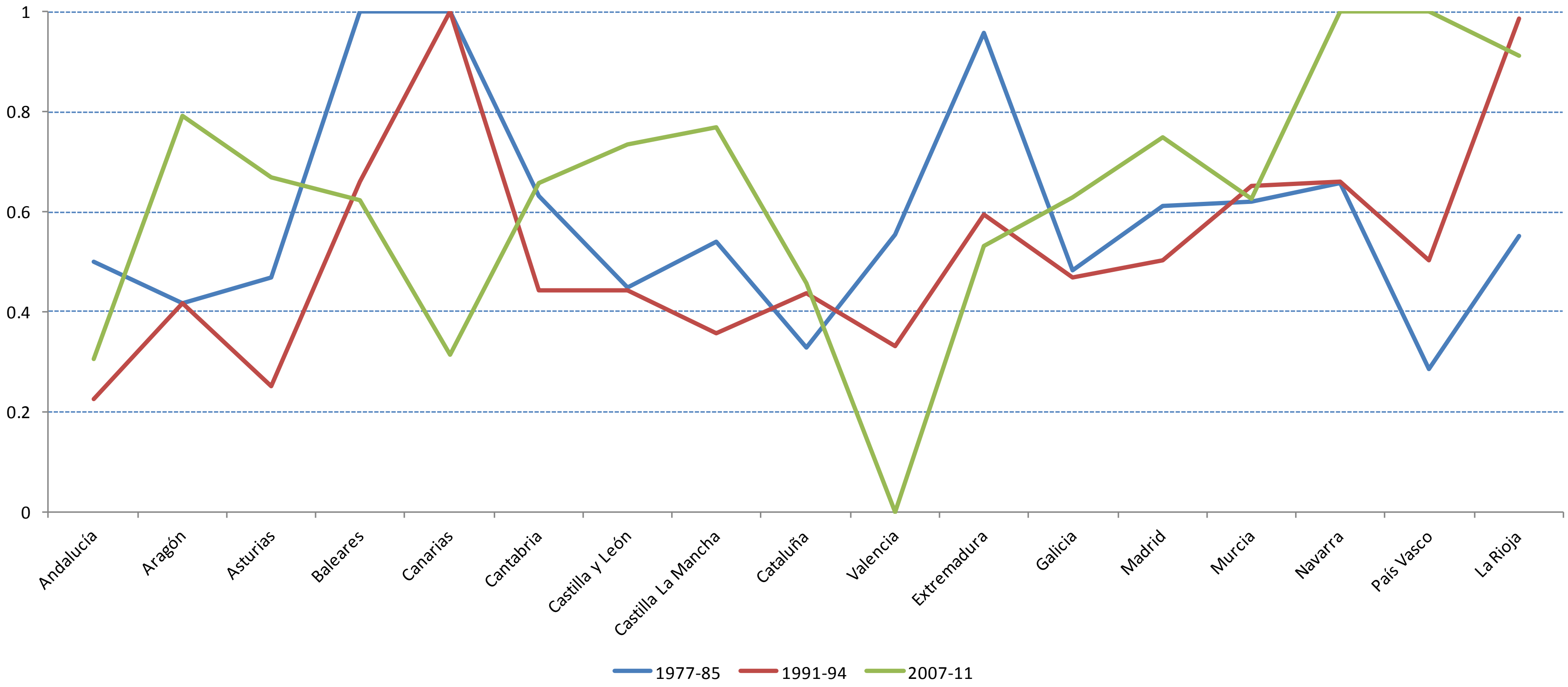
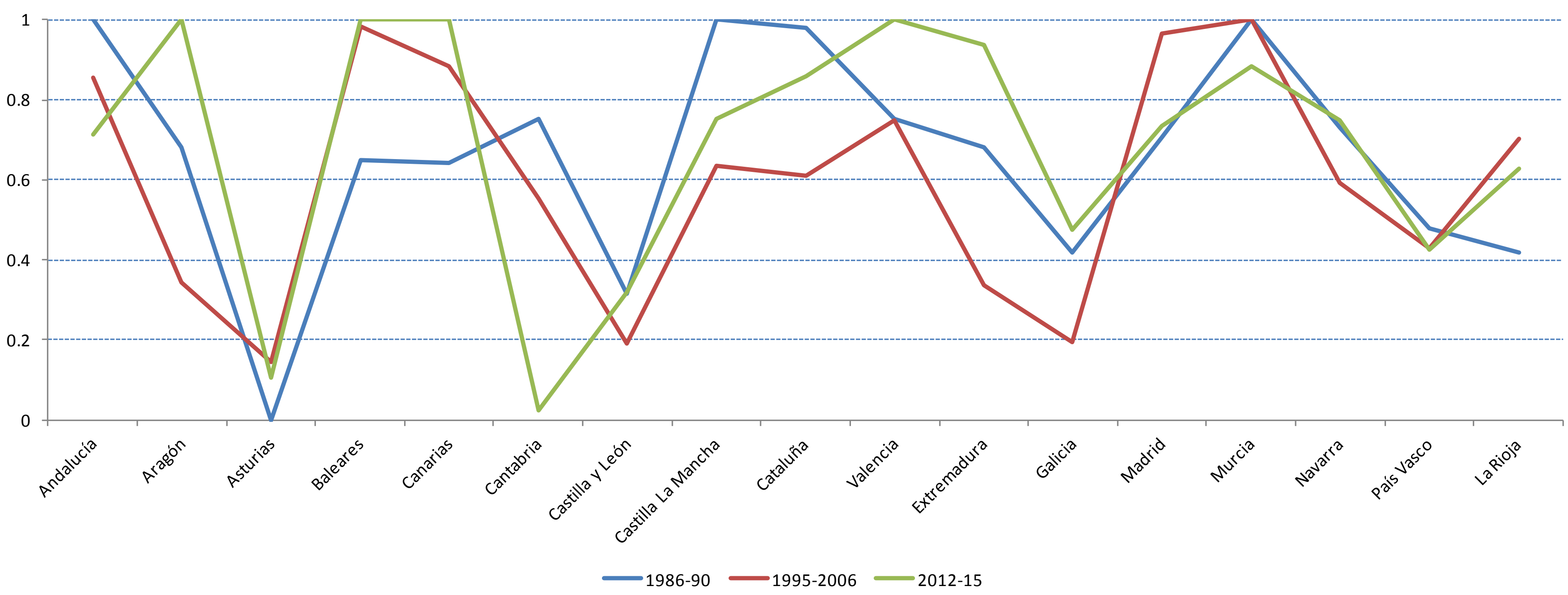


Figure 6. Resilience during recovery periods



4.2. MFA of resilience in the Spanish regions

The complete data for the 17 Spanish regions comprises 3 different resilience indicators measured in six consecutive periods (figure 4) and 13 supplementary variables. In this section, such information is analyzed simultaneously by MFA to deepen three issues. Firstly, a comparison of the three ways of measures the resilience. Secondly, the relationship structure between the resilience indicators, including the temporal effect (six periods) and the supplementary variables. And finally, a characterization of the regions in terms of their resilience and their most related features contained in the supplementary variables.

