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Regional Diversification Opportunities and Smart Specialization Strategies

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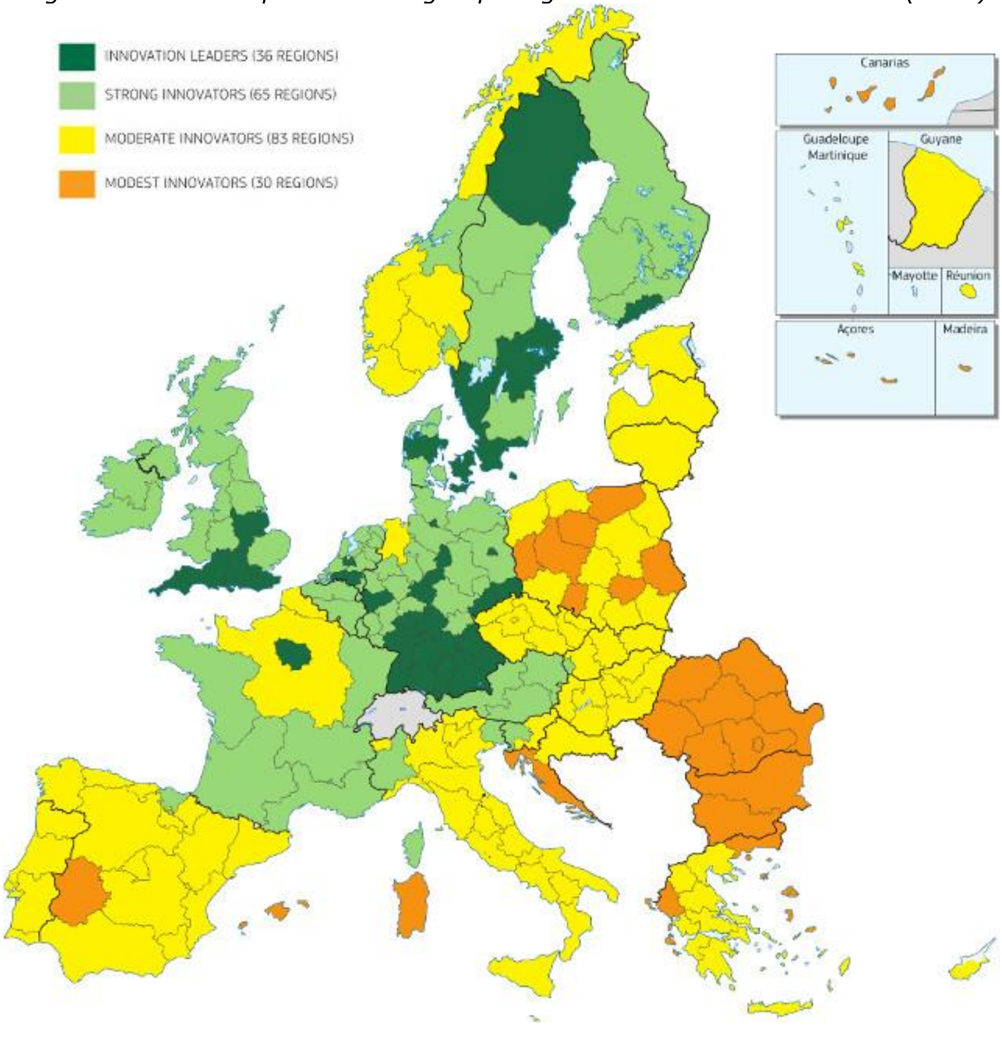
INTRODUCTION

Since the 1980s, income differences between European Union (EU) states have declined at the same time as regional inequalities within countries have increased (Puga, 2002). Across many states of the EU regional development is increasingly polarized (Overman et al., 2002). Although regional income convergence followed the introduction of the Euro (Beyer and Stemmer, 2016), the economic crisis that began in 2008 reversed this process leading to a growth in inequality within and between countries (Cuadrado-Roura et al, 2016; Crescenzi et al., 2016). Achieving economic and social cohesion through European integration is one of the main goals of the EU. Inasmuch, the recent growth of development differences across European regions calls for significant policy action.

Innovation and knowledge creation is widely acknowledged as a fundamental driver of regional competitiveness and development (Solow, 1956; Romer, 1990). As a result, regional and national governments, and international organizations have ranked innovation-based policies high on their agendas. For instance, in 2000, the Lisbon Agenda established the goal of making the EU "the most competitive and dynamic knowledge-based economy in the world". More recently, the Europe 2020 Agenda highlighted the need to close the gap in R&D investment with other leading countries (European Commission, 2010).

Most all economic activity is geographically concentrated and innovation is no different, tending to concentrate in core regions of the European Union. Moreno et al. (2005) show that some urban areas tend to host a disproportionate amount of European innovation, while intermediary and less developed regions lag behind. Similarly, the Regional Innovation Scoreboard (European Commission, 2016) elaborates a synthetic indicator of regional innovative performance and uses it to classify regions as *innovation leaders*, *strong innovators*, *moderate innovators* or *modest innovators*. Two important results are evident in Figure 1. On the one hand, within country differences suggest that geographical variations in knowledge production are not fully explained by national innovation systems. On the other hand, a core-periphery pattern exists: *i)* a core of regional innovation leadership is evident around an axis from Munich to London, with some additional hot spots in the north of Europe (some Scandinavian regions); *ii)* a periphery of moderate and modest regional innovation exists in southern and eastern regions of Europe.

Figure 1: Regional Innovative performance group. Regional Innovation Scoreboard (2016).



Scholars have elaborated several arguments to explain this concentration of innovation. First, from a "resource availability" perspective, cities are ideal hosts for innovation activities, because they are endowed with larger pools of human capital and various types of critical infrastructures such as universities or research centres (Glaeser et al., 1992; Bettencourt et al., 2007). In a related vein, a second set of arguments refers to "agglomeration effects", the advantages arising from the co-location of firms, universities or research centres among other socioeconomic actors. These advantages are mostly related to external economies of scale and scope (Marshall, 1920; Jacobs, 1969; Duranton and Puga, 2000), and with the positive effect of geographical proximity that enhances efficient knowledge exchange and spillovers (Jaffe et al., 1993; Storper and Venables, 2004). In fact, the diffusion of knowledge, in particular tacit knowledge, strongly decays with distance (Audretsch and Feldman, 1996). In the context of innovation this is a key issue, because the production of ideas is a complex process based on knowledge recombination (Nelson and Winter, 1982; Kline and Rosenberg, 1986). Although the internal capabilities of actors play a role in their innovativeness, they have limited capacities. Thus, their ability to access and exploit external knowledge is important to innovate (Cohen and Levinthal, 1990). Therefore, innovative actors, wishing to capture valuable external knowledge, tend to co-locate. Third, co-location and collaboration is said to contribute to create a "unique set of institutional conditions" that foster innovation (Fitjar and Rodríguez Pose 2011).

Consequently, not all regions are equally equipped to innovate because innovative capacities are spatially concentrated; nor do all regions have the same capacity to innovate on the basis of public R&D investment, because this transformation strongly depends on local conditions. For instance, more peripheral regions in the EU tend to have a lower quality of human resources and training, higher distance to the technological frontier, weaker economic structure with no leadership in any major technological domain, poorer institutional conditions and, lower and more fragmented private R&D investment to complement public R&D efforts (Rodríguez-Pose, 1999, 2001). All this has raised important challenges on how to increase the efficiency of (public) R&D expenditures, because such conditions hinder the impact of public R&D policies (Isaksen, 2015). This has become even more pressing since the last crisis, when many regions in Europe, suffering from rapid increases in unemployment, have had few opportunities to recover (Crescenzi et al., 2016; Beyer and Stemmer, 2016). The rise of unemployment urged on the need to develop new activities to compensate for losses, that is recovering regional growth through structural change within the region. Therefore, investments in innovation and R&D to transform regional economies by opening new growth paths, i.e. diversifying the economy by developing new domains of specialization, is increasingly positioned at the centre of European Cohesion Policy (Boschma, 2014).

However, such diversification should not be blindly replicated across European regions. Replication without regard for local conditions and for broader regional network characteristics would produce a duplication of innovative efforts and fragmentation. With fragmentation, regional critical mass is not attained, the potential gains from scale and agglomeration vanishes, and the potential for complementarities within Europe diminishes (Foray et al., 2011). Ultimately, this is likely to damage the sustainability of new regional pathways and reduce the efficiency of the innovation diversification policy.

