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Regional benchmarking in the smart specialisation process: Identification of reference regions based on structural similarity

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Abstract

One of the most basic conditions required for drawing lessons from regional benchmarking is to compare homogeneous regions and learn from equivalents. This condition is not met when regions for comparison are chosen based on their high performance, overlooking their regional context or structural conditions. This paper aims to provide a new methodology for the identification of homogeneous regions for regional benchmarking; identifying groups of homogeneous regions using variables that are similar in nature; focusing solely on structural conditions, thereby overcoming the flaws produced by mixing variables of a different nature (comparing structural indicators with performance and / or behavioural indicators). Thus, regional benchmarking can be of great help in making strategic decisions within the process of the design and implementation of regional Research and Innovation Strategies for Smart Specialisation (RIS3), taking into account the relative position of the region to other regions in Europe. Following the RIS3 approach of looking beyond the regional administrative boundaries, benchmarking based on structural similarity enables the region to identify its competitive advantages through systematic comparisons with other regions or to map the national and international context in search of examples to learn from, or to mark a difference with.

Keywords: regional benchmarking, structural similarity, policy learning, smart specialisation.

[a] The views expressed are purely those of the authors and may not in any circumstances be regarded as stating an official position of the European Commission.

1 – Introduction

This paper presents a methodology for benchmarking regions across Europe according to their structural similarity evaluated on the basis of social, economic and geographical characteristics. We collect regional data for European Union member states to construct a full matrix of inter-regional distances and we use it to analyse the case of the Basque Country in Spain. We present a web-based interactive tool that allows regional policy makers to perform similar analyses and we discuss how the methodology can be effectively employed in the design and implementation of smart specialisation strategies (RIS3).

The main motivation for this paper is the increasing need to ground strategic development decisions at the regional level in the field of innovation and research policy, based on sound analytical evidence, systematic comparison with relevant peers, and the transfer of good practices. With the aim of reaching the objectives of the Europe2020 Strategy, the European Commission has conditioned the disbursement of European Regional Development Funds under the thematic objectives most directly related to research and innovation, on the existence of RIS3. These are defined as integrated, place-based economic transformation agendas that focus policy support and investments on key challenges and needs for knowledge-based development, building on national/regional strengths, competitive advantages and potential for excellence (European Commission, 2012).

An effective transfer of good policy practices and solutions between regions, as well as a systematic comparison with peers aimed at supporting the identification of distinctive new areas of specialisation for the future, is a key component on which RIS3 should build. A sound exercise of regional benchmarking is, in this respect, an indispensable means for policy makers to identify what practices could and should be transferred and, more generally, what examples should be followed. This paper aims to provide an easily accessible tool to perform regional benchmarking in the context of research and innovation policy.

The literature on regional innovation systems has highlighted the vast richness and diversity of regional innovation patterns, showing that there are no "one size fits all" policies (Tödtling and Trippl, 2005; Nauwelaers and Reid, 2002). As the OECD (2011) puts it, the core competitive strategy of a region should establish a unique value proposition, bearing in mind the particular structural characteristics of the region. As Porter (1998, 2003) claims, these regional policies should pursue two goals: the development of unique regional strengths in some key areas of innovation and competitiveness (in Porterian terminology, "strategic positioning"); and a broad focus on the remaining competitiveness and innovation factors, avoiding the development of weaknesses that are too great in comparison with those of competing regions (named "operational efficiency" by Porter).

What should the role of benchmarking be in this respect? Very often, benchmarking has been understood as entailing the systematic comparison of one organisation (sector, territory, policy etc.) with another, in order to replicate their 'best practices' (Lundvall and Tomlinson, 2001). One problem with this view is that, according to Smith (2001, p. 268) "quantitative comparisons usually have to assume that there is qualitative uniformity among the objects being compared or counted: like has to be compared with like". Mainstream economic theory makes this assumption; but most innovation analyses rest on the idea of heterogeneity between firms, industries and economic spaces (Smith, 2001). Besides, the replication of best practices would be at odds with the necessary diversity required by the system to innovate and goes against the very idea of strategy (Huggins, 2008).

Choosing the regions for comparison is the first step of any regional benchmarking exercise. As we will see, it is not a trivial issue. As we will explain in the following sections, regional comparisons should be made in terms of homogenous structural conditions, that is, aspects that cannot be changed in the short term and that affect the way innovation takes place in the region. While numerous studies claim this point, very few put it into practice in a consistent way.

In this paper, we first discuss the shortcomings of the usual practices for selecting reference regions that; compare best performers or make use of typologies of regions obtained by means of cluster analysis. Then, we present an alternative methodology for the identification of reference regions and we show how the proposed approach can be useful for developing and improving a regional RIS3.

The paper is organised as follows. Section 2 characterises benchmarking exercises in order to understand their potential contribution to the design and implementation of RIS3. Section 3 reports a systematic literature review on the topic. Section 4 introduces our approach for the identification of reference regions. Empirical results for the Basque Country are illustrated in Section 5. Section 6 introduces and explains the main functionalities of a web-based interactive tool for regional benchmarking. Section 7 offers concluding remarks.

2 - Benchmarking and RIS3

2.1 Benchmarking characterisation

Competition is an important incentive for policy learning attempts. As a result of increasing competition among countries and regions stemming from globalisation, benchmarking exercises, initially developed for comparing firm performances, have been progressively transferred and applied also to the territorial context, first to national governments, then to European Union policies and to regions (Koellreuter, 2002).[1]

There are evident risks in taking a concept developed for one specific unit of analysis (the company) and applying it to another, different unit (the territory). First, territorial innovation systems are much more complex than companies (Soete & Corpakis, 2003; Polt et al., 2001). Second, firms from the same industry are much more homogeneous than regions from the same country (Arrowsmith et al., 2004, Sisson et al., 2002). Furthermore, the ultimate goal for companies is relatively simple (to maximise profit), whereas territories are characterised by frequent trade-offs among multiple goals that public policies try and/or are compelled to pursue simultaneously (Schuldi, 2003).[2] Iurcovich et al. (2006) underline that – due to the fact that regional performance relies on political, economic and social factors beyond the control of a single authority – regional benchmarking differs considerably from firm benchmarking where 'copy and paste' of best performances or best practices can be applied more easily. In the same vein, Arrowsmith et al. (2004) and Sisson et al. (2002) highlight that for business benchmarking, the management has the coercive power that is necessary to implement the lessons learnt from the benchmarking exercise, whereas in territorial benchmarking that coercive power is frequently lacking.[3]

For all these reasons, the evolutionary theory at the basis of the innovation systems approach denotes the notion of best practice as meaningless and even detrimental for the diversity that is required to propel innovation in territories (Edquist, 2001; Paasi, 2005). The literature on innovation systems argues that the systemic context conditions and ultimately

[1] As Fagerberg (2003) reminds us, although the concept may be new in this particular context, the practice it describes is not new at all. The most ambitious benchmarking exercise was carried out in the late 19th century, when the Meiji Government of Japan sent out emissaries to western countries to bring back a blueprint for the design of a modern state.
[2] Smith (2001) is absolutely right when he claims that firms' structures and goals are also diverse. But their diversity is of a second level, in comparison with those of countries and regions.
[3] If the head of a department does not agree with the strategy set for the company, he/she could be fired. However, the government cannot expel an agent from the territory that does not agree or follow the approved strategy.

defines what is good or bad (Tomlinson y Lundvall, 2001). This is empirically determined rather than adjusted to theoretical predictions (Balzat, 2006).

As Lundvall and Tomlinson (2001) show, in contrast to a naive and simplistic benchmarking, an 'intelligent' or 'systematic' type of benchmarking needs to be designed and implemented. This type of benchmarking should take into account the context in which practices or policy have been developed (Nauwelaers et al., 2003). Instead of merely pursuing a copy-and-paste approach, it encourages the identification of 'good' practices (instead of 'best' practices), it recognises relative strengths and weaknesses and examines performance areas using more cost-effective and efficient processes than those based on trial and error (Balzat, 2006; Paasi, 2005; Nauwelaers et al., 2003). Lately, regional benchmarking analyses have evolved substantially in this direction (Huggins, 2008; Pappaioannou et al., 2006).