The MFA of the three resilience tables (figure 4) lead to choose the first two factors that explain more than the 50% of the total variance of the table (the first 37.65% and the second 20.78%). This is considered enough to project variables (the supplementary ones included) and individuals in planes formed by factor 1 in the horizontal axis and factor 2 in the vertical one (figures 7, 8 and 9). These graphs make it possible to analyze the three issues mentioned above. It may be convenient to briefly recall how a variable graph is interpreted. In this graph, the factorials coordinate of every variable is joined by an arrow with the origin of coordinates. Two points close in the graph mean that the arrows are separated by an angle close to zero degrees, so both variables are surely positively correlated. If the angle is close to 180 degrees, then the correlation is negative and if it is close to 90 degrees, the correlation is close to zero. Besides, the value of the coordinate of one point is the linear correlation of the variable with the corresponding factor. Variables that are close to a factor have strong correlation (positive or negative) with this factor and very weak with the other factor.

The comparative analysis of the three resilience measurement methods is carried out using the RV coefficients (table 7) and the variables graph (figure 7). The RV values show the existence of a common structure between the 3 tables that is stronger between group 1 (our resilience index) and the remaining two.

Table 7. RV relation coefficients between groups

	Group 1	Group 2	Group 3
Group 1	1.000		
Group 2	0.746	1.000	
Group 3	0.744	0.431	1.000

The detected common structure is supported because the resilience indicators point roughly to the same direction according to each period. Thus, the three resilience indicators of period 4 point to left in the variable graph (figure 7) any similarly occurs in the rest of periods except 1 and 3. It should be noted that employment resilience indicators in periods 1 and 3 are enough separated of the two remaining indicators (composite and GDP). This feature reflects that the common structure between the 3 tables is not so strong, showing that in these periods there will be clear differences between the three methods for measuring the resilience of the Spanish regions.

The second issue, the analysis of the structure of relationship between resilience indicators and supplementary variables, is done giving a meaning to the two factors using, again, the variables graph (figure 7).

The first is an opposition factor, that is to say, it opposes resilience indicators of the period 5, which shows the last crisis, 2007-2011, with respect to the rest of considered periods, mainly those of recovery, 2, 4 and 6. Therefore, regions that have positive (negative) scores in factor 1 are more (less) resilient than the mean in period 5 and, in general, less (more) resilient in recovery periods. It would be noted that regions with scores close to zero can be regions with resilience around the mean in all these periods or regions with resilience over the mean in all these periods that are experiencing a compensation effect.

The second is also an opposition factor since resilience indicators of the recovery period 2 are opposite of resilience indicators of the crisis periods 1 and 3. Therefore, regions that have positive (negative) scores in factor 2 are more (less) resilient than the mean in period 2 and less (more) resilient periods 1 and 3. It would be noted that regions with scores close to zero may experience a compensation effect like that of factor 1.

It is remarkable that it has shown a behavior of the resilience that has already been pointed out in section 4.1. Some regions are more resilient in recovery periods and, in turn, there are less resilient in crisis periods and vice versa. The characterization of the regions will allow us to detect later those regions.

The supplementary variables related to the socioeconomic characteristics of the regions are projected in the variables graph (figure 7, variables in blue). These variables are the averages of the 6 periods considered. We have chosen the mean because, making a detailed analysis of their evolution, it has been verified its stability and high correlation over time. In this way, a simpler analysis can be done without having to enter each of the 13 variables for each of the 6 periods considered.

The supplementary variables industry and public capital point clearly towards the right and vocational training and human capital also do it, but more weakly. In consequence, these variables are positively correlated with indicators of resilience of crisis period 5. It is noteworthy that public capital is highly correlated with resilience indicators of period 5 and that industry is opposite to resilience indicators of periods 6 and 4 (negative correlated with them). Conversely, bachelor, market services, productive specialization and social capital point to the left, therefore there are positively correlated with the resilience indicators of all recovery periods. Bachelor, market services, productive specialization points also towards down so, there will be more intensely correlated with resilience indicators of period 6 and with the employment resilience indicators of periods 1 and 3.

In consequence, regions with positive factorial scores on factor 1 (more resilient than the mean in crisis period 5 and less in recovery periods) are over the mean in industry and social capital and under the mean in bachelor, market services and productive specialization. The most resilient regions in this period, 2007-2011, are characterized by an industry-centered productive structure and more than the average public and human capital of all regions.

Likewise, they are characterized by having a high percentage of people with vocational training.

And finally, in the recovery stages, we can say that the variable social capital, which points to the left, is related to recovery periods, especially with period 2. It is not a very intense but positive relationship (see table of correlations, Table A2). The efficiency variable also points to the left, although with a low correlation with factor 1. This explains that there is a certain relationship between efficiency and resilience in recovery periods, which is more intense in periods 4 and 6, taking into account our indicator of resilience. Finally, the variables of bachelor, market services and productive specialization will be positively related to the recovery indicators by their position in the plane, especially of the period 6. It stands out the opposition of the variable industry to these last variables. This implies that industry negatively correlates with bachelor, market services and productive specialization, and then we expect a negative relationship of industry with the recovery variables especially with those of period 6. Therefore, we could say that the most resilient regions in the recovery periods are those that stand out for their specialization in market services and for having people with a high school education level (bachelor), as well as a higher than average social capital. In contrast, the percentage of industry in its economy is barely significant.

All the interpretations of the variables graph (figure 7) are supported by the correlation matrix of resilience indicators and supplementary variables (Table A2). Indeed, although some correlations coefficients are not too intense, they confirm what was said above.

With the simultaneous representation of the indicators of resilience and socioeconomic variables in the same graph, it has been possible to establish an interesting relationship between them, and an interpretation of the influence of these socioeconomic variables on the resilience of the regions.

Once the factors have a meaning, we are ready to address the final issue, the characterization of the regions in terms of their resilience and their most related features contained in the supplementary variables. To do this, each Spanish region is projected in the factorial plane 1-2 taking all the information related to the resilience, that is, the global points of MFA are obtained (figure 8). In order not to lengthen this section, only the positions of some regions are commented on.

According to the interpretation of Figure 7, the regions farther to the right in the plane will be those that are above the average in terms of resilience in the crisis of period 5. If we look at tables 4 and 7 that contain the indicators of resilience we observe that País Vasco, Navarra, La Rioja and Aragón are the ones that best behave in that period, and therefore their situation in the plane. The cases of Navarra and Aragón are peculiar since they are placed in the middle of the global point's graph. This may be due to the compensation effect noted above. Navarra is one of the regions that are best placed in period 5 but also in the rest of the periods its resilience is around the mean. That is why his position has remained centered on the plane. Aragón behaves very well in the crisis of period 5 but also in the recovery of the last period (6); therefore it is placed in an intermediate position in the plane. In times of crisis, País Vasco stands out because of their greater resilience. It is an industry-centered region with greater public capital and human capital and also it has the highest percentage of people with vocational training.

As we have explained before, the factors are of opposition, which explains the situation of Valencia in the left side of the plane since it is the one that behaves worse in the period 5 and the one that behaves better in the period of recovery 6, opposite situation to the País Vasco.

If you look at the crises of periods 1 and 3, the indicators point in the direction of the left and down. In that quadrant are located the regions of Baleares and Canarias, which are the best behave in terms of resilience in these times of crisis. The most resilient regions in the crises of periods 1 and 3, Baleares and Canarias, stand out for having a higher than average productive specialization, and in particular, their economy is mainly focused on market services, as we can see in Figure 7. They also stand out for having a higher percentage than the average of people with bachelor.