Recently an alternative strategy has emerged. It is founded on two basic ideas (Foray et al., 2011). First, regions cannot do everything in science, technology, and innovation. They should *specialize*, i.e. focus on certain domains in order to fulfill the potential for scale, scope, and spillovers. Second, they have to be *smart* in order to promote the domains in which they can develop a unique, distinctive and original knowledge base. Thus, the region has to find new specializations in technological domains that build on their existing strengths (Boschma, 2014). This has been termed the "Smart Specialization" strategy (Foray et al., 2009). The EU has moved rapidly to adopt smart specialization at the core of European cohesion policy. Thus, smart specialization strategies have become an ex-ante conditionality for strategic use of the European Structural and Investment Funds in the current programming period 2014-2020 (European Commission, 2012). Similarly, with projects such as Smart Specialisation for Regional Innovation (FP7 SmartSpec), the EU has promoted scientific research on the development, application and impact of Smart Specialization strategies at regional level.

Consequently, the distribution of structural funds under the thematic objectives related to R&D, innovation, and ICT, and SMEs support is now conditional on the existence of regional Research and Innovation Strategies for Smart Specialization (RIS3). RIS3 strategies are defined as integrated, place-based economic transformation agendas that focus policy support and investment on key challenges and needs for knowledge-based development, building on national/regional strengths, and getting stakeholders fully involved to encourage innovation and experimentation (European Commission, 2014).

At this time there is an increased awareness of the need for regions to develop new growth paths built around diversification into new domains of specialization. There is also increased awareness about the need to be selective or smart when it comes to refocusing the regional economy. However, the million-dollar-question is: which technological domains should policy makers support? The aim of this report is to propose a framework to help policy makers provide more informed answers to this question, and reconcile it with the *entrepreneurial discovery process*. This framework assesses all potential domains in which regions might diversify on the base of two criteria: *i)* their relatedness with existing regional capabilities, and *ii)* their knowledge complexity. This framework is developed in the following sections. Section 2 explains the rationale for the first criterion, i.e. the link between regional variety, relatedness, and diversification. Section 3 focuses on the second criterion, discussing the link between knowledge complexity and regional development. Section 4 operationalizes the framework by linking the relatedness and complexity. A series of examples are used to illustrate the proposed framework. Section 5 offers a brief conclusion.

RELATEDNESS AND REGIONAL DEVELOPMENT

Knowledge production in the economy can be seen as a process of recombination. Actors (firms, universities, individuals) search among existing knowledge subsets and combine them into new forms adding to knowledge stocks available for future recombination (Schumpeter, 1939; Weitzman, 1998). Individual economic agents are heterogeneous in terms of the technologies they have worked with, their capacity to absorb and develop technological information, and the routines that they have constructed to identify and guard knowledge assets (Nelson and Winter, 1982). These capabilities, knowledge sets and routines are key for the performance of the actor in terms of market success, innovativeness, and survival. However, economic actors can only master a limited set of capabilities and knowledge sets and so most are specialized (Nooteboom, 2000). Access to complementary knowledge resources is typically gained through processes of learning and interaction with other specialized agents. The routines that guide these processes are often tacit, difficult to codify and so not easy to imitate or transfer (Cowan et al., 2000, Howells, 2002). Therefore, it is important to identify the conditions for successful knowledge transfer and recombination. Two important factors have to be considered.

On the one hand, knowledge transfers tend to decay with geographical distance (Jaffe et al., 1993; Audretsch and Feldman, 1996). When two actors are geographically close to each other, planned and unplanned meetings can occur more frequently and at a lower cost. Moreover, face to face communication makes the exchange more efficient thanks to rapid feedback, non-verbal communication, easier coordination and trust formation (Lorenz 1999; Storper and Venables, 2004). This is even more so when tacit knowledge is involved. With distance, (planned and unplanned) face to face meeting is less frequent and more costly, so knowledge transfers decay. However, although geographical proximity enhances knowledge exchanges, it is neither a necessary nor a sufficient condition for them to occur (Boschma, 2005). On the other hand, for effective knowledge exchanges, actors need to be able to identify, understand and absorb external knowledge. Thus, they need absorptive capacity (Cohen and Levinthal, 1990) and cognitive proximity (Nooteboom, 2000), i.e. actors have to be able to learn from outside and require shared knowledge experiences or a similar "language". For instance, the exchange of knowledge between an engineer in telecommunications and an astrophysicist will be much easier than the exchange of knowledge between the same engineer on telecommunications and a middle age historian, because the conceptual universe, the language or the cognitive bases in the first case are much closer than in the second one.

At the regional level, this means that industrial or technological variety might be a source of knowledge spillovers that favor innovation (Jacobs, 1969), but only if regional industries or technological domains are cognitively related (Frenken et al. 2007). So, it is not just a matter of regional variety *per se*. With unrelated variety, the different industries or technological domains within a region may have no/weak complementarities. Cognitive distance hinders inter-industry knowledge spillovers and innovation. However, an increasing number of related industries/technological domains in a region, i.e. related variety, increases the opportunities for recombination and innovation (Frenken et al. 2007). There are empirical studies on the impact of variety on regional growth for the Netherlands (Frenken et al., 2007), Italy (Boschma and Iammarino, 2009), UK (Bishop and Gripaios, 2010), Finland (Hartog et al., 2012), Spain (Boschma et al., 2012), Germany (Brachert et al., 2013), Portugal (Rebelo and Gomes da Silva, 2013) and Europe (Van Oort et al., 2015). Although these studies vary in their approach (for instance in terms of spatial scale, industrial classification, time period, related variety measure and controls), they tend to conclude that related variety has a positive impact on employment growth, value-added growth, and innovation, while unrelated variety has a negative impact on economic performance.

Related variety also plays an important role in the process of regional diversification. Capabilities cannot be moved easily, so the process of new path creation is affected by technological and cognitive constraints. Citing Neffke et al. (2011), new regional growth paths "... do not start from scratch but are strongly rooted in the historical economic structure of a region" (p. 261) In fact, regional diversification is a branching process in which regions develop new industries or technological domains by staying close to their existing capabilities (Frenken and Boschma, 2007). Thus, the existing capabilities in a region define not only the products and technologies the region can make today but also define which new industries or technological domains will be feasible and most likely to develop in the future, i.e. it is a path dependent process. Since cognitive proximity enhances the redeployment of competencies across industries or technological domains, it increases the survival probability of actors investing in the new path (Buenstorf and Klepper, 2009; Klepper, 2010) and so the probability for the region to diversify successfully.

The case studies of Glaeser (2005) for Boston, Belusi and Sedita (2009) for Italian clusters, or Treado (2010) for Pittsburgh illustrate that the capacity of regions to develop new growth paths involves the reorganization of existing regional assets. More recent research shows how regional growth paths are strongly conditioned by architectures of capabilities that are spatially bounded. This is illustrated for different regions at varied spatial scales from the national level (Hidalgo et al., 2007), to Swedish regions (Neffke et al., 2011), Spanish regions (Boschma et al., 2013), US metropolitan areas (Rigby, 2015; Boschma et al., 2015; Essletzbichler, 2015) and European regions (Kogler et al., 2016). These results clearly show that the probability of a region to diversify into a new industrial or technological domain increases with the degree of relatedness between existing activities and the potential new growth trajectory. Similarly, the probability of a region to abandon an industry or technological domain decreases as the degree of relatedness between this domain and the existing portfolio of activities in the region increases.

Therefore, in order to diversify the economy, moving the economic structure of the region towards related industries or technological domains is a valuable strategy. Developing new growth paths in related industries or technological domains increases the probability of regional competitive advantage because the shorter cognitive distance enhances mutual learning, knowledge spillovers and actors' redeployment of skills from one domain to another.

KNOWLEDGE COMPLEXITY AND REGIONAL DEVELOPMENT

The amount and complexity of knowledge in the economy have increased very fast. Products are not only the combination of labor and capital but also of knowledge. For instance, the production of apples needs land, machines, and labor, but also knowledge on irrigation techniques, fertilizers, conservation techniques, transport… Thus, apple production progressively becomes a more complex activity.