As Groenendijk (2010, p. 182) puts it, "different purposes and contexts call for different types of benchmarking". Three main types of regional benchmarking are possible: benchmarking of organisations in the regional innovation system; benchmarking of particular public policies; and benchmarking of policy and innovation systems (Groenendijk, 2010; Iurkovich et al., 2006). Since the main concern of this paper is to develop a benchmarking methodology for the design of regional RIS3, only the latter type of regional benchmarking will be dealt with.

An intelligent regional benchmarking of policy and innovation systems should follow several steps. The first question it should address is the identification of comparable regions. As we will see in the next Section, this basic starting point is poorly understood in most regional benchmarking analyses. Once the regions have been identified, it makes sense to prioritise those with better performance, since these will be the ones that will provide the best lessons.[4] Whether performance is good or bad should be established through empirical comparisons (Lall, 2001; Balzat, 2006; Edquist, 2008). Hence, the second step will be to identify, among the territories that share similar structural conditions, those that exhibit better performance.

The third step of the benchmarking exercise should determine what causes these performances to be better or worse. Otherwise, benchmarking runs the risk of raising

[4] Certainly, it might also make sense to consider the others later on. As Polt (2002) or Salazar and Holbrook (2004) point out, unsuccessful cases and those that do not achieve the best results can also provide information and be a source of learning. But, as Iurcovich et al. (2006) argue, apart from being more difficult to obtain complete information about those mediocre or worst-in-class, there would be more scepticism in one's own region with regard to knowledge taken from those worse performing regions. There would also be uncertainty about getting things right if they are implemented in a different way compared to the worst cases.

awareness about the existence of problems, without being able to really identify them.[5] As noted by Edquist (2001), a proper diagnosis consists of both the identification of performance problems and the analysis of their causes. Weak performing regions should reflect on how they differ – e.g. in terms of framework conditions, activities or input indicators – from regions with better performance (OECD et al., 2004).

Finally, benchmarking exercises are of no use if their implantation, policy assimilation, control and revision are ignored (Balzat, 2006; Paasi, 2005; Polt, 2002). Proper implementation, aside from requiring a full understanding of the changes needed in the system, should involve policy-makers and stakeholders, their coordination and a continuous evaluation (Nauwelaers and Reid, 2002; Nauwelaers et al., 2003).

2.2 Linking benchmarking and RIS3

Having described what benchmarking analysis is about, let us now see how benchmarking could contribute to the development of regional RIS3. We will structure the following account according to the six steps that the RIS3 Guide (European Commission, 2012) proposes for the design of RIS3.

The first step in the design of a RIS3 is the analysis of the regional context and potential for innovation. It should be based to a great extent on a benchmarking analysis (Walendowski and Roman, 2012). As the OECD (2005) stated, benchmarking analyses can help to identify the strengths and weaknesses of territories. In that sense, benchmarking can be one of the main pillars of the intelligence methods (foresight, market watch etc.) that should be used in this diagnostic phase (Koellreuther, 2002).

The second and third steps of RIS3 design are 'Governance: ensuring participation and ownership' and 'Elaboration of an overall vision for the future of the region'. As Iurcovich et al. (2006) highlight, the regional benchmarking process raises local stakeholder awareness on the relative position of the region, which may motivate and commit regional politicians and decision-makers. Even more so, given that the relevant regional stakeholders should be actively involved from the beginning of the benchmarking exercise, the RIS3 process could take advantage of those spaces or fora.

[5] The final report of the Expert Group on "Benchmarking S&T Productivity" (2002) for the European Commission states that: "Benchmarking must aim at deeper insights into the processes behind performance. Benchmarking in this sense must not stop at the quantitative comparison of different indicators. Rather, such a comparison is only the starting point for further analysis." (p. 8).

Priorities set to develop a regional unique value proposition – whose identification constitutes the fourth step of RIS3 design – must be based on the relative strengths and weaknesses revealed by the benchmarking analysis performed in an international perspective in the first step. However, regions can set different strategies and goals even if they share similar structural characteristics (Niosi, 2002). In that sense, the analysis of strengths and weaknesses should be accompanied by an analysis of the priorities established by other regions, making the most of the Eye@RIS3 online database that provides information on other regions' envisioned priorities.[6]

As the benchmarking exercises effectively develop a deeper understanding of the determinants of innovation and competitiveness, they provide inestimable information on the design of the right policy mix, roadmaps and action plans that constitute the fifth step of the RIS3 strategy.

Finally, with regard to monitoring and evaluation, the sixth step of RIS3, benchmarking allows the territory to monitor and assess whether it is accomplishing its own mission or targets ("x-effectiveness") or reducing the gap or difference between its performance in a particular area and the best performing competitors ("x-inefficiency"), see Niosi (2002). That is, the benchmarking process "can serve as an ongoing policy impact assessment and evaluation tool" (Iorcovich et al., 2006, p. 7).

3 - Literature review on the identification of reference regions

3.1 Options for regional comparison

As stated above, the first and crucial question to be addressed by a benchmarking exercise that aims to support regional RIS3 is the following: with which territories should one compare oneself? There are three options: it can be compared with targets set for the region, with the region's evolution, or with other territories (Edquist, 2008).

Traditionally, benchmarking exercises have taken place according to an intraregional perspective (rather than an interregional approach) due to, among other factors, their requirement of fewer resources. Anyway, the aforementioned first two options do not pose

[6] http://s3platform.jrc.ec.europa.eu/eye-ris3.

any problem with regard to who should be chosen for comparison. Furthermore, nowadays the most frequent and growing type of benchmarking is multi and interregional benchmarking (Huggins, 2008). That is why in this Section we will focus on the comparison with other regions. Several options arise in this regard.

Reference regions could be:

- Neighbouring regions
- Regions in the same country
- Regions that wish and agree to cooperate and learn from each other
- Regions facing similar problems or challenges

Once again, the first three cases do not pose any problems of identification. The main reason to conduct such a comparison is quite evident as well. Looking at neighbouring regions might be of interest when looking for complementarities and synergies, or at the extent to which the functional region spreads beyond administrative boundaries. Considering the regions of the same country allows us to exclude the national context and circumstances affecting the region. Observing regions that want and agree to share their experiences and knowledge permits us to gain a deeper understanding of the reasons behind their performance and access information not publicly available otherwise.

Comparing with regions that must deal with similar problems or context is, however, the kind of regional benchmarking that the majority of analysts deem theoretically the most rewarding (Besant & Rush, 1998; Dunnewijk et al., 2008; Soete and Corpakis, 2003). Indeed, in order to compare oneself with others, a key requirement is what Papaioannou et al. (2006) call the comparison principle, which states that comparisons should take place among analogous entities. Regions can also learn from those which are very different. But, as explained in Section 2, regional benchmarking and mutual learning require that the context is taken into account. A comparison is likely to be more valuable when it is carried out between fundamentally equivalent entities (Archibugui and Coco, 2004; Archibugi et al., 2009). Thus, the first step is the identification of homogeneous conditions in which the comparison exercise will be carried out.

Even if unanimously acknowledged in the theory of benchmarking, this principle of comparing homogeneous regions has not been the norm in practical and everyday benchmarking exercises.[7] Regions have usually been compared to those that exhibited a better performance, whether they shared similar characteristics or not. In fact, early benchmarking exercises have been criticised for limiting comparisons to relative performances, merely providing lists or rankings without a proper analysis of the causes of those different performances (Papaioannou et al., 2006; Huggins, 2008; Polt, 2002). Which factors should be taken into account in order to establish two regions as homogeneous? In the following, we describe how the relevant literature has addressed this question, before outlining our approach in the subsequent part.

3.2 Literature on the identification of reference regions

As mentioned before, many authors and studies have highlighted the need to compare homogeneous entities according to a range of characteristics, since regions can learn more from such comparisons. Among these authors or institutions that underline the convenience of comparing regions with similar challenges, we have tried to identify which factors they use to qualify regions as homogeneous. Table 1 sums up the results of our literature review. The list of authors or sources can be found in the rows of the table; the list of dimensions used to characterise this homogeneity is depicted in the columns. Clearly, the dimensions pointed out are of a structural nature. They cannot be changed in the short term and affect the degree or the way that innovation takes place in the region. In that sense, they constitute background conditions that should be taken into consideration when dealing with the design of a regional RIS3.