Figure 7. Variables in the factorial plane (1-2)

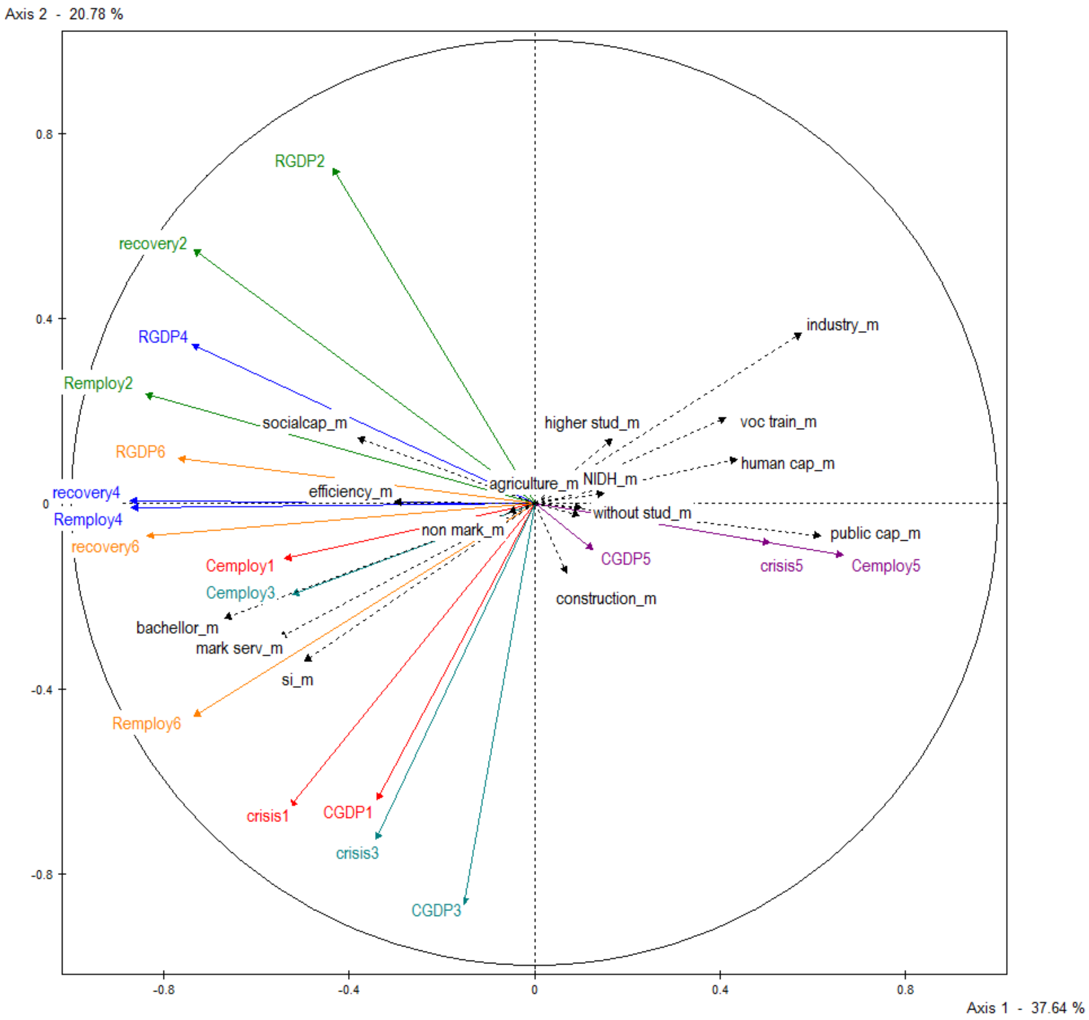
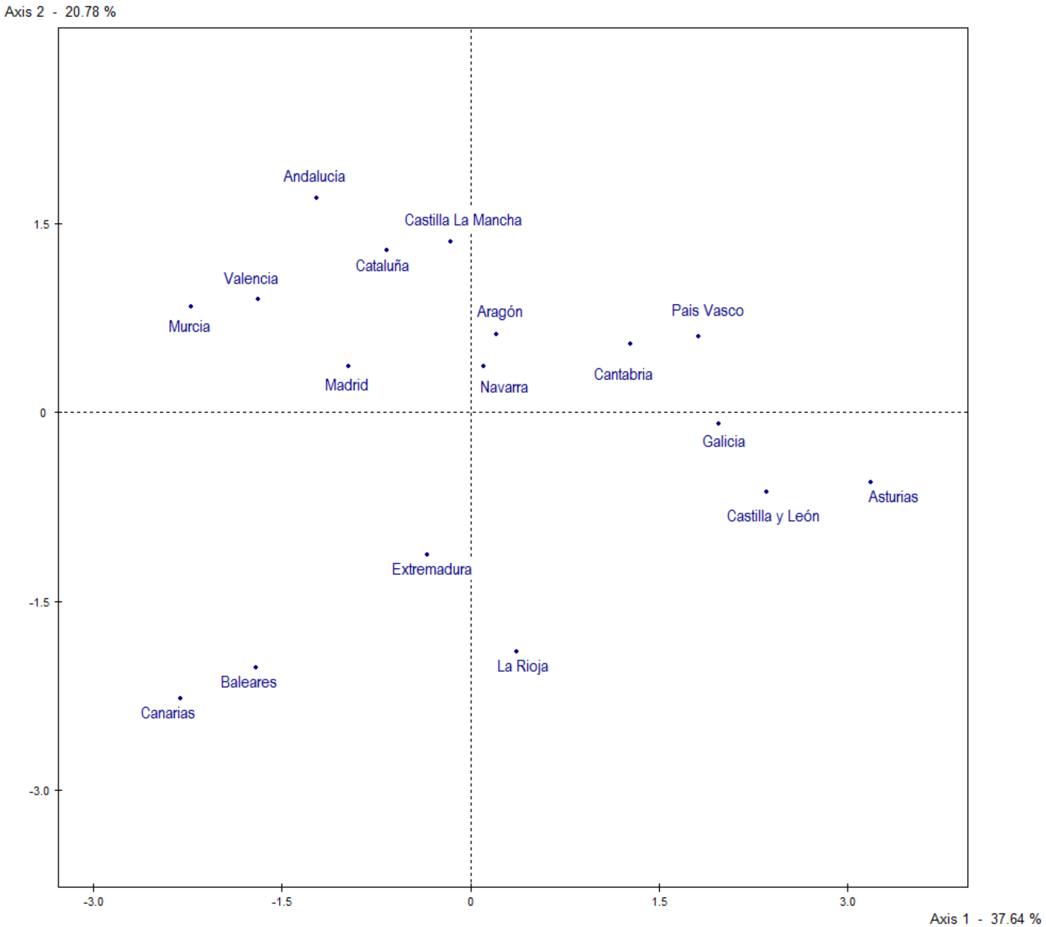


Figure 8. Global points in the factorial plane (1-2)



MFA also provides the partial points of each region that are represented in Figure 9. This graph allows us to come back to the first issue, the common structure between the three indicators of resilience. As explained at the beginning of the section, the structure of the three tables is common but not excessively strong, especially weak between groups 2 (GDP indicators) and 3 (employment indicators). The analysis of the partial points is done in function of the variability of the partial points with respect to its respective global point, denominated within-variability. Thus, regions with little within-variability are stable in terms of their position according to the three types of resilience indicators used. In contrast, regions with high within-variability indicate that their position in the factorial plane will change greatly depending on the type of indicator used.