As discussed above, the individual acquisition of all this knowledge through learning is not possible anymore, because it is too time-consuming and too costly. Consequently, specialization is necessary: "what used to be a degree in philosophy, split into several branches, one being natural philosophy, which later split into physics, chemistry, and biology and later into other disciplines such as ecology, earth sciences and psychology" (Hausmann and Hidalgo, 2011, p. 16). In similar fashion, individual economic actors build their own coherent sets of knowledge and capabilities to perform a limited range of functions, but since they cannot master all the different knowledge functions, interaction with other actors is required for successful production and innovation.

Regions are created through the interaction of many such actors (individuals, companies, public institutions). The knowledge complexity of regional economies is related to the amount and variety of knowledge and capabilities that these agents possess along with the structures that coordinate those capabilities. Thus, the regional economy will be more complex when the agents that define the economy hold larger and more diverse knowledge sets, when those knowledge sets are more sophisticated or less routine, and when that knowledge is more effectively integrated. The fact that more complex forms of knowledge are often jointly embedded across sets of interacting agents within local spaces only serves to make such knowledge tacit and thus a more robust source of long-run regional advantage (Maskell and Malmberg 1999; Gertler, 2003).

So, if a region is able to produce and innovate in a particular industry or technological domain, it is because the region host all the specific knowledge and capabilities required for it, and it is able to mobilize and combine them in a useful way. In contrast, if the region misses some of the required capabilities, it will fail in producing and innovating in that industry or technological domain. Consequently, the complexity of the knowledge involved in an industry or technological domain and the complexity of the regional economy are two sides of the same coin. While the first refers to the number of capabilities that the industry or technological domain requires, the second relates to the set of capabilities locally available (Hidalgo, 2009). Then, if a region is able to innovate and elaborate products in an industry or technological domain that require many knowledge and capabilities combined in sophisticated ways, it means that the regions hosts larger sets of specific knowledge and it is able to mobilize and combine them efficiently, i.e. its output is indicating that it is a complex economy. Then, the complexity of the region is high because it is able to produce and innovate in highly complex and sophisticated industries or technological domains. However, if the region has thinner knowledge bases, fewer capabilities or it is not able to properly coordinate and organize them, it will fail in producing and innovating in these complex industries or technological domains. In this case, the region is less complex because its output basket is composed of less complex industries or technological domains. Thus, for instance, a region producing and innovating in the domain of nuclear power engines has a more complex economy than a region producing and innovating in the furniture manufacturing domain.

The study of complexity has several implications for regional development (Hidalgo and Hausmann, 2009). Firstly, non-complex knowledge requires fewer capabilities and capabilities that are common in many locations. These widely available capabilities are called ubiquitous capabilities. Consequently, non-complex knowledge can easily be (re)produced because many regions can readily acquire the required set of capabilities. In contrast, complex knowledge combines numerous components and techniques a number of which are rare or non-ubiquitous. Few locations can accumulate all the capabilities to generate complex forms of knowledge and the goods and services in which they are embedded. The regions with the capacity to generate complex forms of knowledge tend to be more diversified regions with integrated economic agents that share capabilities. Hence, less ubiquitous and more complex products tend to be produced in a few specific and diversified locations. Since this complex knowledge is difficult to imitate and not very geographically mobile (Markusen, 1996; Balland and Rigby, 2017), it becomes a source of sustainable differentiation and competitiveness for regions hosting it.

Secondly, complex regional economies already have a large set of capabilities and knowledge pieces available. This makes them more adaptable by the diversity of their resources. As discussed in section 2, regional development is a path dependent process. So, the current mix of available capabilities in a region defines both, the set of possible activities of today, and the set of new possible activities of tomorrow. In complex regional economies, generally more diversified, the set of existing capabilities is larger. Then, the number of possible recombinations for developing new activities is larger too. Similarly, if the region acquires a new capability, it can also be combined with a larger set of capabilities. This increased number of possible recombinations favours the adaptability of the regional economy and its capacity to diversify into new differentiated domains (Balland et al., 2015). Moreover, complex technological domains tend to be in their early stages of development. So, their potential for growth is higher, as for instance is the case for electronics or biotechnology. Similarly, less complex technological domains or industries tend to be more mature and with a lower potential for growth (Klepper, 1997), e.g. the case of technologies on mechanical domains. Consequently, regions have good reason to try and specialize in complex technological domains because these represent a key source of long-run competitiveness and growth.

Several studies explore these issues empirically. Hidalgo and Hausmann (2009) have studied the link between the complexity of the economy and its level of development. They obtain two important findings by analyzing the composition of national export flows. First, there is a strong positive correlation between economic complexity of a country and its income per capita, meaning that more complex countries tend to have higher income per capita. Second, there is a positive correlation between the economic complexity of the region and its future growth. For a similar level of income per capital, more complex economies tend to grow faster in the future. Likewise, Hartmann et al., (2017) have used similar methods and data to study the link between economic complexity and income inequality. They show that countries exporting more complex products have less income inequality than countries exporting simpler products. They also find that increases in economic complexity are accompanied by decreases in income inequality. Finally, Balland et al., (2017) have used data on patenting activities of European regions to study how regions diversify their innovative activities into new technological domains. They show that diversifying into more complex technological domains is more rewarding because it increases the innovativeness of the region. But the effect of complexity on the capacity of the region to diversify into new technological domains is ambivalent. On the one hand, more complex domains are more attractive, but on the other hand entering on them is more challenging, i.e. the risk of failure is higher.

To sum up, moving towards more complex domains it is a valuable strategy to build a regional advantage. Complex knowledge does not travel easily in space (Balland and Rigby, 2017), which allows regions to limit direct competition with many other. Developing new growth paths in more complex domains is a way to upgrade the existing economic structure of the region. This favors regional competitiveness, innovation, and growth, and might even reduce income inequality (Hartmann et al., 2017).

A POLICY FRAMEWORK FOR DIVERSIFICATION

Smart specialization policy aims at promoting regional renewal by branching the region into new related industries and technological domains. Smart specialization is a grounded policy framework neither reinforcing already locally strong activities nor engaging in blind diversification into fashionable industries and technological domains because they were successful elsewhere. However, this policy still requires prioritization of industries and technological domains. Building on the conclusions of section 2 and 3, the concepts of relatedness and complexity are useful to establish these priorities because they look at both the existing activities and the upgrading potential of new potential activities for the region.

In this section of the report, a first goal is to explain how the concepts of relatedness and complexity can be measured and operationalized. The second goal is to elaborate a framework based on relatedness and complexity criteria to asses, for each region, the advantages and risks of each possible direction: to establish priorities among industries or technological domains. Finally, the report turns to an application of the framework for four European regions to illustrate how it works. For the sake of clarity, in what follows, the report will refer only to technological domains, but the same logic applies for industries or products.

Operationalizing relatedness and complexity

The first issue is to operationalize the concept of relatedness. Figure 2 represents the technological structure of a region in network terms. Each node represents a technological domain. In total, the whole economy is composed of 14 technological domains. The links between nodes represent relatedness between domains: if two technological domains are linked, it means that both domains are cognitively related above a certain intensity threshold. If such a link does not exist, it means that the technological domains are not related to one another, because they rely on different resources, capabilities and knowledge bases. Relatedness between industries or technological domains can be measured in a number of different ways (Balland, 2016). The different measures used so far rely on SIC-codes classifications (Frenken et al., 2007; van Oort et al., 2015), co-occurrence of products within the same plant, firm, region or country (Hidalgo, et al., 2007; Neffke et al., 2011), co-occurrence of technological classes within the same patent (Kogler et al., 2013; Boschma et al., 2015; Rigby, 2015), citation flows, input-output linkages, or inter-industry labour flows (Neffke and Henning, 2013). The figures presented in this report follows Balland et al. (2017) using normalized co-occurrences of technological classes within patents.