One of the dimensions included in Table 1, even though it was mentioned by more than one author, is not a truly structural or background condition that these variables should reflect with regard to innovation: GDP per capita as an indicator of economic development. The reason for this lies in the two-way causal relationship between GDP per capita and innovation (Lall, 2001). As Lall argues, the majority of analysts consider the principal causal relationship to flow from innovation to technological and competitive performance. Since the main goal of regional benchmarking is to improve innovative and competitive performance, a circular argument would be established if GDP per capita is placed among the factors that explain such performance. That is why we have decided to exclude this dimension from the group of

[7] Smith (2001, p. 271) reports the same for benchmarking on R&D activities: “Despite the fact that the points made here have been known for a very long time as problems in using R&D data, comparisons of aggregate R&D intensities rarely take them into account. As a result, comparisons are usually meaningless (although frequently taken with great seriousness by policymakers and even analysts)”.

factors that should be borne in mind when identifying groups of homogeneous regions for benchmarking in the context of regional RIS3.

Despite numerous studies that argue that comparisons or benchmarking exercises should be carried out with similar regions, or should correct and account for differences in their structural conditions, very few have put this idea into practice. Perhaps one of the most significant cases in which this strategy was actually used is the Index of the Massachusetts Innovation Economy (John Adams Innovation Institute, 2009), in which the economy and innovation in the state of Massachusetts are only compared with those states that display an elevated concentration of employment in specific clusters.

Another way to take the context into account is to introduce some control variables (e.g. size and industrial structure of the territory) in the regression analysis that try to explain a given performance. See, for instance, Fagerberg's and Smith's papers cited above. Nevertheless, even when controlling for these effects in the statistical analysis, this method does not directly generate a list or group of homogeneous regions.

In reports like the Global Competitiveness Report (Schwab, 2009), each of the sub-indices is combined in order to construct a composite index of competitiveness and each is given a different weight, according to the level of development of the country; and countries are mainly compared with those pertaining to the same stage of development. But, as stated before, GDP per capita is the result rather than the starting point of the innovation and competitive process. Furthermore, as a result of different sets of policies and strategies two regions that have very different structural conditions could reach the same level of GDP per capita (Niosi, 2002). Therefore, GDP per capita is not appropriate for identifying groups of regions facing similar challenges arising from their common structural conditions.

Table 1: Factors used for qualifying regions as homogeneous according to the literature review

	GEO-DEMOGRAPHY	HUMAN RESOURCES	TECHNOLOGY STRUCTURE	SECTORAL STRUCTURE	FIRM STRUCTURE	OPENNESS	INSTITUTION & VALUES	OTHERS
Akerblom et al., 2008				Industrial structure				
Anderson & Mahroum, 2008				Economic structure			Institutional framework	
Archibugi & Coco, 2004	Geograpghy						Cultural factors	Economic factors
Archibugi et al., 2009	Size & infrastructure	Human resources						Income
Arundel & Hollanders, 2008			Patterns of innovation					
Atkinson & Andes, 2008				Industrial structure				
Balzat, 2006							Social values & political goals	Economic development
Fagerberg & Srholec, 2007	Geography, demography & natural resources						History	
Fagerberg et al., 2007	Geography, demography & natural resources						History	
Iurcovich et al., 2006	Geography, size			Economic & industrial structure			Language	
John Adams Innovation Institute, 2009				Cluster structure				
Koellreuter, 2002	Geographical proximity			Economic & industrial activities				
Lall, 2001								Level of development
Nauwelaers et al., 2003	Size			Economic specialisation	Firms size	Openness	History, cultural & social capital	
OECD et al., 2004	Size			Industry specialisation			Institutional factors	
OECD, 2005	Geography			Industrial structure			Policy context & culture	
Paasi, 2005	Size & natural resources			Economic structure			Culture & history	Development level
Schwab, 2009								GDP per capita
Smith, 2001	Size			Industrial structure				GDP per capita

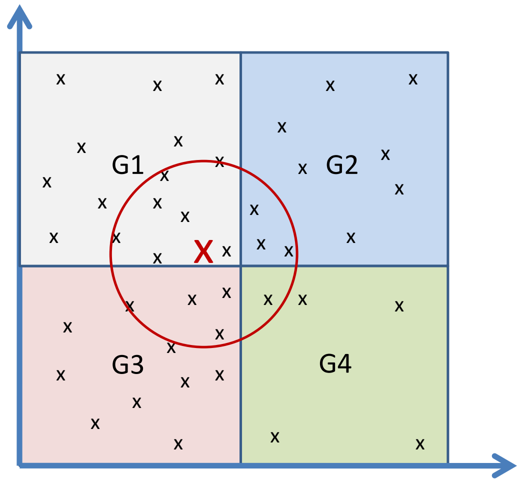
The last main alternative for the identification of homogeneous or reference regions identified in our literature review is the one that resorts to regional typologies in order to identify groups of regions with similar patterns. Recent attempts in this vein are, for instance, Dunnewijk et al. (2008), Hollanders et al. (2009), Verspagen (2010), OECD (2011), Camagni and Capello (2013). Regional typologies seek the identification of common patterns in the territories and therefore might be considered as an alternative instrument for identifying similar regions. Nevertheless, the problem rests in the variables chosen to construct the typologies. The review by Navarro and Gibaja (2009) points out that existing typologies include or mix up variables of a very different nature: those of structural conditions, behaviours and performance, an issue that has also been mentioned by Camagni and Capello (2013).[8] In doing so, they do not show the influence of structural conditions (e.g. industrial specialisation) and behavioural variables (e.g. R&D expenditure) on output or income indicators (e.g. patents or productivity). Hence, those typologies are contrary to the main objective of benchmarking analysis: to go beyond the elaboration of performance rankings, and to try to understand the different processes and reasons behind that performance. Therefore, existing typologies have not isolated the variables that are relevant for the identification of similar regions according to their structural conditions, even though this is possible, as we show below.[9]

Even if a typology is elaborated by only using variables measuring structural conditions, the resulting group still might not include the most similar or homogeneous regions with regard to another particular region. This is reflected in Figure 1.

[8] Although not in connection with typologies but with the composite index of innovation, FORA (2007) first raised this problem. They openly criticised the European Innovation Scoreboard because it mixed up framework or input indicators with performance or output indicators in the elaboration of the summary index (Navarro, 2011).

[9] The problem is even worse when, as in the Regional Innovation Scoreboard typology, the taxonomy is not based on innovation patterns built upon a range of underlying indicators, but on one single dimension (such as the summary of innovation) (Walendowski et al., 2011).

Figure 1: Possible distribution of a typology of regions according to structural conditions



Suppose that, after conducting a cluster analysis with indicators related to structural conditions, regions have been classified into four groups (G1, G2, G3 and G4) and one particular region (represented by the larger X in red) is close to the borderline of G1. It is evident that many of its most similar regions are not in G1, but in the other groups. Therefore, if we use the results gained through cluster analysis and only compare with those reference regions found in G1, we miss many of those regions similar to the region of interest.

To sum up, even if the theoretical literature on regional benchmarking warns unanimously about the risk of comparing apples with oranges, and stresses the need for comparing regions with similar structural conditions, most empirical benchmarking exercises have not applied that principle. More often than not, territorial benchmarking exercises have chosen the best performers when making comparisons, overlooking the different contexts that may exist between those best performers and the region for which the benchmarking exercise is carried out. This is one of the most important reasons why benchmarking exercises (and even regional RIS3; see McCann & Ortega-Argilés, 2011) have been only reluctantly taken into account by less developed regions in the EU. The empirical attempts to take into account the different regional contexts have by and large not been satisfactory. The elaboration of regional typologies has been the most common way to address this issue. But even when conducting cluster analysis with variables only related to structural conditions, the resulting groups may miss many of the pertinent regions. There is a need for a new approach in the identification of reference regions for regional benchmarking, which we outline in the following Section.

4 - A new approach for the identification of reference regions

4.1 Proposal of variables for the identification of regions with similar structural conditions

There is no universally accepted theoretical model that determines which regional factors or dimensions should be included under the term structural conditions and how they affect innovative behaviour and performance (Soete and Corpakis, 2003). There are several strands of literature dealing with regions and innovation, but none is fully satisfactory. The most advisable conduct seems to embrace an explorative and eclectic approach in this regard (Dunnewijk et al., 2008). As Fagerberg (2003) acknowledges, much formal theorising in the social sciences relies on simplified models which often fail to take into account specific contexts. In the benchmarking field, it would be more useful to resort to "appreciative theory (Nelson and Winter, 1982), i.e. theorising that stays close to the empirical nitty-gritty, attempts to outline and interpret 'stylised facts' and find out what the implications for policy may be" (Fagerberg, 2003, p. …). In this way, we have tried to embrace the design of a method to identify reference regions for the kind of benchmarking needed for regional RIS3.