We have only represented the partial indicators of those regions whose within-variability is greater in axis 1 (Canarias) and in axis 2 (La Rioja); as well as the regions with lower within-variability among the partial individuals, Valencia (less inertia in axis 1) and Aragón (less inertia in axis 2). With this analysis, the differences that exist between the different indicators of resilience selected are detected. Depending on the selected indicator, some regions such Canarias and La Rioja would vary their position in the plane and consequently their characterization in terms of resilience. In this sense, it is observed that the partial 1, which represents our indicator of resilience, is the closest in all cases to the middle point, which would justify the use of both GDP and employment for the characterization of resilience.

Table 8 shows the regions with greater and lesser within-variability in factors 1 and 2. Canarias and Baleares stand out for the greater variability in axis 1, while La Rioja and Castilla La Mancha in axis 2. In the opposite extreme, with lower variability in axis 1 is Valencia and Aragon in axis 2. In general papers that try to explain the resilience of the regions are centered in the indicator of Martin (2012) taking the employment. Well, according to our analysis, their conclusions could vary significantly if instead of taking the employment they took the GDP, as shown in figure 9. Therefore, we consider that taking both indicators can soften the results because our indicator is situated in an intermediate position between both.

Table 8. Within-variability partial points

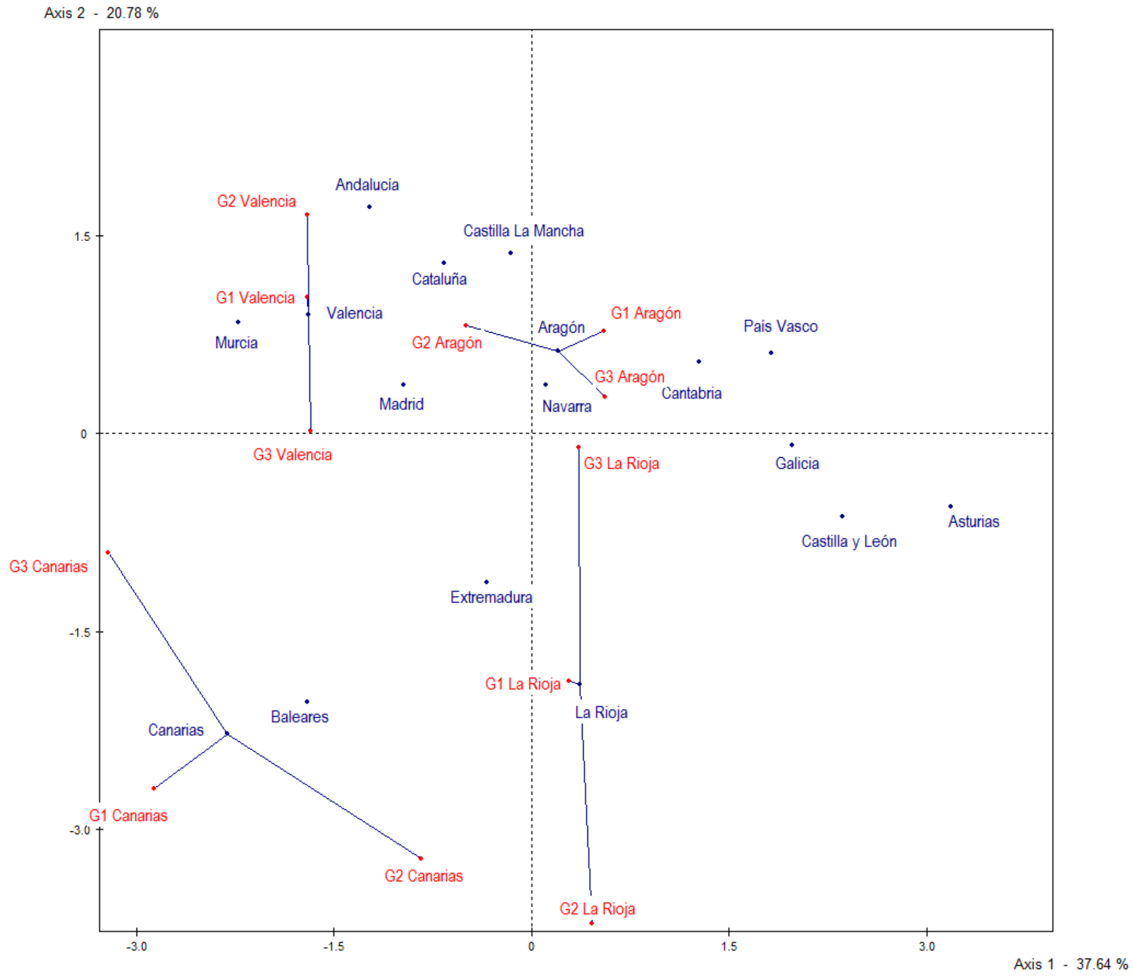
Cases having the greatest within inertia

axis 1	Inertia	axis 2	Inertia
Canarias	24.806	La Rioja	16.046
Baleares	19.087	Castilla La Mancha	10.162
Extremadura	15.679	Andalucía	10.063
Galicia	7.148	Castilla y León	9.830
Asturias	5.816	Navarra	8.581
Andalucía	5.620	Baleares	7.642
Aragón	5.515	Canarias	7.249
Castilla La Mancha	3.384	Asturias	6.590
Navarra	3.036	Extremadura	6.248

Cases having the smallest within inertia

axis 1	Inertia	axis 2	Inertia
Valencia	0.004	Aragón	0.453
La Rioja	0.113	País Vasco	0.731
Cataluña	0.552	Galicia	0.877
Murcia	0.760	Madrid	1.342
Cantabria	1.699	Cantabria	1.399
Castilla y León	2.063	Valencia	3.369
Madrid	2.155	Cataluña	3.707
País Vasco	2.563	Murcia	5.710
Navarra	3.036	Extremadura	6.248

Figure 9. Global and partial points in the factorial plane (1-2)



5. Summary and conclusions

The aim of this study is to analyze what are the characteristics of a region that could influence in its resilience. For this, first of all we will construct a composite index of resilience for the 17 regions of Spain in the period 1977 to 2015, using DEA approach. And in a second stage, we will analyze the factors that make regions more or less resilient and we will compare our index of resilience to Martin (2012) index.

We study the case of Spanish regions because we consider that it is an interesting example of differences between regions when a crisis occurs. In fact, with the last economic crisis we have seen that Spain has been one of the most affected countries in relation to increasing of unemployment.