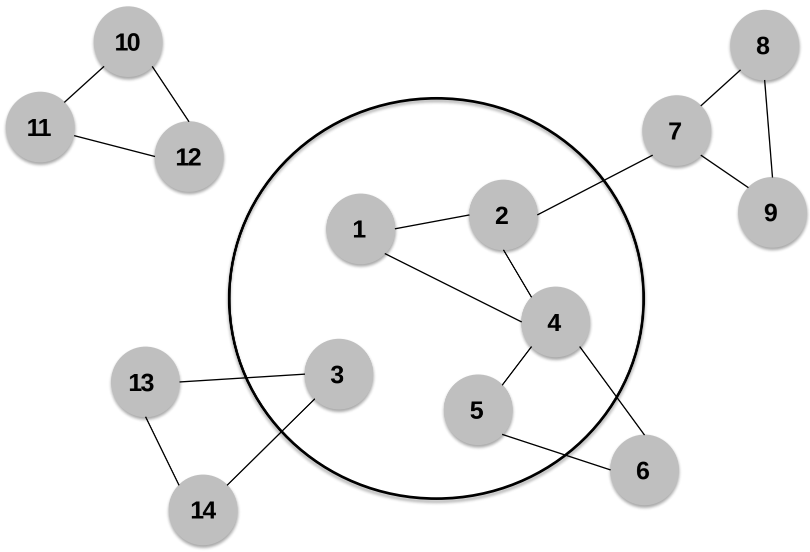
The large circle in Figure 2 represents the regional boundary. Thus, the nodes within the large circle represent the technological domains in which the region is already specialized, i.e. they figure prominently in the range of knowledge-based capabilities that the region possesses. In this case, the region is specialized in technological domains 1 to 5, some of use similar capabilities and so are related, and some of them are not. The region is not specialized in technological domains 6 to 14.

This network representation of the technological structure of the region can be used to identify its diversification opportunities. According to the relatedness framework of section 2 and according to the smart specialization policy principles, it is easier for the region to evolve towards new domains that are connected with the existing regional strengths. Thus, in Figure 2, domain 12 represents a risky strategy. Although it might be considered worldwide as a promising domain in terms of technological potential and employment creation, the region has no related capabilities to it. Successfully diversifying into this domain would probably require a massive amount of investment. The technological domain 12 belongs to a technologically related group of domains (with domains 10 and 11), but none of them are really implanted in the region. Domain 6, on the other hand, is related to existing regional specializations (domains 4 and 5). That is, the region can more easily connect to 6 and embed it within the existing structure of the regional economy. Consequently, the probability of a successful diversification into 6 is higher. For domain 7, the region has some related capabilities (domain 2) that may enhance the emergence of this new path. However, it also lacks important components, because domains 8 and 9, also related to 7, are not present in the region. This hinders the capacity of the region to branch out towards domain 7.

With this approach, it is possible to classify all knowledge subsets, identified by patent classes or sub-classes, by their proximity or distance, their degree of relatedness, to the existing set of knowledge production capabilities in the region. This can be quantified with the relatedness density index. This index measures, for a particular technological domain, how many of its related technology types exist in the region. In the case of the region in Figure 2, relatedness density for domain 6 is 100%, because of its related domains, 4 and 5 are both in the region. Contrary, the relatedness density of industry 7 is 33% because while domain 2 is present in the region, domains 8 and 9 are not (1 out of 3). Similarly, the relatedness density of domain 8 is 0, because neither domain 7 nor domain 9 are present in the region. Therefore, relatedness density quantifies how close a potential new technology is to the existing technological portfolio of a given region.

Smart specialization policy based on the relatedness framework is therefore not a one size fits all policy. Although the framework can be applied to any region, the revealed opportunities are unique to each region. Regions differ in terms of their current economic structure, which offers opportunities and constraints in the technological trajectories that they might follow. On the one hand, regions differ in the local conditions of the supportive environment, such as accessibility, available resources, urban density or institutional structures (McCann and Ortega-Argilés, 2105; Isaksen, 2015). On the other hand, more diversified regions tend to be more adaptable because they have larger recombination possibilities. Figure 3 shows the average relatedness density between the existing technological domains in the region and all the potential alternatives for all European regions. The technological portfolio of regional activities is obtained from the patenting profile of regions, and relatedness between technological domains is computed by normalizing co-occurrences[1] of technological domains in patent documents (Balland et al., 2017).

Figure 2: network approach to the economic structure of regions



The higher the average relatedness in regions, the closer, on average, are their existing set of activities to those missing in the region, and thus their potential diversification capacities are higher. Two facts characterize the figure. Firstly, the opportunities for new path creation are heterogeneously distributed across regions, and even within countries, large differences exist. Secondly, a core-periphery distribution appears. Central Europe, in particular, north of Italy, south of Germany and Austria, show the higher levels of average relatedness density. Contrary, eastern and southern regions in Europe as well as the northern regions of UK and Norway show lower scores, meaning that their branching alternatives to renewing their region are lower or riskier.

In order to evaluate technological opportunities and possible evolutionary pathways, the second criterion of our framework focuses on technological complexity. As discussed in section 3, the complexity of a technology refers to its degree of sophistication, the number of capabilities required and the particular way they are combined. The complexity of a regional economy refers to the capacity of the region to produce complex technologies, meaning that the region hosts all the requested capabilities to produce those technologies, and it is able to properly combine them. Then the economic complexity of a region is tightly defined by the complexity of the technological domain in which it specializes (Balland and Rigby, 2017). In fact, regions can only increase their economic complexity by increasing the number of complex technological domains in which they specialize.

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1 We used the 'relatedness' function as implemented in the 'EconGeo' R package: https://github.com/PABalland/EconGeo

Figure 3: Average relatedness

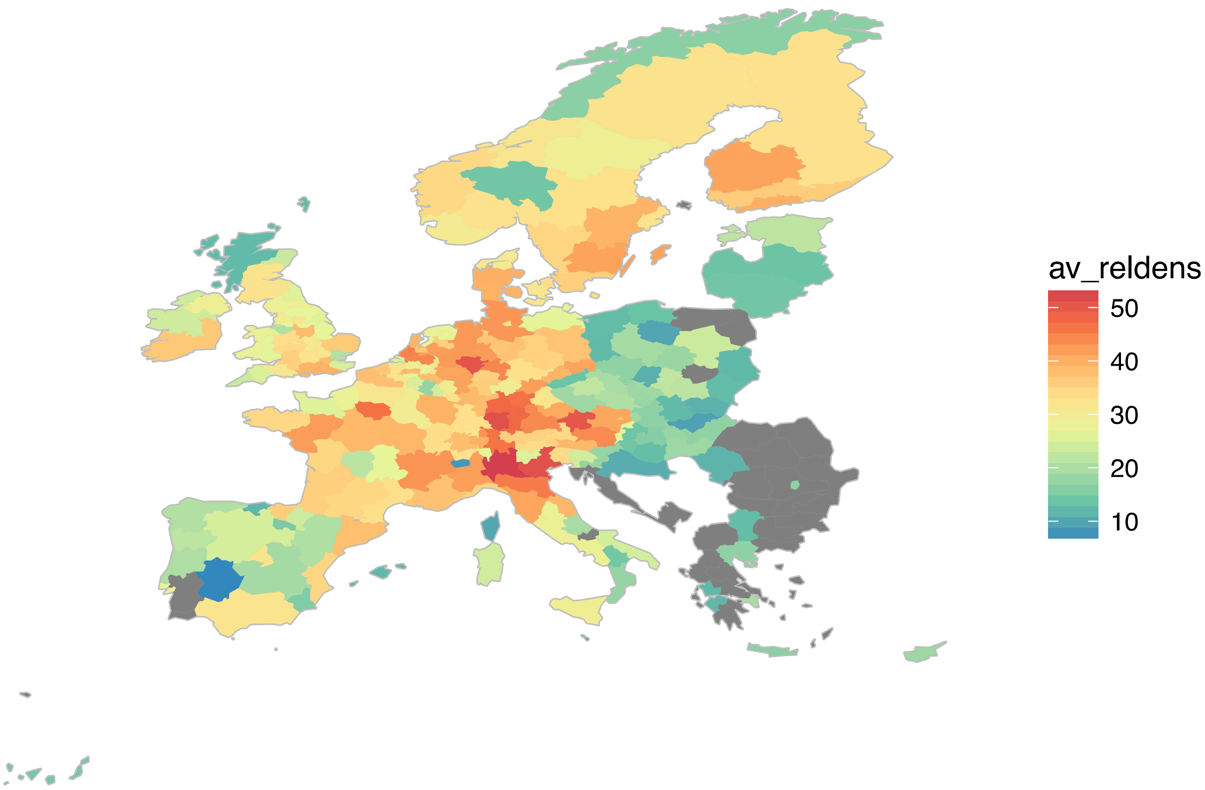
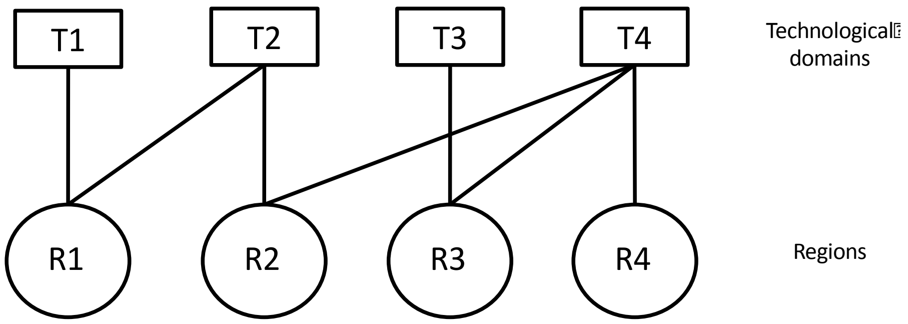