By reviewing different strands of the literature that has tried to somehow specify what kind of context factors make territories more comparable among each other, we identified seven dimensions: geo-demography, human resources, technology specialisation, economy and industry specialisation, firm structure, openness, and institutions and values (see Section 3.2).[10] The next step was to identify variables that reflect the multifaceted nature of those dimensions more appropriately. The selection of these variables is strongly conditioned by data availability, usually quite scarce with regards to some crucial regional issues (such as governance, social capital, openness etc.) (Iurcovich, 2006; Dunnewijk et al., 2008). Fortunately, quite recently, new databases have been developed in some of these fields that have allowed us to enrich the scope of the dimensions taken into consideration in our previous preliminary attempts to develop a methodology for the identification of reference regions (see Navarro et al., 2011, 2012).

The list of elements that might be used to identify regions with similar structural conditions and the sources for the indicators that have been used are summarised in Table 2 and explained in more detail below. As statistical units to define regions we will use NUTS2, except in Belgium, Germany and the United Kingdom, where NUTS1 will be used instead.[11]

[10] For the above mentioned reasons, GDP per capita (income levels or degree of economic development) has been rejected.

[11] The choice between NUTS2 or NUTS1 has been based on the level where relevant regional powers rest in each country (Baumert, 2006).

i. Geo-demographic indicators

Within the geo-demographic dimension we have included five elements.

The population of a region, mentioned by many of the studies we have cited, might be used as a proxy for the size of the region, with the advantage that population data are available in Eurostat.

Among demographic factors, there are two frequently used in innovation economics: urbanisation and ageing. For the first one, the traditional 'population density' has been substituted by a variable provided by the European Commission's Directorate-General for Regional Policy that gauges the percentage of the population living in cities and commuting zones, because this offers a better proxy for agglomeration economies.

As for ageing, we consider it more accurate to simultaneously take into account the percentage of the population aged 65 years or over and those aged 15 years or under, both taken from Eurostat.

Regarding geographic factors, accessibility indices allow us to simultaneously take into account local infrastructure and proximity to markets. Due to their complexity, these indices are not updated very often. Hence, we use the multimodal accessibility index computed by ESPON in 2006 as a measure of accessibility.

Table 2. Elements for the identification of reference regions

DIMENSIONS	ELEMENTS	VARIABLES	SOURCES	COMPONENTS
1. Geo-demography	Regional size	Total Population	Eurostat	Total Population
	Ageing	Population >= 65	Eurostat	Ageing
		Population <15	Eurostat	
	Urbanisation	Pop. in urban and comm. areas	DG Regio	Pop. in urban and comm. areas
	Accessibility	Multimodal accessibility	ESPON	Multimodal accessibility
2. HHRR educ. level	HHRR educational level	Pop. with upper secondary and tertiary ed.	Eurostat	Pop. with upper sec. and tert. ed.
3. Technological specialisation	Technological distribution (patents)	Electrical engineering	OECD REGPAT	
		Instruments	OECD REGPAT	pat.f.01
		Chemistry	OECD REGPAT	pat.f.02
		Mechanical engineering	OECD REGPAT	pat.f.03
		Other fields	OECD REGPAT	
	Technological concentration (patents)	GINI index of 35 subfields	OECD REGPAT	GINI index of 35 subfields
4. Sectoral structure	Economy's sectoral distribution	Agriculture, forestry and fishing (A)	Eurostat LFS[1]	
		Industry (except const.) (B-E)	Eurostat LFS[1]	
		Construction (F)	Eurostat LFS[1]	
		Wholesale and retail trade, transport etc. (B-I)	Eurostat LFS[1]	emp.total.f.01
		Information and communication (J)	Eurostat LFS[1]	emp.total.f.02
		Financial and insurance activities (K)	Eurostat LFS[1]	emp.total.f.03
		Real estate activities (L)	Eurostat LFS[1]	
		Professional, scientific and technical activities (M-N)	Eurostat LFS[1]	
		Public administration (O-Q)	Eurostat LFS[1]	
		Arts, entertainment and recreation (R-U)	Eurostat LFS[1]	
	Sectoral concentration	Top of 5 subsectors (2 digits) (% total employment)	Eurostat LFS	Top of 5 subsectors (2 digits) (% total employment)
	Industrial sectoral structure	Mining and quarrying (05-09)	Eurostat LFS	
		Food, drinks and tobacco (10-12)	Eurostat LFS	
		Textiles, apparel and leather (13-15)	Eurostat LFS	
		Wood, paper and printing (16-18)	Eurostat LFS	emp.ind.f.01
		Chem., pharm., rubber, plastic and refined petroleum (19-22)	Eurostat LFS	emp.ind.f.02
		Non-metallic mineral products (23)	Eurostat LFS	emp.ind.f.03
		Basic metals and metal products (24-25)	Eurostat LFS	emp.ind.f.04
		Electric, electronic, computer and optical equipment (26-27)	Eurostat LFS	
		Machinery (28)	Eurostat LFS	
		Transport equipment (29-30)	Eurostat LFS	
		Other manufacturing (31-33)	Eurostat LFS	
5. Firm size	Firm size	Average firm size	Eurostat SBS	Average firm size
6. Openness	Trade openness	Total exports (% GDP)	Fraunhofer ISI and Orkestra	Total exports (% GDP)
7. Institutions & values	Multilevel government	Decentralisation	BAK Basel Economics	Decentralisation
	Social and institutional capital	Quality of institutions	Charron et al.	social.inst.capital
		Feeling of safety of walking alone in local area after dark	ESS	
		Most people can be trusted or you can't be too careful	ESS	
	Entrepreneurial / innovative attitudes	Important to think new ideas and being creative	ESS	Ent.innov.att
		Important to try new and different things in life	ESS	

Note: (1) Data compiled through a request to Eurostat.

ii. Educational level of human resources

This dimension refers to the educational level of human resources. We will not assess the situation of younger generations of school/university age, because this is an input rather than a structural variable that can be affected by public policies so as to improve the performance of the regions and their potential. Instead, we compute the percentage of the population aged 25-64 that has reached an upper secondary or tertiary educational level because this is a more appropriate way to measure the structural difference.

iii. Technological specialisation

The technological areas of specialisation in a region are defined according to two sub-blocks: technological distribution and technological concentration.

For the former, we estimate the percentage distribution of patents based on the Patent Cooperation Treaty (PCT) among the five large technology fields. The five sectors are: Electrical engineering (I), instruments (II), chemistry (III), mechanical engineering (IV) and other fields (V). These have been obtained from IPC codes by making use of WIPO's IPC technology concordance table. This data has been computed on the basis of the OECD's January 2013 regional patent database. Given the small number of PCT patents in several regions, we have opted to add the patents applied for over the period 2005-2010.

For the latter, the Gini coefficient is calculated on the basis of patent distribution at two-digit technology fields, adding the patents for the period 2005-2010.

iv. Sectoral structure

In order to characterise the regional sectoral structure, we focus on employment from three different points of view: distribution of total economic employment, its concentration, and distribution of industrial employment.

Regarding the distribution of total economic employment we consider ten major sectors of Eurostat's regional economic accounts (based on the new NACE rev2: Agriculture, forestry and fishing (section A), Industry (except construction) (B, C, D & E), Construction (F), Trade, transportation, accommodation and food service activities (G, H & I), Information and communication (J), Financial and insurance activities (K), Real estate activities (L), Professional, scientific, technical, administration and support service activities (M & N), Public administration, defence, education, human health and social work activities (O, P & Q), Arts, entertainment, recreation and other services (R, S, T & U). These data are for the year 2011.

In addition to the percentage distribution of total economic employment, it is interesting to use a summary indicator of concentration. In order to do so, we compute the share of employment in the top five subsectors (measured at 2 digits of NACE rev2) in each region.