In conclusion we can say that our results show that regions focus on industry and with higher public and human capital are more resilient in periods of crisis but regions focus on market services are more resilient in recovery periods. Moreover, the results differ a lot if we take into account our index of resilience or Martin (2012) index. These results have been obtained with the use of a new method of analysis in this type of work such as the MFA. Thanks to the simultaneous representation of the indicators of resilience and the socioeconomic variables we have been able to establish relationships between them and to characterize the Spanish regions

So, as can be seen in the results, the different productive structures and the patterns of regional specialization have different effects on resilience in the Spanish regions. The conclusion drawn by most studies is that the analysis of productive structures, regional specialization and their differences in relation to the national average can explain regional economic growth and, naturally, in relation to the possible convergence or divergence of the regions in a country in terms of productivity and per capita income. Additionally, the effects of a crisis can differ substantially across industries. Some manufacturing, mining and energy and construction sectors, for instance, tend to be much more affected by business cycles than service sectors (Maroto, 2012). Thus, when a region has a relatively large share of industries with a higher-than-average sensitivity to the business cycle, they can—ceteris paribus—are expected to be significantly affected during a recession (De Groot et al., 2011).

Bristow (2010) suggested that the most resilient regions were already specialized in more dynamic and less sensitive sectors. Additionally, these resilient regions have steadily maintained their specialization patterns, and reinforced their competitive advantages during and after the crisis.

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Appendix

Table A1. Mean of variables by periods

1977-85	$crisis_1$	β_{GDP1}	$\beta_{employ1}$	efficiency	NIDH	agriculture	industry	construction	market services	non-market services	si	public capital	without studies	bachellor	vocational training	higher studies	human capital	social capital
Andalucía	0.499	0.418	0.462	0.712	0.524	6.383	15.477	8.487	52.357	17.297	0.340	3.533	75.727	18.317	1.217	4.740	2.270	77.807
Aragón	0.418	0.408	0.373	0.732	0.609	6.220	24.180	7.813	48.983	12.803	0.327	6.513	71.270	20.440	1.587	6.703	2.430	81.630
Asturias	0.469	0.469	0.217	0.652	0.584	3.450	33.447	8.900	42.857	11.347	0.320	3.780	71.337	21.207	1.997	5.460	2.363	82.237
Baleares	1.000	1.000	0.888	1.000	0.628	1.917	8.253	10.647	70.893	8.287	0.527	3.100	72.497	22.233	0.680	4.590	2.217	101.013
Canarias	1.000	0.528	1.000	0.785	0.584	3.800	11.783	7.750	62.693	13.970	0.437	4.517	69.240	23.987	1.153	5.620	2.270	85.267
Cantabria	0.633	0.144	0.633	0.706	0.601	4.897	25.373	7.640	50.713	11.380	0.343	3.933	68.493	22.577	2.627	6.303	2.420	94.797
Castilla y León	0.448	0.448	0.289	0.638	0.586	8.297	21.780	7.307	47.523	15.093	0.310	5.680	71.817	20.373	1.613	6.197	2.387	78.763
Castilla La Mancha	0.540	0.347	0.525	0.575	0.528	12.180	18.827	9.350	45.520	14.123	0.287	5.160	78.510	16.593	1.063	3.833	2.187	82.183
Cataluña	0.329	0.188	0.326	0.803	0.633	2.223	29.243	7.257	51.993	9.280	0.370	3.063	65.947	25.690	2.220	6.143	2.390	88.433
Valencia	0.554	0.386	0.532	0.733	0.590	4.033	24.167	7.483	53.290	11.030	0.363	3.517	71.960	21.903	0.893	5.243	2.227	85.570
Extremadura	0.959	0.959	0.000	0.477	0.473	11.060	13.950	11.073	44.583	19.333	0.283	4.410	78.697	16.157	1.023	4.123	2.213	60.013
Galicia	0.483	0.268	0.480	0.605	0.564	8.347	24.190	8.010	47.447	12.013	0.313	3.227	76.233	17.847	1.327	4.593	2.140	84.460
Madrid	0.612	0.282	0.612	0.952	0.654	0.320	16.507	7.513	59.270	16.380	0.410	3.983	56.673	30.997	1.573	10.757	2.670	84.837
Murcia	0.621	0.463	0.589	0.708	0.569	7.607	19.630	6.890	50.560	15.310	0.330	3.493	75.173	19.230	1.073	4.523	2.157	89.143
Navarra	0.656	0.162	0.656	0.843	0.664	6.093	28.333	6.430	43.640	15.500	0.303	4.763	64.773	25.453	2.840	6.933	2.453	89.393
País Vasco	0.286	0.000	0.286	0.844	0.676	1.630	32.250	5.270	48.693	12.163	0.357	4.077	62.707	25.607	4.603	7.083	2.497	91.437
La Rioja	0.552	0.552	0.154	0.814	0.618	10.637	30.480	5.657	43.597	9.630	0.310	4.917	74.090	18.070	2.193	5.647	2.363	75.747

1986-90	$recovery_1$	δ_{GDP1}	$\delta_{employ1}$	efficiency	NIDH	agriculture	industry	construction	market services	non-market services	si	public capital	without studies	bachellor	vocational training	higher studies	human capital	social capital
Andalucía	1.000	0.857	0.966	0.732	0.555	6.590	15.382	10.406	49.930	17.692	0.320	4.720	67.832	22.950	3.390	5.828	2.294	113.378
Aragón	0.682	0.624	0.480	0.736	0.646	5.766	24.202	7.634	48.262	14.136	0.322	7.952	64.254	23.506	4.506	7.734	2.458	122.396
Asturias	0.000	0.000	0.000	0.661	0.622	3.330	32.638	9.070	41.950	13.018	0.310	4.810	64.470	24.366	4.174	6.990	2.432	85.776
Baleares	0.648	0.348	0.648	1.000	0.676	1.820	8.088	9.072	71.264	9.750	0.534	4.232	63.696	26.914	3.012	6.378	2.288	186.900
Canarias	0.641	0.238	0.641	0.800	0.616	3.762	9.030	10.734	61.656	14.814	0.422	5.878	62.370	26.990	3.572	7.068	2.330	138.056
Cantabria	0.751	0.751	0.208	0.728	0.624	5.242	23.824	7.460	50.730	12.746	0.338	5.250	59.014	27.204	5.956	7.826	2.530	123.330
Castilla y León	0.315	0.177	0.315	0.658	0.618	7.580	21.216	8.774	45.992	16.434	0.300	7.028	65.584	22.330	4.686	7.400	2.452	96.404
Castilla La Mancha	1.000	1.000	0.327	0.618	0.568	11.702	20.852	10.254	41.998	15.196	0.268	6.664	71.222	20.764	2.912	5.102	2.228	114.178
Cataluña	0.980	0.859	0.863	0.809	0.664	2.004	28.790	7.596	52.030	9.580	0.368	4.004	59.346	27.794	5.494	7.366	2.400	126.306
Valencia	0.752	0.594	0.737	0.729	0.618	3.920	24.074	7.560	52.760	11.684	0.356	4.662	64.678	25.574	3.378	6.370	2.270	133.884
Extremadura	0.682	0.596	0.608	0.519	0.508	12.628	11.958	13.148	41.932	20.332	0.264	5.604	73.390	18.584	2.628	5.398	2.278	54.374
Galicia	0.417	0.417	0.021	0.625	0.584	8.684	20.956	9.694	47.046	13.618	0.302	4.324	69.378	22.024	3.228	5.370	2.194	88.250
Madrid	0.707	0.550	0.695	0.922	0.701	0.208	17.282	7.064	59.394	16.050	0.414	5.150	51.780	32.352	4.436	11.432	2.662	97.688
Murcia	1.000	0.697	1.000	0.751	0.594	8.918	19.288	9.700	47.154	14.942	0.300	4.870	65.228	24.464	4.290	6.018	2.214	144.156
Navarra	0.730	0.690	0.417	0.851	0.705	5.636	31.428	6.516	43.012	13.408	0.308	6.740	59.256	25.212	6.638	8.894	2.496	143.852
País Vasco	0.479	0.305	0.479	0.850	0.701	1.824	32.284	5.868	47.824	12.196	0.352	5.596	55.470	26.330	8.554	9.646	2.594	123.986
La Rioja	0.418	0.266	0.418	0.756	0.635	10.866	26.900	6.292	43.894	12.046	0.298	6.302	66.982	20.364	4.854	7.800	2.458	130.022