Figure 4 shows a bimodal network representation of the technological portfolio of regions, based on the economic complexity framework developed by Hidalgo and Hausmann (2009). On the bottom of the figure, there are four regions within which knowledge production takes place. The top of the figure indicates possible technological domains that may be followed. The links between the nodes at the top and the bottom of the figure indicate which technological domain each region is producing. For instance, while region 1 is producing technological domains 1 and 2, region 2 is producing in technological domains 2 and 4. From this figure, regional diversity refers to the number of technological domains that are explored by a region, for instance, 2 for region 1, and 2 for region 2. Likewise, ubiquity refers to the number of regions that produces a specific technology, for instance, 1 for technology 1, and 3 for technology 4 (Balland and Rigby, 2017).

Diversity and ubiquity are, respectively, crude approximations of the complexity of capabilities available in a region or required by a technological domain. But they can be used simultaneously in an iterative process to evaluate the complexity of technological domains and the economic complexity of regions (Hidalgo and Hausmann, 2009; Hausmann and Hidalgo, 2011; Balland and Rigby, 2017). The main idea is that, on the one hand, complex regions are diversified regions that produce non-ubiquitous technologies, and these non-ubiquitous technologies are produced by other diversified regions. On the other hand, complex technologies are non-ubiquitous technologies that are produced by diversified regions, and these diversified regions are producing other non-ubiquitous technologies.

Figures 4: network approach to complexity



By using this method, Balland et al. (2017) classify the different European technological domains (IPC classes) by their degree of complexity and highlight those that have a higher potential to upgrade the regional economy. Balland et al. (2017) compute an index of knowledge complexity of technologies using the eigenvector method from regions - technologies matrices. Technically, they use the eigenvector associated with the second largest eigenvalue of the projected one-mode technology-technology matrix[2]. Tables 1 and 2 show the technological domains with the highest and lowest complexity ranking respectively. On the top of the list are electronic engineering related domains dealing with ICT issues. On the bottom of the list, mechanical related domains prevail. While top classes tend to be in their early or growing stage of development, bottom classes tend to be in mature stages with a smaller potential for growth.

Table 1: Top 5 patent classes by complexity (2005-2009)

IPC	Technological class	1-digit tech. domain	Nb of patents	Compl.	Ubiquity
H04L	Transmission of digital information, e.g. telegraphic communication	Electrical engineering	24566	100	71
H01Q	Aerials	Electrical engineering	3037	96.97	67
H04H	Broadcast communication	Electrical engineering	783	96.97	49
H04J	Multiplex communication	Electrical engineering	1576	96.97	53

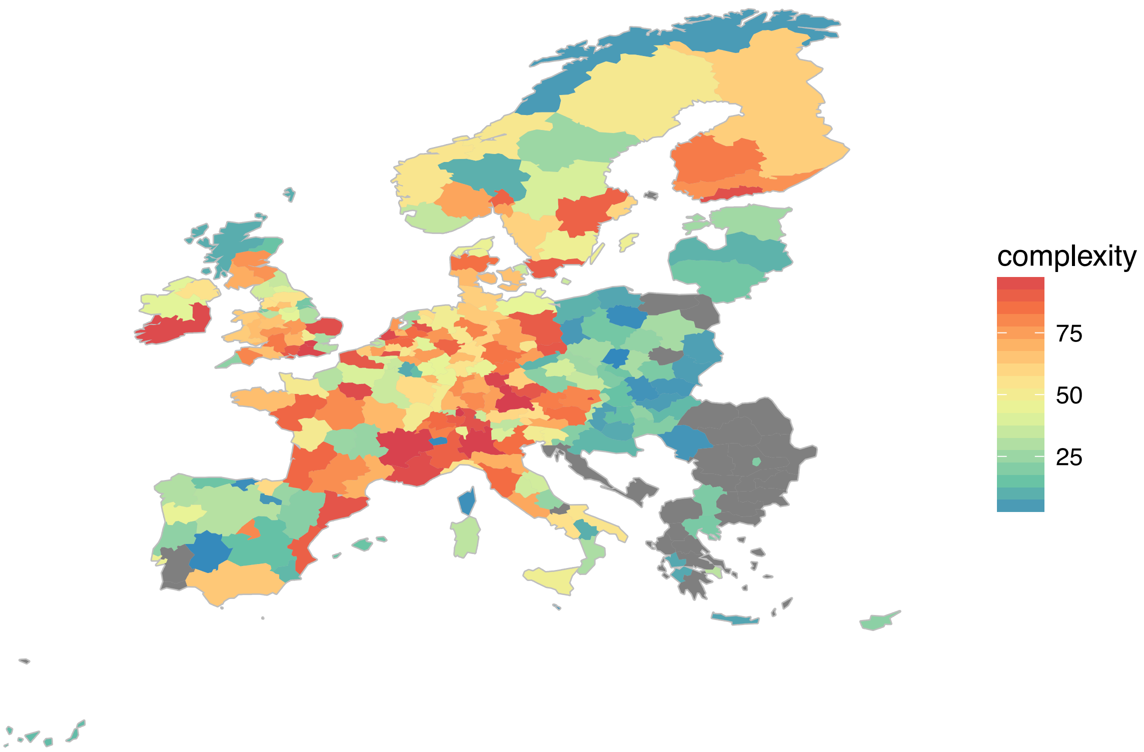
Table 2: Bottom 5 patent classes by complexity (2005-2009)

IPC	Technological class	1-digit tech. domain	Nb of patents	Compl.	Ubiquity
F23C	Methods or apparatus for combustion using fluid fuel or solid fuel suspended in air	Mechanical engineering	193	3.12	40
F24C	Other domestic stoves or ranges; details of domestic stoves or ranges, of general application	Mechanical engineering	154	3.12	44
F24J	Production or use of heat not otherwise provided for	Mechanical engineering	253	3.12	50
F25B	Refrigeration machines, plants, or systems; combined heating and refrigeration systems; heat pump systems	Mechanical engineering	298	3.12	43
F23N	Regulating or controlling combustion	Mechanical engineering	97	3.12	36

[2] We used the 'TCI' function as implemented in the 'EconGeo' R package: https://github.com/PABalland/EconGeo

Figure 5 shows the regional counterpart of the tables, i.e. the economic complexity of European regions based on their patenting activities. The economic complexity index for European regions is quite heterogeneous. Although regions in eastern countries have lower scores, the within country differences are larger than the between country differences. In fact, most of the western and northern countries in Europe host both regions with relatively high complexity and regions with relatively low complexity. The economic complexity is highest in well-known metropolitan areas such as Munich (Oberbayern - Germany), Zurich (Switzerland), Milan (Lombardy - Italy), Lyon-Grenoble (Rhône-Alps - France) and London (UK). Additionally, knowledge complexity is moderately high in other capital cities or national leader regions such as Paris (Île-de-France – France), Southern and Eastern Ireland (Dublin), Vienna (Austria), Southern Sweden and Helsinki (Finland). Eastern countries concentrate most of the regions with low scores in the complexity index. But low complexity regions also exist in western and northern countries of Europe. They tend to be more rural regions that strongly rely on natural resources such as Extremadura (Spain), Nord-Norge (Norway) or Highlands and Islands (UK).

Figure 5: Economic complexity of European regions (2005-2009)



A policy framework

Used simultaneously, the relatedness and complexity criteria can be used as a 'smart specialization framework' that could help policy makers and other stakeholders to assess technological opportunities and possible development trajectories for regions (see Figure 6). Balland et al., (2017) show that technologies which are currently not found within each region can be classified by their relatedness density (horizontal axis), and their degree of complexity (vertical axis). Therefore, regional policy makers can make informed decisions about the direction for diversification by assessing the risk and expected benefits of each technological domain that remains as yet underdeveloped within a region.