Even if the above allows a first approximation to the economy's sectoral structure, it is obvious that the disaggregation of industry (excluding construction) is not satisfactory. Industrial sectors are more oriented towards exporting and less limited by the local market, which allows them to develop and specialise more. Inspired by the OECD STAN database classification, we divide industrial employment in eleven large sectors (see Table 2). The data was provided by Eurostat, on special request in order to extract this information from the Labour Force Survey for the year 2011.

v. Firm structure

Among the structural statistics, Eurostat publishes data on the average size of local units for most European NUTS. In principle, this indicator might be used as a proxy for business size, which Nauwelaers et al. (2003) mention. However, a detailed examination of such data uncovers strange patterns (particularly for German regions that only report employment for units that have at least 10 employees, thus overestimating business size). Therefore, we have adjusted the Eurostat regional figures on the basis of a firm's average size at national level, because the latter does not have this bias.

vi. Openness

As stated by Nauwelaers et al. (2003), the degree of openness of the economy is another aspect that fundamentally distinguishes regions. We have included one indicator to assess this element: total exports over GDP in 2009.

vii. Institutions and values

There are many relevant institutional aspects that characterise regions. We have divided those that we have been able to find data for into three elements: multilevel government, social and institutional capital and entrepreneurial and innovative attitudes.

The level of decentralisation or devolution to sub-national levels of government that characterises multilevel government is difficult to measure. To do so, we have included the composite index developed by BAK Basel Economics for the Assembly of Regions (2009).

In order to assess social and institutional capital, we have incorporated three indicators. The first one is a recent index on the quality of the institutions computed at regional level by Charron et al. (2012). This index appraises low levels of corruption, high protection of the rule of law, governmental efficiency and accountability and is based on survey data. The general situation regarding social stability in a region is operationalised through the subjective perception collected in the European Social Survey for 2008 (responses to the question 'Feeling of safety of walking alone in local area after dark'). Social capital has also been operationalised through a second variable from that survey ('Most people can be trusted or you can't be too careful').

The element 'entrepreneurial/innovative attitudes' is also measured with two proxies from the European Social Survey: "It is important to think new ideas and being creative" and "It is important to try new and different things in life".

4.2 Procedure for obtaining reference regions from variables

Having defined a set of variables to identify reference regions, several transformations are required in order to construct a distance matrix that measures the distance between a particular region and each of the other regions.

i. *Corrections for outliers, asymmetry and kurtosis, normalisation and concentration of components*

One or several indicators are used as proxies for each of the elements we have included. Firstly, these indicators are corrected for outliers, asymmetries and kurtosis using the procedure outlined in Annex A. Secondly, in order to add them up, variables are normalised using the mini-max method, re-scaling them so all values fall between 0 and 100.

Once these indicators have been normalised, we proceed to concentrate the information they convey in as few components as possible (mentioned in the last column of Table 2). When a single variable is used as proxy for the element, the variable is kept. If the element is measured by two variables (as is the case of ageing), we aggregate them by means of a simple average. If there are more than two indicators (e.g. technological distribution of patents), we carry out a principal component analysis (PCA) and we retain the minimum number of components required to explain most of the variability of the data.[12] Following this procedure we keep the 22 components in the last column of Table 2.

ii. Weighting

The following step of the procedure consists in assigning weights to each of the components. As explained in JRC European Commission-OECD (2008), there are different ways to do this. In this study we explore two main alternatives:

- Giving equal weights. We have considered three different possibilities: a) equal weights to each of the 22 components, b) equal weights to each of the components within one dimension, and then equal weights to each of the seven dimensions and c) equal weights to each of the components within one macro-dimension, and then equal weights to each of the four macro-dimensions. These macro-dimensions are based on the frequency with which the seven dimensions are cited in the literature. As we can see in Table 1, geo-demography, sector structure and innovation and values are mentioned more often than the other four dimensions we have included in the analysis. Hence, we have considered four macro-dimensions, the first three being equal to the most cited one and the fourth being the aggregation of the educational level of human resources, technological structure, firm structure and openness.
- Assigning weights based on the factor loadings of principal components. The three aforementioned possibilities have also been explored. Hence a single PCA incorporating all 22 components has been carried out, as well as PCAs for each of the seven dimensions and the four macro-dimensions. In each case, we retain the main components following the criterion that has been stated above. In the first case, the weights for each component are computed by aggregating the squared factor loadings in each of the retained components, which have been multiplied by the percentage of the variance each component explains. In the second and third case, this step has to be iterated once more, performing a PCA with the seven components (four in the case of the macro-dimensions) that have been thus computed.

The resulting weights from the different weighting methods can be seen in Annex B.

[12] This generally means keeping components with an eigenvalue greater than one, which individually explain at least 10% of the variability of the data and together at least 60% of such variability.

iii. Aggregation

Once the weights have been set, there are also different alternatives to aggregate the components in order to calculate the distance matrix. Here, we explore two alternative aggregation methods as well:

- Additive quadratic aggregation. The total distance between two regions is calculated using the following formula:

  $$d\ (i, i') = \sum_{j=1}^{k} m_j\ (x_{ij} - x_{i'j})^{\ 2}$$

  where *j* is the variable, *i* is the first region, *i'* the second region and m_j is the weight assigned to the variable. This method allows for compensation in a non-linear way.

- Geometric aggregation. In this case the distance is calculated as:

  $$d\ (i, i') = \prod_{j=1}^{k}\ (1 - \left| x_{ij} - x_{i'j} \right|)^{m_j}$$

  This is also an alternative for non-linear compensability.

iv. Obtaining the distance matrix

With the distance between one NUTS and the others, we obtain a distance row; and with the distance rows of all the regions, the distance matrix. Among all the possible distance matrices calculated according to the aforementioned weighting methods, we have given preference to the matrix based on the fourth alternative, i.e. weights that arise from performing a single PCA analysis on the 22 components. This allows for variability on the weights according to the variability observed in the data without having to constrain these weights to conform to the seven dimensions or four macro-dimensions. Between the two alternative aggregation methods, we have opted for the first one, the additive quadratic aggregation.

v. Sensitivity

The sensitivity of the results has been tested by means of Spearman correlation coefficients. This was done by computing the correlation coefficients between the distance row for each region for one particular combination of weights/aggregation method and the corresponding row for another combination of weights/aggregation method. The 205 resulting coefficients are averaged to summarise the correlation of selecting the proximity of regions according to different combinations of weighting and aggregating methods. The results are presented on Annex C. As can be seen there, Spearman correlation coefficients are quite high, ranging on average between 0.84 and 0.92. This confirms the idea that the order of the regions would be quite similar if another combination of weighting and aggregating methods had been chosen.

vi. Cluster and individual approaches

Based on this chosen distance matrix, two different approaches may be followed:

- Firstly, a typology of regions can be established via cluster analysis to identify groups of regions with similar structural conditions that will influence their economic and innovative performance.
- Secondly, the row indicating the distances between the selected region and the other regions can be extracted from the distance matrix. Based on that row, those interested in analysing a particular region can arrange any other region according to these distances.

Each approach responds to different needs or interests. Obtaining a typology of regions is particularly interesting for policy-makers or analysts who work with regions at the European regional level as a whole, because it provides a collective vision of Europe's regions. As we have mentioned above, there are already many typologies on regional innovation patterns. However the common flaw they share for benchmarking analysis is that they mix different types of variables: structural conditions, economic and innovation output variables and input variables. The typology we present here is only based on variables that reflect the structural conditions of the regions and, hence, the abovementioned error is not committed.

The second approach is a better option for those who are interested in the benchmarking analysis of a particular region. This procedure has significant advantages over the cluster analysis that groups regions according to similarities:

- Given that the cluster analysis process does not reveal the distance between the centre of gravity of the group and each component, it is possible that the components furthest from the centre are in fact closer to regions assigned to other categories, rather than those in its own group. Cluster analysis does not usually allow for direct visualisation of the distance between a given region and regions placed in other groups.