1991-94	crisis2	β_{GDP2}	$\beta_{employ2}$	efficiency	NIDH	agriculture	industry	construction	market services	non-market services	si	public capital	without studies	bachellor	vocational training	higher studies	human capital	social capital
Andalucía	0.225	0.000	0.225	0.745	0.576	7.233	13.470	9.700	50.073	19.528	0.323	6.705	59.855	27.065	6.215	6.865	2.380	133.580
Aragón	0.416	0.248	0.416	0.741	0.675	5.643	23.388	7.663	47.703	15.608	0.315	10.270	57.528	25.448	7.968	9.058	2.533	146.155
Asturias	0.252	0.252	0.169	0.666	0.642	2.990	27.815	10.108	43.933	15.150	0.303	6.868	57.055	27.850	6.840	8.255	2.590	117.340
Baleares	0.659	0.659	0.637	1.000	0.711	1.835	7.670	7.580	71.898	11.018	0.543	5.630	54.185	33.725	5.580	6.510	2.350	190.345
Canarias	1	1.000	1.000	0.772	0.632	3.570	8.920	8.090	62.218	17.203	0.433	7.810	52.968	32.458	6.658	7.918	2.445	133.878
Cantabria	0.443	0.437	0.443	0.734	0.650	5.188	22.368	7.525	50.333	14.595	0.333	7.575	51.505	30.365	9.565	8.565	2.615	138.143
Castilla y León	0.444	0.444	0.214	0.660	0.643	7.028	20.900	8.880	44.958	18.233	0.293	9.455	58.683	25.495	7.230	8.593	2.565	116.245
Castilla La Mancha	0.358	0.085	0.358	0.648	0.594	12.100	19.743	10.255	41.210	16.695	0.263	9.143	64.015	25.220	5.028	5.738	2.303	129.763
Cataluña	0.436	0.436	0.306	0.810	0.703	1.860	27.843	7.703	52.013	10.583	0.365	5.835	50.210	31.355	9.968	8.468	2.490	165.065
Valencia	0.331	0.268	0.331	0.753	0.640	3.620	23.470	7.678	52.163	13.070	0.353	6.405	56.475	29.955	6.468	7.103	2.370	139.273
Extremadura	0.594	0.594	0.000	0.534	0.533	11.160	10.468	13.535	42.773	22.070	0.275	7.848	65.125	24.610	4.010	6.255	2.353	70.370
Galicia	0.469	0.469	0.146	0.650	0.609	8.853	19.518	9.703	46.093	15.838	0.295	6.158	61.928	26.058	5.593	6.423	2.313	82.818
Madrid	0.502	0.497	0.502	0.882	0.726	0.250	16.808	7.755	58.300	16.888	0.405	7.145	45.660	34.258	6.568	13.515	2.745	104.883
Murcia	0.651	0.211	0.651	0.768	0.610	8.988	18.830	9.425	45.918	16.840	0.290	6.785	58.528	27.778	7.555	6.140	2.260	145.525
Navarra	0.66	0.274	0.660	0.837	0.722	5.470	32.043	7.478	41.673	13.335	0.303	10.310	49.420	27.785	11.523	11.273	2.643	197.005
País Vasco	0.504	0.251	0.504	0.829	0.725	1.905	29.805	6.463	48.155	13.673	0.345	7.988	48.320	27.985	12.553	11.143	2.723	150.168
La Rioja	0.986	0.986	0.248	0.816	0.689	10.285	27.528	6.328	42.825	13.035	0.293	8.395	56.755	24.993	8.853	9.400	2.593	140.428

1995-2006	recovery2	δ_{GDP2}	$\delta_{employ2}$	efficiency	NIDH	agriculture	industry	construction	market services	non-market services	si	public capital	without studies	bachellor	vocational training	higher studies	human capital	social capital
Andalucía	0.854	0.639	0.854	0.864	0.628	6.980	13.332	9.780	50.428	19.479	0.324	8.637	46.228	33.871	9.239	10.663	2.577	477.948
Aragón	0.344	0.344	0.331	0.851	0.735	5.892	25.883	8.319	44.603	15.307	0.303	13.858	44.394	30.163	11.913	13.531	2.756	459.443
Asturias	0.146	0.096	0.146	0.827	0.686	2.817	24.269	10.746	46.797	15.373	0.313	11.382	45.301	32.961	10.672	11.067	2.754	275.907
Baleares	0.984	0.338	0.984	1.000	0.744	1.643	7.940	8.487	69.981	11.949	0.519	6.848	37.441	43.786	9.131	9.643	2.508	560.522
Canarias	0.884	0.526	0.884	0.792	0.673	2.225	7.689	9.121	63.452	17.513	0.448	9.542	41.238	37.421	10.363	10.979	2.564	608.400
Cantabria	0.552	0.346	0.552	0.850	0.706	4.563	22.308	9.663	49.100	14.366	0.325	11.461	39.433	35.052	13.943	11.572	2.758	382.932
Castilla y León	0.189	0.000	0.189	0.802	0.702	8.718	21.722	9.135	43.041	17.384	0.280	13.596	47.091	30.231	10.216	12.463	2.758	364.255
Castilla La Mancha	0.635	0.402	0.635	0.738	0.641	12.914	20.352	10.430	38.683	17.621	0.250	11.635	50.014	33.413	7.524	9.048	2.507	372.054
Cataluña	0.611	0.455	0.611	0.910	0.770	1.792	26.845	7.526	53.844	9.998	0.379	7.823	39.133	35.075	13.203	12.589	2.664	474.470
Valencia	0.749	0.732	0.749	0.851	0.691	3.178	22.586	8.945	52.170	13.121	0.352	8.923	38.563	39.844	9.914	11.678	2.583	523.944
Extremadura	0.337	0.337	0.303	0.638	0.593	12.621	10.814	11.971	40.903	23.688	0.268	11.116	47.478	36.259	6.492	9.771	2.558	225.792
Galicia	0.195	0.195	0.000	0.731	0.662	6.919	20.989	10.316	45.510	16.265	0.294	9.607	47.227	33.190	9.498	10.086	2.562	176.623
Madrid	0.965	0.965	0.902	0.999	0.795	0.241	15.729	7.733	61.210	15.087	0.429	9.149	33.773	36.924	9.194	20.109	2.968	287.387
Murcia	1.000	1.000	1.000	0.822	0.668	7.926	19.057	8.873	47.520	16.624	0.306	8.483	43.343	35.037	10.383	11.237	2.527	641.716
Navarra	0.594	0.594	0.468	0.926	0.782	4.173	31.606	8.377	41.675	14.171	0.301	14.183	38.138	30.323	15.767	15.773	2.793	719.341
País Vasco	0.429	0.429	0.314	0.961	0.800	1.783	30.858	7.333	46.039	13.987	0.333	10.968	38.171	28.599	17.436	15.794	2.905	479.591
La Rioja	0.704	0.430	0.704	0.895	0.739	10.363	28.054	7.900	40.473	13.208	0.278	11.452	46.396	29.472	12.109	12.023	2.676	533.261