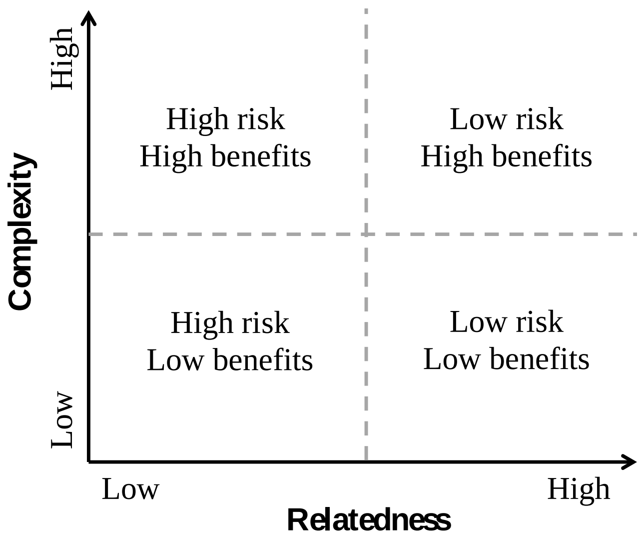
When the relatedness density of a potential new technology (horizontal axis) is high, this means that many of the technological capabilities required to develop that technology are already present in the region. Consequently, the region can more easily develop along this new technological trajectory as the risk of diversification failure along this path is lower. When the relatedness density of a technology within a region is relatively low then this signifies that the technological capabilities required to develop this knowledge class are underdeveloped in the region.

Consequently, the risk for the region in terms of developing this new technological possibility is greater.

Turning to complexity, a proxy for the relative value of a new growth path, when the complexity of a potential new technology (vertical axis) is high, the expected benefits for regional development are larger because complex technologies offer greater possibilities for building and sustaining regional competitive advantage. In fact, by producing complex technologies, the economic complexity of the region increases too. More complex economies tend to be more competitive, have higher income per capita and grow faster. The expected benefits of moving towards technologies with low complexity are smaller, because non-complex technologies tend to be more mature (lower growth potential), and more ubiquitous (higher competition). So, the upgrading potential of this strategy tends to be lower.

Figure 6 illustrates how the framework introduced by Balland et al. (2017) works. All potential technologies in which a region can diversify are classified on the base of their relatedness density (horizontal axis) and complexity (vertical axis). Thus, policy makers can assess the relative risks and benefits of all the possible alternatives. Ideal technological opportunities fall in the top-right corner, reflecting the situation of technology that is currently underdeveloped in the region, highly complex, and highly related to pre-existing regional capabilities. Conversely, the least appealing opportunities are located in the bottom-left corner, i.e. high risk and low added value. Finally, the top-left and the bottom-right cases are more ambiguous and require a real political choice about the amount of risk considered as acceptable compared to the expected benefits.

Figure 6: Policy framework to assess industries and technological domains



Source: Balland et al. (2017)

The core idea of the framework is that regional specific assets and capabilities define, for each region, not only the set of opportunities to develop new growth paths, but also limits on those choices. By operationalizing this concept, we are able to eschew the one-size fits all policy model and offer place-based policies adapted to the particular conditions of the region (Todtling and Trippl, 2005; Barca, 2009; Boschma, 2014; McCann and Ortega-Argilés, 2015).

The complexity axis introduces a key dimension to prioritize selection of smart specialization strategies, but it should not be used in isolation from the relatedness dimension. Given the expected benefits for the regional development of diversifying into complex technological domains, policymakers might be tempted to unconditionally try to diversify into complex technologies. By doing so, we are back to the one-size fits all policies: all regions trying to develop the same new, fashionable (reflected by its level of complexity) domains regardless of their actual capacity to succeed in such a movement. Consequently, this reproduces again the problems of duplication and fragmentation that, so far, have diminished the efficiency of innovation policy in Europe (Foray et al., 2011). This is precisely why one needs to combine complexity with relatedness. Firstly, it gives to the policy maker additional information to discern between alternatives with similar relatedness. Secondly, it may be useful to set long-term objectives, i.e. define the domains in which the region would like to be, and then define the intermediary steps of diversification that the region should follow to progressively acquire the requested set of capabilities. In the end, each time the region diversifies into a technological domain or abandon it, the set of regional capabilities changes, and so do the degree of relatedness with other domains.

This framework does not give a fully answer to the million-dollar question of "which domain should the policy maker chose to support?", but it aims to unveil hidden opportunities (high relatedness, high complexity) and threats that could have emerged from myopic and short-term strategies (high complexity, low relatedness). By systematically assessing all the possible alternatives with two criteria, it provides relevant information to take a more-informed decision. Picking winners that are badly embedded in the current industrial and technological space of the region or building cathedrals in the desert is still an option, but it requires massive investments. This framework suggests that this is a risky decision often associated with policy failure. Instead, the framework presented here identifies alternatives to develop new growth paths that better fit the specificities of the region. In this sense, we should keep in mind that policies for new path creation are (and will remain) risky because the perfect predictability of recombinations is impossible. To deal with that, the proposed framework provides a powerful tool to identify regional potentials and to target better-embedded activities for diversification. Similarly, the framework is based on universal relatedness patterns between activities. However, the actual connectivity of the two activities in the region might be hindered by the existence of local bottlenecks of different nature. The identification of these bottlenecks and their dissolution may require additional local expertise.

The original smart specialization approach proposed by Foray et al., (2011) strongly claims that the decision process about the "direction to go" has to be open. They argue that top-down approaches to establishing priorities were "very scientific and rational in their ways of identifying priorities, targets, and objectives", but they were "actually very irrational in their quasi-ignorance of essential knowledge in this matter" (Foray et al., 2011, p7). Therefore, they propose a bottom-up approach to define priority areas, because "entrepreneurs in a broad sense (firms, higher education institutions, independent inventors, and innovators) are in the best position to discover the domains of R&D and innovation in which a region is likely to excel given its existing capabilities and productive assets" (Foray et al., 2011, p7) - referred to as the *entrepreneurial discovery process*.

Taken in the abstract, the entrepreneurial discovery process and the framework presented in this report would be contradictory. While the first claims for an open-ended process, the second aims at identifying beforehand the regional potential areas that could be stimulated. Rodrik (2004) challenges this apparent opposition. He acknowledges the importance of market forces, but the existence of information and coordination externalities are good reasons "to believe that diversification is unlikely to take place without directed government action. Therefore, governments still play a crucial role" (Rodrik, 2004, p8), and strategic collaboration between private sector and the government is necessary.

Following Boschma and Gianelle (2014), it is important to "first economic activities with greater potential are identified with relatedness methods, after which an entrepreneurial discovery process is activated and harvested within the boundaries of these pre-defined areas" (Boschma and Gianelle, 2014, p12). Thus, the presented framework helps to restrict the scope of the entrepreneurial discovery process, but it still remains fundamental for two reasons. Firstly, to arbitrate between the different areas in the same quadrant and to arbitrate in the ambiguous choices between high-risk/high-benefit vs. low-risk/low-benefit quadrants. Secondly, to identify actual bottlenecks in the region that are hampering connectivity across domains. In that sense, this may be a promising way to combine bottom-up and top-down approaches in the definition of priorities for smart specialization (McCann et al., 2017).