- From each region's ordered row of distances, the number of NUTS to be compared can be selected. In cluster analysis the number of regions varies among groups. The number of regions in which our target region is included might not be appropriate for our purposes.[13]

5 - An illustration for the Basque Country

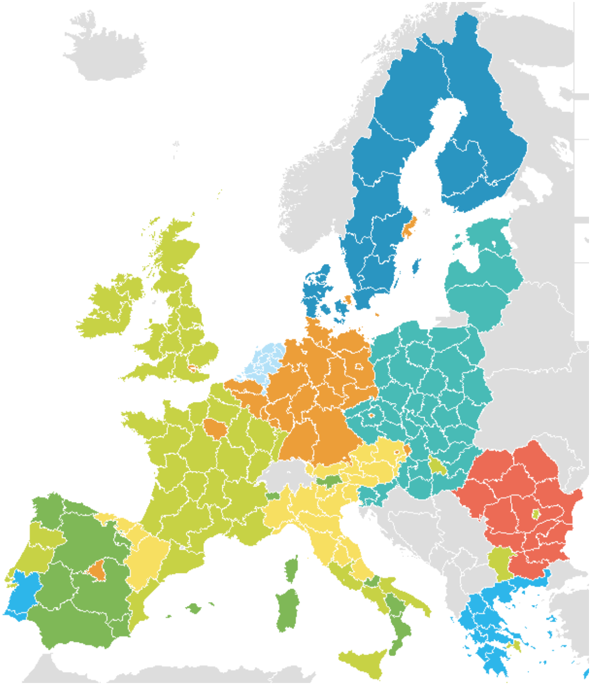
Using the difference matrix that has been computed by assigning weights through PCA to the 22 components and aggregating them using the additive quadratic method, in this Section we present an illustration of the reference regions for the Basque Country according both to the cluster approach and the individual approach, which selects the 30 closest regions. The results are presented in Map 1.

As can be seen in Map 1, the cluster approach provides a division of regions in groups that have a strong national bias. In the case of the Basque Country, it is grouped with some of the regions in Northern Spain, but also with regions in the north of Italy and Austria. For the individual approach, we have chosen the same number of regions (23 counting the Basque Country) as resulted from the cluster approach. This gauges the degree of differences between both groups of regions. The first point we notice is that the individual approach provides a spread of regions from a larger variety of countries, maintaining the Spanish regions that were in the cluster group and including even another Spanish region (Catalonia). Most of the Italian and Austrian regions disappear and are substituted by regions mainly from Germany and the UK and also a few from other countries. Based on our knowledge of the Basque Country, we consider that the characteristics of the reference regions from the individual approach fit better with those of the Basque Country. Therefore, they constitute a reasonable group of regions to be considered in further stages of a benchmarking exercise.

[13] In comparison with the results of the cluster analyses conducted using the other potential distance matrixes, the cluster groups obtained from the distance matrix we use are quite similar in terms of number of regions. Nevertheless, groups 3 and 9 are composed of 12 regions, and group 4 is composed of 47 regions. There are too few regions to compare in the first two groups, and besides they are concentrated in just one or two countries (in group 3 there are only Bulgarian and Romanian regions; and group 9 is composed only of Dutch regions); while in group 4 there are possibly too many regions to compare.

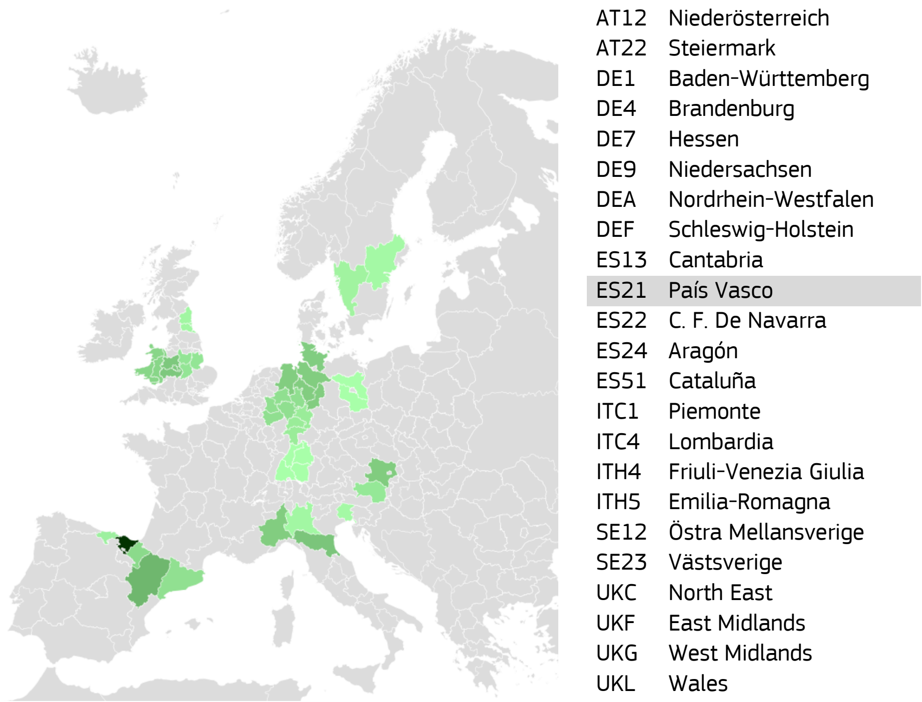
Map 1. Reference regions for the Basque Country

a) Cluster approach



AT11	Burgenland
AT12	Niederösterreich
AT21	Kärnten
AT22	Steiermark
AT31	Oberösterreich
AT32	Salzburg
AT33	Tirol
AT34	Vorarlberg
ES13	Cantabria
ES21	País Vasco
ES22	C. F. de Navarra
ES24	Aragón
ITC1	Piemonte
ITC3	Liguria
ITC4	Lombardia
ITH2	Prov. Aut. di Trento
ITH3	Veneto
ITH4	Friuli-Venezia Giulia
ITH5	Emilia-Romagna
ITI1	Toscana
ITI2	Umbria
ITI3	Marche
ITF1	Abruzzo

b) Individual approach



As part of this illustrative example, we also offer the characterisation of structural conditions in the Basque Country and its reference regions (RR), in comparison to European Union (EU) and national Spanish averages.

Compared to the EU regions' average and in terms of geo-demography, human resources education and technological specialisation (see Table 3), the Basque Country and its RR are characterised by a large ageing population (both in terms of larger proportions of elders and smaller proportions of youngsters), a high degree of urbanisation and connectivity, and also by its technology specialisation in mechanical engineering and instruments. With regard to Spanish regions, the Basque Country's specialisation reproduces the aforementioned patterns. Besides, it stands out in terms of more developed human capital. Finally, in comparison with its RR, the Basque Country is more urbanised and specialised in mechanical engineering.

As Table 4 displays, the Basque Country and its RR appear to be strongly specialised in industry and professional, scientific and technical activities; and, within manufacturing, in basic metal and metal products, machinery and transport equipment. This specialisation is more pronounced in the Basque Country than in the RR.

There are also noticeable differences between the Basque Country and RR, on the one side, and the EU regions' average, on the other, concerning the level of decentralisation, quality of institutions and, to a lesser extent, social capital (see Table 5). We observe the same pattern in the comparison between the Basque Country and Spain, except for the decentralisation index.

Finally, we observe that the Basque Country's values are closer to those of RR coming from the cluster approach than the individual approach in Tables 3 and 5, and the opposite in Table 4. This is related to a fact highlighted previously: the apparently more pronounced influence of national factors in the group of RR obtained by a cluster analysis than by an individual approach. Usually, dimensions such as geo-demography, education, institutions and values are more homogeneous within a country than across countries; and the opposite occurs in sector and industry specialisation in large countries.