2007-11	crisis3	β_{GDP3}	$\beta_{employ3}$	efficiency	NIDH	agriculture	industry	construction	market services	non-market services	si	public capital	without studies	bachellor	vocational training	higher studies	human capital	social capital
Andalucía	0.305	0.305	0.152	0.967	0.686	5.346	10.896	9.302	53.354	21.096	0.356	10.914	33.682	40.178	12.308	13.832	2.572	981.302
Aragón	0.792	0.792	0.329	0.876	0.796	5.042	23.172	8.574	46.572	16.638	0.310	18.300	33.160	33.330	15.850	17.660	2.772	829.372
Asturias	0.668	0.177	0.668	0.821	0.743	2.364	20.200	10.694	49.466	17.272	0.330	16.330	33.214	35.264	15.414	16.108	2.772	585.930
Baleares	0.624	0.445	0.602	0.998	0.735	1.322	7.148	8.006	68.044	15.474	0.498	8.744	26.548	48.414	12.184	12.854	2.514	821.268
Canarias	0.313	0.313	0.139	0.782	0.692	1.390	6.406	8.294	65.138	18.768	0.472	10.748	31.974	41.810	13.110	13.106	2.562	880.862
Cantabria	0.657	0.302	0.657	0.910	0.763	3.388	19.422	9.840	51.426	15.930	0.338	16.134	29.512	35.544	19.018	15.926	2.762	869.868
Castilla y León	0.734	0.710	0.666	0.814	0.771	8.370	19.266	8.852	45.416	18.100	0.292	18.096	36.198	33.944	13.842	16.016	2.726	789.066
Castilla La Mancha	0.768	0.768	0.563	0.787	0.687	10.918	18.046	9.794	41.138	20.598	0.270	13.144	37.486	38.998	11.128	12.388	2.536	779.752
Cataluña	0.456	0.195	0.456	0.918	0.805	1.576	22.230	7.334	57.394	11.456	0.398	9.692	33.682	34.654	15.712	15.952	2.668	820.542
Valencia	0.000	0.000	0.000	0.993	0.720	2.710	18.166	8.832	55.642	15.060	0.372	9.706	29.650	40.940	14.296	15.114	2.606	904.026
Extremadura	0.530	0.454	0.494	0.660	0.658	11.380	9.792	11.426	42.144	25.710	0.280	15.920	32.378	45.144	9.784	12.694	2.558	478.404
Galicia	0.629	0.445	0.607	0.831	0.727	5.560	19.004	9.788	48.058	17.822	0.310	13.854	33.850	37.690	14.184	14.276	2.638	407.616
Madrid	0.749	0.568	0.715	0.992	0.840	0.152	13.116	7.090	64.718	15.088	0.466	11.896	22.940	39.812	10.854	26.394	2.962	586.216
Murcia	0.625	0.625	0.054	0.919	0.698	6.218	16.740	7.940	50.806	18.558	0.330	9.564	32.582	41.270	12.472	13.676	2.534	1108.558
Navarra	1.000	1.000	0.900	0.945	0.838	3.492	29.786	8.376	43.826	15.166	0.312	16.812	25.064	35.868	19.836	19.232	2.790	1247.152
País Vasco	1.000	0.554	1.000	1.000	0.877	1.386	28.640	7.466	47.962	14.752	0.342	14.498	25.270	30.850	22.860	21.020	2.944	1012.226
La Rioja	0.912	0.912	0.579	0.945	0.766	8.650	25.666	8.448	42.610	14.844	0.284	15.300	30.388	36.982	15.860	16.770	2.736	936.830

2012-15	recovery3	δ_{GDP3}	$\delta_{employ3}$	efficiency	NIDH	agriculture	industry	construction	market services	non-market services	si	public capital	without studies	bachellor	vocational training	higher studies	human capital	social capital
Andalucía	0.712	0.548	0.653	0.961		6.119	10.523	5.968	55.995	22.747	0.384	11.450	30.056	41.418	13.714	14.811	2.773	489.480
Aragón	1.000	1.000	0.182	0.852		6.514	22.901	5.945	47.396	17.387	0.315	18.900	29.990	34.258	17.118	18.630	2.949	406.970
Asturias	0.107	0.014	0.107	0.807		1.793	19.036	7.675	52.522	18.816	0.353	16.790	30.533	34.265	16.478	18.724	3.013	325.930
Baleares	1.000	0.681	1.000	0.998		1.073	6.148	5.542	70.847	16.475	0.537	9.270	22.495	48.141	14.331	15.028	2.680	444.230
Canarias	1.000	0.878	0.817	0.774		1.116	5.534	5.898	67.796	19.698	0.506	11.140	29.726	40.793	14.538	14.943	2.746	405.420
Cantabria	0.024	0.000	0.024	0.911		2.654	20.287	6.575	53.585	17.154	0.364	16.480	24.108	37.199	21.632	17.067	2.954	488.920
Castilla y León	0.318	0.316	0.110	0.804		9.298	18.914	6.276	46.617	18.965	0.301	18.860	32.015	38.127	14.403	15.455	2.942	433.580
Castilla La Mancha	0.753	0.748	0.280	0.746		12.443	17.315	6.425	42.481	21.452	0.277	13.590	31.480	38.717	14.295	15.503	2.736	333.670
Cataluña	0.860	0.851	0.407	0.891		1.563	22.116	4.887	59.461	12.048	0.420	10.330	31.067	35.045	16.789	17.099	2.839	383.470
Valencia	1.000	0.985	0.620	1.000		2.541	19.131	5.798	56.736	16.106	0.388	10.000	28.153	44.102	12.795	14.950	2.818	426.180
Extremadura	0.935	0.836	0.737	0.689		10.802	9.564	8.190	43.732	27.862	0.298	16.910	29.974	43.084	12.436	14.506	2.713	219.290
Galicia	0.474	0.474	0.007	0.792		5.170	18.886	7.132	50.233	18.618	0.330	15.240	28.735	38.836	15.862	16.567	2.815	184.100
Madrid	0.734	0.730	0.244	0.945		0.140	12.047	4.878	67.215	15.675	0.493	12.650	19.704	39.455	12.175	28.666	3.189	330.970
Murcia	0.885	0.880	0.308	0.875		6.281	17.299	5.142	51.831	19.590	0.343	9.880	29.675	41.198	13.746	15.382	2.758	543.660
Navarra	0.750	0.749	0.157	0.932		3.195	32.229	5.598	43.882	15.454	0.325	16.700	23.934	34.619	22.128	19.314	2.976	623.300
País Vasco	0.426	0.426	0.000	1.000		1.216	28.830	5.362	48.720	15.958	0.349	15.440	23.538	29.930	24.295	22.231	3.134	593.200
La Rioja	0.627	0.498	0.561	0.971		8.539	25.840	5.985	43.208	16.333	0.290	16.250	25.516	40.942	16.450	17.086	2.912	392.780