Applying the framework to selected cases as a further illustration

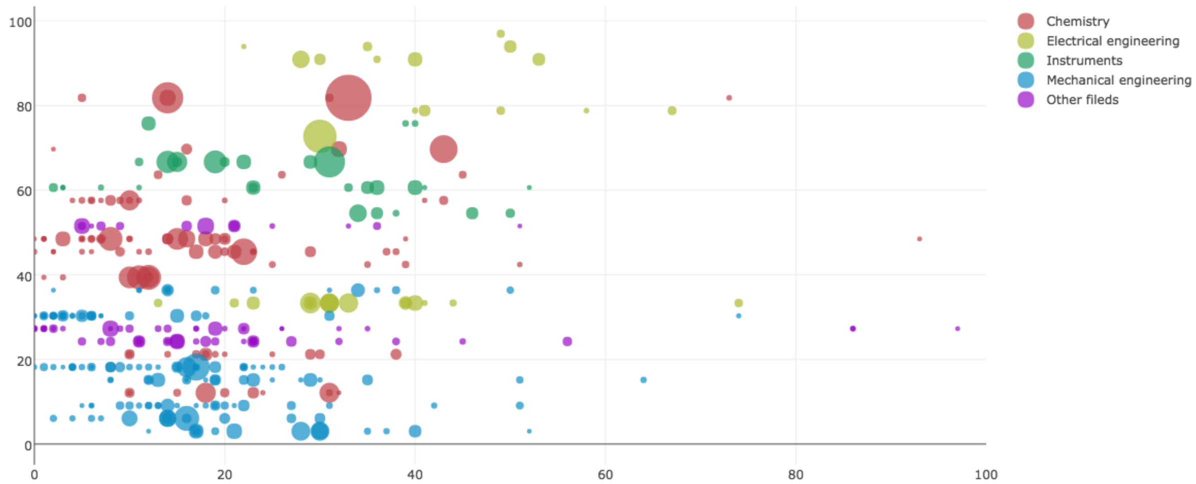
In this section of the report, our 'smart specialization framework' is applied to four NUTS2 regions in Europe. Figures 7 to 10 show and assess the potential choices for four different types of regions: a Central region (Île-de-France, FR10, France), a High-Tech region (Noord-Brabant, NL41, Netherlands), an Old Industrial region (Lancashire, UKD4, United Kingdom), and a Peripheral region (Extremadura, ES43, Spain). Following Balland et al. (2017), the OECD-Regpat database is used to build these figures. This database includes information on all patent applications to the European Patent Office from 2005 to 2009, the location where they were produced and their technological classes. Based on the framework developed in this report, Figures 7 to 10 show relatedness density in the horizontal axis and technological complexity on the vertical axis for each of the regions identified. The nodes (circles) represent technological classes in which the region does not exhibit competitive advantage (Relative Comparative Advantage lower than 1). Since these technologies are not present in the region, they are all potential candidate trajectories or growth paths along which the region may develop. The size of the nodes represents the total number of patents in the technological class, though note that all such classes are smaller than we might expect within the region, based on the share of patents in these classes at the European level. The color shows the 1-digit classification of the technological classes. The distribution of the nodes in each of the figures makes clear that not all regions are in the same situation to build new growth trajectories: the size and content of the list of choices, as well as their accessibility, vary from one region to another.

Île-de-France is a central region in Europe. By hosting Paris, it is one of the biggest, most densely populated agglomerations on the continent, and it concentrates approximately 20% of the French population. The GDP of Île-de-France represents 4.7% of the European GDP, and in GDP per capita terms, with a value that almost doubles the EU average, it is in the top ten of Europe (Eurostat). The successive Regional Innovation Scoreboards (RIS) have classified Île-de-France region as an Innovation Leader during the last decade, with an innovation performance well above the EU average.

One of the indicators of the RIS is patent applications. In the period 2005-2009, Île-de-France was the region with most patent applications to EPO. These patents were produced in a very diversified set of technological domains. In fact, Île-de-France has a competitive advantage in 29% (159) of all possible technological classes, and it produced at least one patent in 91% of all technological classes. The region is patenting a lot in domains related to chemistry, such as pharmaceuticals or organic fine chemistry, and in the domains of electrical engineerings, such as digital communication and audio-visual technology. Contrary, technological domains in mechanical engineering are much less relevant. As a result, the economic complexity of the Île-de-France region is high.

This diversified portfolio of activities is revealing the existence of a large set of capabilities these regions could rely on to branch out towards new activities. Figure 7 shows that Île-de-France has a relatively high relatedness with several new technological domains. Many of them belong to the electrical engineering and chemistry categories already quite present in the region, but there are also others that relate to mechanical engineering, and to a lesser extent to instruments. Thus, Île-de-France has several possibilities to diversify at low risk. They involve both high and low complex alternatives, making the second criteria of the framework relevant to choose the direction by discriminating among the low-risk alternatives. Since more complex technologies tend to have higher upgrading and growth potential, they should be privileged. Consequently, diversifying towards "amplifiers", "information storage" or "voice recognition and speech processing", appearing on the top-right part of the graph seems a good choice.

Figure 7: FR10 – Île-de-France (France)



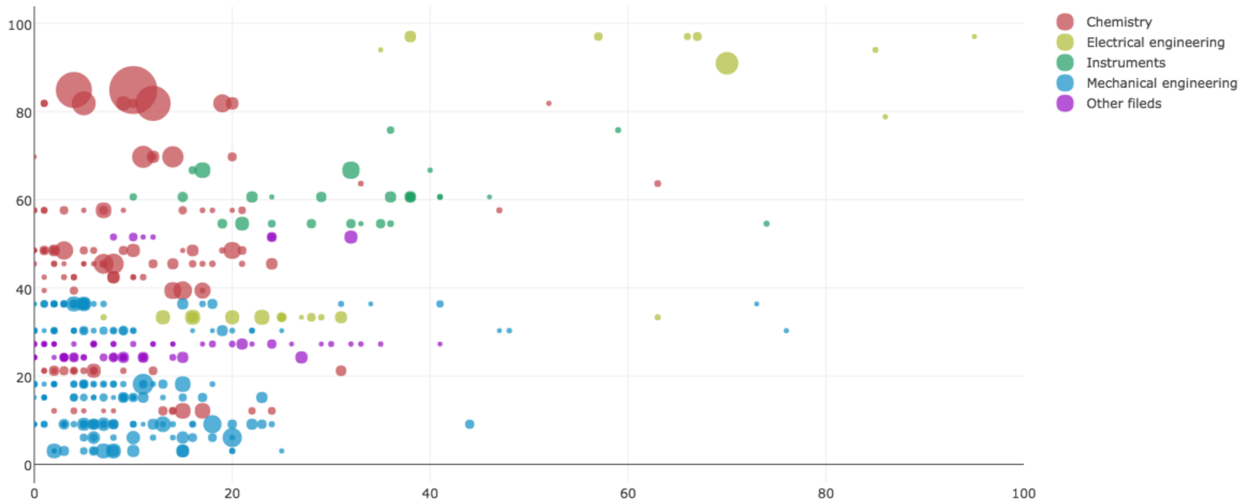
The second illustrative case is about Noord-Brabant. Noord-Brabant is not a capital region, but it is recognized to have a strong technological profile because of the area around Eindhoven, also known as Brainport, host several high-tech companies such as Philips, ASML, VDL group, NXP or DAF Trucks. The GDP of the region represents around 15% of the Dutch economy. In per capita terms, it is on the Dutch average, i.e. around 40% above EU average, but below the level of leading European regions (Eurostat). According to the Regional Innovation Survey, Noord-Brabant is an innovation leader performing above the EU average and has been classified as such during the last decade too.

The RIS identifies the patenting capacity of Noord-Brabant as one of the main strengths of the region compared to the EU28. From 2005 to 2009, in spite of its relatively small size, the region ranks in the top ten of patenting regions. This patenting activity is also quite diversified and the patents were produced in a large variety of technological domains: Noord-Brabant has at least one patent in 76% of the technological classes, and has a comparative advantage in 21% of the technological classes. The main areas of specialization of Noord-Brabant are linked to electrical engineering and instruments, but in this case, the pattern is more accentuated. These two categories represent more than 70% of all patent applications of the Noord-Brabant.

Figure 8 shows the technological domains in which Noord-Brabant may diversify by redeploying its existing capabilities. The menu of *low-risk* paths is shorter for Noord-Brabant than for Île-de-France, i.e. the number of technological domains with relatively high relatedness is smaller. This is so because Noord-Brabant is less diversified, and because its current technological domains of specialization are more concentrated into electrical engineering and instruments categories. However, while for Île-de-France the low-risk options were of high and low complexity, for Noord-Brabant they tend to be concentrated in the high complexity quadrant. These alternatives concern communication technologies (wireless, multiplex, secret…) and remain focused on electrical engineering categories. Investing in more radical diversification strategy, for instance towards chemistry technological domains, remains quite risky.