Table 3. Characterisation of the Basque Country and its reference regions (RR) in terms of geo-demography, human resources education and technological specialisation

DIMENSIONS	ELEMENTS	VARIABLES	Basque Country	RR (Individ.)	RR (Cluster app.)	EU	Spain
1. Geo-demography	Regional size	Total Population (millions)	2.1	4.4	2.0	2.4	2.7
	Ageing	Population >= 65 years old (%)	20.1	19.5	20.3	17.6	18.0
		Population <15 years old (%)	14.3	15.6	14.9	16.4	15.4
	Urbanization	Pop. in urban and comm. areas (%)	80.0	72.5	54.6	60.9	70.6
	Accessibility	Multimodal accessibility index	93.4	107.7	98.4	86.2	68.9
2. Human resources educational level	Human resources educational level	Pop. with upper secondary and tertiary ed. (%)	68.1	73.9	69.3	73.6	54.8
3. Technological specialisation	Technological distribution (patents)	Electrical Engineering (% of total)	11.4	17.1	16.4	19.0	12.4
		Instruments (% of total)	15.0	15.1	13.3	13.4	12.7
		Chemistry (% of total)	21.4	25.4	21.3	27.5	29.1
		Mechanical Engineering (% of total)	37.1	31.2	33.6	29.2	29.6
		Other fields (% of total)	15.2	11.2	15.3	11.0	16.3
	Technological concentration (patents)	GINI index of 35 subfields	0.4	0.5	0.5	0.6	0.5

Table 4. Characterisation of the Basque Country and its reference regions (RR) in terms of sector structure

DIMENSIONS	ELEMENTS	VARIABLES	Basque Country	RR (Individ. app.)	RR (Cluster app.)	EU	Spain
4. Sectoral structure	Economy's sectoral distribution	Agriculture, forestry and fishing (A) (%)	1.3	2.6	3.9	6.6	5.2
		Industry (except const.) (B-E) (%)	21.0	19.5	21.2	17.4	15.3
		Construction (F) (%)	6.1	7.1	8.2	7.3	7.3
		Wholesale and retail trade, transport,... (B-I) (%)	23.4	23.7	25.6	23.8	28.5
		Information and communication (J) (%)	3.3	2.7	2.1	2.4	2.4
		Financial and insurance activities (K) (%)	2.8	2.8	3.0	2.6	2.2
		Real estate activities (L) (%)	0.4	0.8	0.6	0.7	0.5
		Professional, scientific and technical activities (M-N) (%)	11.1	9.7	8.5	7.9	8.9
		Public administration (O-Q) (%)	23.5	25.2	20.8	24.4	22.4
		Arts, entertainment and recreation (R-U) (%)	7.3	5.6	6.2	5.0	7.5
	Sectoral concentration	Top of 5 subsectors (2digits) (% total employment)	8.4	8.5	8.3	8.4	9.1
	Industrial sectoral structure	Mining and quarrying (05-09) (%)	3.8	9.1	7.3	12.0	11.2
		Food, drinks and tobacco (10-12) (%)	6.0	10.8	10.5	15.4	20.7
		Textiles, apparel and leather (13-15) (%)	0.9	3.2	6.9	6.0	5.2
		Wood, paper and printing (16-18) (%)	6.2	7.1	8.4	8.1	7.2
		Chem., pharm., rubber, plastic and refined petroleum (19-22) (%)	8.9	9.8	8.6	9.6	8.6
		Non-metallic mineral products (23) (%)	3.7	3.4	5.0	4.1	4.7
		Basic metals and metal products (24-25) (%)	26.8	16.1	16.7	13.2	14.6
		Electric, electronic, computer and optical equipment (26-27) (%)	8.1	7.9	8.6	6.8	4.0
		Machinery (28) (%)	12.0	10.4	9.4	6.3	4.5
		Transport equipment (29-30) (%)	18.4	13.5	8.0	8.4	9.1
		Other manufacturing (31-33) (%)	5.2	8.9	10.6	10.1	10.3

Table 5. Characterisation of the Basque Country and its reference regions (RR) in terms of firm size, openness and institutions and values

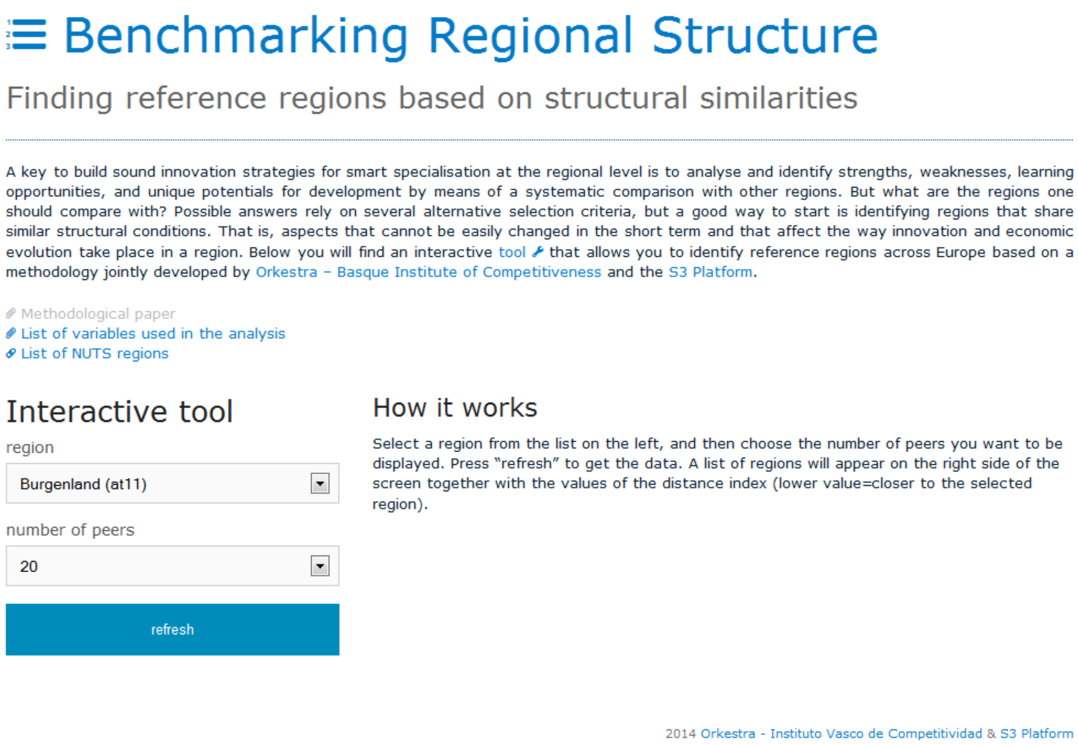
DIMENSIONS	ELEMENTS	VARIABLES	Basque Country	RR (Individ. app.)	RR (Cluster app.)	EU	Spain
5. Firm size	Firm size	Average firm size (number of employees)	6.5	8.8	6.1	6.5	4.5
6. Openness	Trade openness	Total exports (% GDP)	22.0	24.5	28.0	27.5	14.6
7. Institutions & values	Multilevel government	Decentralization index	58.0	56.4	53.1	47.4	58.0
	Social and instituional capital	Quality of institutions index	0.7	0.6	0.2	0.1	0.2
		Feeling of safety of walking alone in local area after dark (1 very safe - 4 very unsafe)	2.0	2.0	2.0	2.0	1.9
		Most people can be trusted or you can't be too careful (0 You can't be too careful - 10 Most people can be trusted)	5.6	5.1	4.9	4.8	5.0
	Entrepreneurial and innovative attitudes	Important to think new ideas and being creative (1 Very much like me - 6 Not like me at all)	2.4	2.4	2.4	2.5	2.5
		Important to try new and different things in life (1 Very much like me - 6 Not like me at all)	2.8	2.9	2.8	2.9	2.9

6 - The web tool for regional benchmarking

As described in previous Sections, smart specialisation is a process at the end of which regional/national strategies should identify activities where an investment of resources is most likely to stimulate knowledge-driven growth. Benchmarking should feed into the whole process of designing and implementing the RIS3 strategy. In order to help regional policy makers performing benchmarking based on structural similarity in the view of initiating a policy learning process, we have developed a web-based interactive tool which follows the methodology described in the paper, is easily accessible and user-friendly and allows the performance of similar analyses to those presented in the previous Section. The tool is accessible via the Smart Specialisation Platform webpage.[14] A snapshot of the user interface is displayed in Figure 2.

[14] http://s3platform.jrc.ec.europa.eu/home.

Figure 2: Snapshot of web tool user interface



The tool consists of a web interface where users can select a region of their interest and specify the number of reference regions they would like to be displayed (10 to 35). After pressing the button "refresh", a list of regions will appear in a table on the right side of the screen together with values from the distance index indicating the structural similarity with the selected region on the left. The lower the value of the distance index, the closer the selected region to the reference region. Just above the selection windows, three links are provided leading to background information on the benchmarking tool: (1) this methodological paper; (2) a table with the list of variables used in the analysis; (3) a link to the list of NUTS codes of European regions.

7 - Concluding remarks

In this study we have presented a methodology for identifying reference regions as a first step for engaging in effective policy learning and useful cross-territorial comparisons, which avoids comparing apples and oranges. As we explained in Section 2, benchmarking can contribute to each of the six steps that the RIS3 Guide (European Commission, 2012) proposes for the design of smart specialisation strategies. Although the method outlined in this study can be used to identify similar regions for any EU region, the comparability principle is even more important for less developed regions. They might feel discouraged by the very demanding RIS3 process and requirements because the examples and practices they are faced with usually come from successful regions with which they do not have much in common.