Table A2. Correlation matrix

	crisis1	CGDP1	Cemploy1	recovery2	RGDP2	Remploy2	crisis3	CGDP3	Cemploy3	recovery4	RGDP4	Remploy4	crisis5	CGDP5	Cemploy5	recovery6	RGDP6	Remploy6	efficiency	NIDH	agriculture	industry	construction	mark serv	non mark	si	public cap	without stud	bachellor	voc train	higher stud	human cap	socialcap
crisis1	1.000																																
CGDP1	0.728	1.000																															
Cemploy1	0.476	-0.015	1.000																														
recovery2	0.103	-0.085	0.325	1.000																													
RGDP2	-0.103	-0.239	0.106	0.908	1.000																												
Remploy2	0.172	0.179	0.205	0.717	0.435	1.000																											
crisis3	0.547	0.294	0.275	-0.062	-0.313	0.116	1.000																										
CGDP3	0.545	0.407	0.149	-0.310	-0.499	-0.075	0.836	1.000																									
Cemploy3	0.387	-0.108	0.834	0.260	-0.025	0.300	0.528	0.247	1.000																								
recovery4	0.417	0.166	0.632	0.630	0.334	0.741	0.359	0.152	0.614	1.000																							
RGDP4	0.120	-0.146	0.362	0.637	0.446	0.732	0.155	-0.135	0.445	0.799	1.000																						
Remploy4	0.420	0.228	0.587	0.622	0.324	0.753	0.329	0.154	0.577	0.984	0.747	1.000																					
crisis5	-0.250	-0.254	-0.227	-0.297	-0.162	-0.440	0.204	0.002	0.038	-0.282	-0.217	-0.333	1.000																				
CGDP5	-0.056	-0.052	-0.100	-0.002	0.050	-0.160	0.383	0.055	0.127	-0.045	-0.005	-0.088	0.802	1.000																			
Cemploy5	-0.213	-0.300	-0.223	-0.451	-0.258	-0.586	-0.004	0.032	-0.119	-0.422	-0.407	-0.486	0.799	0.416	1.000																		
recovery6	0.414	0.426	0.282	0.556	0.324	0.691	0.315	0.144	0.331	0.548	0.494	0.535	-0.360	0.059	-0.546	1.000																	
RGDP6	0.250	0.224	0.219	0.593	0.409	0.656	0.243	0.036	0.307	0.456	0.543	0.432	-0.309	0.113	-0.523	0.960	1.000																
Remploy6	0.705	0.760	0.272	0.287	0.015	0.568	0.391	0.437	0.195	0.580	0.214	0.623	-0.547	-0.257	-0.517	0.684	0.480	1.000															
efficiency_m	-0.049	-0.190	0.451	0.122	-0.051	0.352	0.184	0.091	0.520	0.590	0.430	0.541	0.150	0.050	0.173	0.153	0.081	0.141	1.000														
NIDH_m	-0.331	-0.487	0.170	-0.174	-0.198	-0.045	0.148	0.094	0.389	0.100	0.128	0.042	0.501	0.257	0.550	-0.111	-0.063	-0.326	0.786	1.000													
agriculture_m	0.053	0.292	-0.448	0.114	0.243	-0.155	0.062	-0.057	-0.474	-0.263	-0.226	-0.228	0.132	0.441	-0.130	0.028	0.056	0.011	-0.716	-0.678	1.000												
industry_m	-0.757	-0.693	-0.437	-0.259	-0.030	-0.370	-0.176	-0.291	-0.198	-0.454	-0.149	-0.476	0.501	0.281	0.451	-0.433	-0.274	-0.702	0.114	0.525	-0.050	1.000											
construction_m	0.423	0.570	-0.229	-0.055	0.051	-0.194	-0.236	-0.085	-0.460	-0.317	-0.343	-0.271	-0.308	-0.242	-0.207	-0.006	-0.074	0.237	-0.797	-0.868	0.538	-0.512	1.000										
mark serv_m	0.462	0.262	0.709	0.157	-0.128	0.407	0.195	0.344	0.559	0.623	0.290	0.613	-0.411	-0.441	-0.235	0.349	0.206	0.535	0.594	0.244	-0.701	-0.609	-0.214	1.000									
non mark_m	0.327	0.361	-0.238	0.097	0.120	0.066	-0.086	-0.140	-0.278	-0.142	-0.003	-0.126	-0.127	0.094	-0.210	0.070	0.070	0.127	-0.693	-0.750	0.600	-0.481	0.748	-0.319	1.000								
si_m	0.454	0.245	0.686	0.089	-0.189	0.359	0.246	0.374	0.591	0.595	0.253	0.578	-0.297	-0.377	-0.103	0.334	0.183	0.520	0.670	0.364	-0.756	-0.516	-0.283	0.982	-0.402	1.000							
public cap_m	-0.233	-0.173	-0.424	-0.411	-0.182	-0.582	-0.006	-0.048	-0.230	-0.660	-0.488	-0.638	0.604	0.613	0.450	-0.364	-0.262	-0.523	-0.372	0.089	0.397	0.452	0.045	-0.674	0.245	-0.627	1.000						
without stud_m	0.039	0.412	-0.360	0.009	0.100	-0.151	-0.158	-0.134	-0.509	-0.350	-0.406	-0.280	-0.243	0.006	-0.405	0.056	0.032	0.151	-0.796	-0.853	0.816	-0.212	0.716	-0.481	0.537	-0.566	0.149	1.000					
bachellor_m	0.621	0.370	0.660	0.278	0.029	0.465	0.193	0.306	0.465	0.715	0.468	0.700	-0.474	-0.430	-0.272	0.425	0.298	0.609	0.496	0.106	-0.548	-0.646	-0.057	0.893	-0.187	0.870	-0.723	-0.444	1.000				
voc train_m	-0.467	-0.688	-0.065	-0.169	-0.088	-0.230	0.064	-0.102	0.231	-0.224	-0.096	-0.271	0.529	0.217	0.552	-0.420	-0.334	-0.546	0.393	0.693	-0.363	0.764	-0.647	-0.227	-0.517	-0.112	0.327	-0.536	-0.383	1.000			
higher stud_m	-0.310	-0.504	-0.006	-0.161	-0.130	-0.017	0.016	0.005	0.200	0.065	0.318	-0.002	0.462	0.254	0.513	-0.171	-0.069	-0.427	0.536	0.783	-0.544	0.372	-0.630	0.113	-0.284	0.185	0.212	-0.828	0.076	0.451	1.000		
human cap_m	-0.417	-0.548	-0.175	-0.352	-0.252	-0.231	-0.055	-0.001	0.067	-0.186	0.025	-0.216	0.540	0.231	0.630	-0.438	-0.344	-0.548	0.418	0.763	-0.483	0.527	-0.584	-0.054	-0.298	0.032	0.427	-0.737	-0.151	0.619	0.922	1.000	
socialcap_m	-0.015	-0.237	0.412	0.362	0.180	0.432	0.284	-0.119	0.645	0.503	0.410	0.497	0.123	0.265	-0.100	0.221	0.209	0.111	0.589	0.421	-0.239	0.256	-0.615	0.116	-0.379	0.177	-0.081	-0.361	0.074	0.516	0.089	0.080	1.000