We have shown why usual typologies are generally not useful for identifying comparable regions. Firstly, they tend to mix variables and dimensions of different natures. Secondly, they provide an uneven number of regions in each of the groups, which might result in some small groups that do not offer a significant number of regions for the benchmarking exercise. Finally, the statistical grouping of regions might exclude similar regions that have been assigned to a different group or category. The approach followed in this study offers an alternative to these shortcomings: first, the proximity of regions is only assessed on the basis of structural conditions; second, the individual approach allows flexibility to choose the number of regions and there is no prior restrictive grouping.

The list of comparable regions obtained through the distance matrix may be narrowed down on the basis of qualitative and more specific quantitative data or analysis. Once the final group of homogeneous regions has been identified, their performance can be assessed. It is important to highlight that smart specialisation calls for building competitive advantages through the process of priority setting in a coherent way, while avoiding duplication and fragmentation of efforts. Therefore, detecting synergies is encouraged by the benchmarking exercise, but benchmarking and priority setting should not be about picking winning sectors or copying priority settings of similar or best performing regions. Yet, it is useful to focus on the best performing, structurally similar regions in order to understand the reasons for success or failure and to draw lessons to strengthen the regional strategic positioning ('be unique') and operational efficiency.

Finally, collecting data on reference regions and a region's positioning vis-à-vis other regions are necessary steps but not sufficient. The insights gained here have to feed into the whole RIS3 process and also be considered in the monitoring and evaluation mechanism.

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Annex A. Procedure for the correction of possible outliers, asymmetry and kurtosis

Steps for the correction of possible *outliers*, asymmetry and kurtosis:

1. Tests of asymmetry and kurtosis are calculated.
   a. If the probability of rejecting the hypothesis of the variable being symmetric and mesokurtic is above 0.05, the variable is not corrected.
   b. Otherwise, the presence of *outliers* is tested for in step 2.
2. The number of possible *outliers* is calculated according to the following criteria: number of observations that is outside the $[Q_1-1,5(Q_3-Q_1), Q_3+1,5(Q_3-Q_1)]$ interval, where Q_1 and Q_3 are, respectively, the first and third quartiles.
   a. If the number of *outliers* is less than or equal to 10 (5% of observations), winsorization takes place. Winsorization implies assigning the greatest value within the interval to all observations that are greater than the highest extreme of the interval. Equivalently, the minimum value within the interval is assigned to the observations that fall below the lowest extreme of the interval. Then, asymmetry and kurtosis tests are recalculated.
      i. If the probability of rejecting the hypothesis is above 0.05 the winsorized variable is kept.
      ii. Otherwise, the procedure continues with the original variable in step 3.
   b. If the number of *outliers* is above 10, the procedure continues with step 3.
3. Yeo-Johnson (2000) transformation is applied, choosing the λ value that best corrects the asymmetry.

Annex B. Alternative weights for the components

	Equal			PCA		
	22 components	7 Dimension	4 Macro-dimensions	22 components	7 Dimension	4 Macro-dimensions
dem.pop.avg	4.55%	3.57%	6.25%	5.23%	3.05%	4.50%
dem.aging	4.55%	3.57%	6.25%	3.89%	5.41%	7.98%
dem.pop.urban.sh	4.55%	3.57%	6.25%	4.75%	4.06%	5.98%
mmaccess.2006	4.55%	3.57%	6.25%	5.49%	3.68%	5.42%
educ.isced3_6.sh	4.55%	14.29%	3.57%	4.00%	17.30%	4.56%
pat.f.01	4.55%	3.57%	3.57%	3.49%	3.67%	5.61%
pat.f.02	4.55%	3.57%	3.57%	5.72%	2.43%	3.71%
pat.f.03	4.55%	3.57%	3.57%	3.75%	2.35%	3.59%
pat.pct.field.gini.35	4.55%	3.57%	3.57%	5.05%	3.50%	5.34%
emp.total.f.01	4.55%	1.79%	3.13%	5.43%	1.81%	3.16%
emp.total.f.02	4.55%	1.79%	3.13%	5.02%	1.77%	3.11%
emp.total.f.03	4.55%	1.79%	3.13%	4.23%	1.75%	3.06%
emp.ind.f.01	4.55%	1.79%	3.13%	5.07%	1.85%	3.24%
emp.ind.f.02	4.55%	1.79%	3.13%	4.28%	1.90%	3.32%
emp.ind.f.03	4.55%	1.79%	3.13%	4.30%	1.80%	3.16%
emp.ind.f.04	4.55%	1.79%	3.13%	4.57%	0.51%	0.90%
emp.total.top5	4.55%	1.79%	3.13%	5.29%	1.77%	3.09%
firm.size.avg	4.55%	14.29%	3.57%	3.93%	15.22%	4.56%
open.exports.gdp	4.55%	14.29%	3.57%	5.01%	13.65%	4.56%
inst.decentralization	4.55%	4.76%	8.33%	3.99%	3.83%	6.47%
social.inst.capital	4.55%	4.76%	8.33%	5.45%	3.77%	6.37%
entrepreneurship	4.55%	4.76%	8.33%	2.06%	4.92%	8.31%

Annex C. Spearman correlation between different alternative weighting and aggregation methods

	22 equal	22 equal G	dim 4	dim 4 G	dim 7	dim 7 G	pca 22	pca 22 G	pca dim4	pca dim 4 G	pca dim 7	pca dim 7 G	Average
22 equal		0.989	0.965	0.956	0.853	0.844	0.994	0.983	0.976	0.965	0.821	0.811	0.923
22 equal G	0.989		0.955	0.965	0.839	0.847	0.983	0.993	0.965	0.975	0.808	0.814	0.921
dim 4	0.965	0.955		0.988	0.804	0.795	0.958	0.948	0.987	0.975	0.768	0.758	0.900
dim 4 G	0.956	0.965	0.988		0.795	0.801	0.949	0.957	0.977	0.987	0.759	0.764	0.900
dim 7	0.853	0.839	0.804	0.795		0.985	0.827	0.814	0.844	0.832	0.992	0.978	0.869
dim 7 G	0.844	0.847	0.795	0.801	0.985		0.818	0.821	0.835	0.840	0.978	0.992	0.869
pca 22	**0.994**	**0.983**	**0.958**	**0.949**	**0.827**	**0.818**		**0.989**	**0.964**	**0.953**	**0.791**	**0.781**	0.910
pca 22 G	0.983	0.993	0.948	0.957	0.814	0.821	0.989		0.953	0.961	0.779	0.784	0.907
pca dim4	0.976	0.965	0.987	0.977	0.844	0.835	0.964	0.953		0.988	0.817	0.807	0.919
pca dim 4 G	0.965	0.975	0.975	0.987	0.832	0.840	0.953	0.961	0.988		0.805	0.812	0.917
pca dim 7	0.821	0.808	0.768	0.759	0.992	0.978	0.791	0.779	0.817	0.805		0.985	0.846
pca dim 7 G	0.811	0.814	0.758	0.764	0.978	0.992	0.781	0.784	0.807	0.812	0.985		0.844

Note: the capital letter G denotes the use of the geometric aggregation method.

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Title: **Regional benchmarking in the smart specialisation process: Identification of reference regions based on structural similarity**

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Abstract

One of the most basic conditions required for drawing lessons from regional benchmarking is to compare homogeneous regions and learn from equivalents. This condition is not met when regions for comparison are chosen based on their high performance, overlooking their regional context or structural conditions. This paper aims to provide a new methodology for the identification of homogeneous regions for regional benchmarking; identifying groups of homogeneous regions using variables that are similar in nature; focusing solely on structural conditions, thereby overcoming the flaws produced by mixing variables of a different nature (comparing structural indicators with performance and / or behavioural indicators). Thus, regional benchmarking can be of great help in making strategic decisions within the process of the design and implementation of regional Research and Innovation Strategies for Smart Specialisation (RIS3), taking into account the relative position of the region to other regions in Europe. Following the RIS3 approach of looking beyond the regional administrative boundaries, benchmarking based on structural similarity enables the region to identify its competitive advantages through systematic comparisons with other regions or to map the national and international context in search of examples to learn from, or to mark a difference with.

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