The case of Lancashire, in the Northwest of England, is very different. It represents the case of a declining old industrial region. During the nineteenth century, Lancashire lived the golden era of the textile industry and became one of the most important cotton producers in the world. But during the twentieth century, this industry declined along with the region. Nowadays, Lancashire represents around 1.8% of the United Kingdom population, and its GDP per capital is around 82% of the EU average. RIS (2016) classifies Lancashire as an innovation follower, with an innovation performance around the EU average.

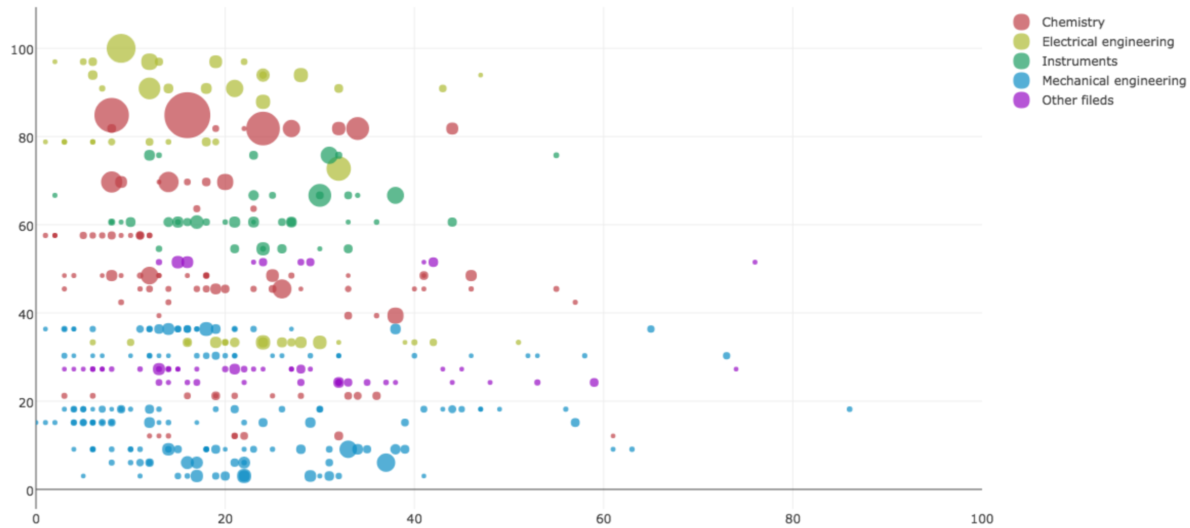
Figure 8: NL41 – Noord-Brabant (Netherlands)



One of the weaknesses of the innovative performance of Lancashire is its patenting activity, that tends to be below the EU average. In fact, in the period 2005-2009, the Lancashire has produced less than 1,000 patents, and it takes up the 160th position among the 251 NUTS2 regions of Europe considered. Moreover, the economy of the Lancashire is less diversified than the previous two cases. Although it has a comparative advantage in 26% of the technological domains, it has at least one patent only in 40% of all the technological domains. The region concentrates its patents in domains of mechanical engineering such as "textile and paper machines" or "transport", and in chemistry domains.

Figure 9 shows how the framework built in this report applies to the case of Lancashire. As with the Noord-Brabant case, Lancashire is closely related to several technological domains which give several alternatives to diversity towards new domains. However, from the complexity angle, the story is quite different. In fact, Lancashire is closely related to non-complex domains mostly in the area of mechanical engineering for the production of devices like furniture, paper products or musical instruments, while complex domains, with high growth potential, are difficult to get access to giving the current strengths of the region. Thus, for Lancashire, there are no low risk – high benefit options. The policy maker has to choose between accepting the higher risk to get higher expected benefits, i.e. going towards chemistry and electrical engineering domains, or adopting a strategy of lower risk and less expected rewards. In those cases, the entrepreneurial discovery process may be particularly relevant.

Figure 9: UKD4 – Lancashire (United Kingdom)

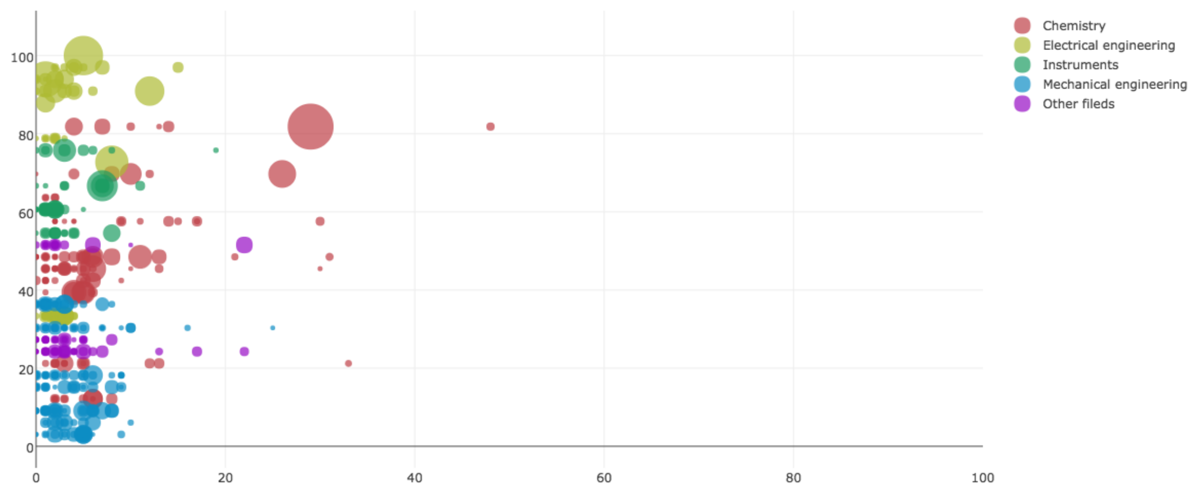


Finally, the case of Extremadura is presented. Extremadura is a peripheral region in Europe that hosts a bit more than 2% of the Spanish population. Its GDP is one of the lowest of Spain (15th out of 17th) and, in per capita terms, it is at 56% of the European average. The Regional Innovation Survey has systematically classified it as a Modest Innovator, and for all the indicators composing this innovation index, except for tertiary education, it is below the EU average. This is also the case for the number of patent applications. In fact, in the period 2005-2009, only 62 patents were produced in the region and they only span 5% of all the technological classes. They were concentrated in the chemistry area: food chemistry and pharmaceuticals.

This weak innovative capacity reveals a scarcity of capabilities or a difficulty in coordinating them properly. This limits the ability of the region to develop new growth paths. In fact, figure 10 shows that the technological domains closely related to the existing set of capabilities in the region are rare. The most related ones are in the chemistry area, where the region has its highest innovation rates. But in any case, they are below the values observed for the previous cases. Thus, Extremadura is in one of the most complicated scenarios for a policy maker: it has many alternatives in the high-risk side, both with high and low expected benefits, but none in the low-risk side.

Given that for Extremadura any diversification strategy has to deal with low relatedness density, i.e. high risk, should it go for complex or non-complex domains? On the one hand, if the assumed risk is high in any case, it makes sense to go for complex technological domains because the expected benefits are also higher. On the other hand, complex technological domains require a larger set of capabilities, and this makes the jump even more risky for Extremadura. By going towards complex domains, it is not only that it has to build on unrelated capabilities but it has to do that with many of them. By trying to diversify into non-complex technologies, Extremadura also faces low relatedness problem, but a number of capabilities it needs to build is also lower. So, the probability of success is a bit higher.

Figure 10: ES43 – Extremadura (Spain)



CONCLUSIONS

In this policy note, we have discussed how regions can set the direction to develop new growth paths. Rather than blindly replicating best practices from elsewhere, we discussed how regions can smartly choose their new domains of specialization based on their already existing regional strengths and the upgrading potential of technologies.

On the one hand, we have argued that efficient knowledge exchange occurs more easily and intensively when actors involved are geographically close and share a common base of knowledge. This is when regions are endowed with a variety of related industries or technological domains. On the other hand, we have argued that complex knowledge has a stronger potential to upgrade regional economy and build a unique competitive advantage that fuels higher growth rates.

We build a framework to help policymakers to assess all the alternative possible directions in which the regional economy can diversify on the base of their expected risk (relatedness density) and the expected benefits (knowledge complexity). The higher the relatedness of the target domain with the existing local competencies, the lower is the risk of taking this path. Similarly, the higher the complexity of the new technology, the higher is the expected value for the region. Therefore, the proposed framework is useful because it provides context-based information on all possible alternatives for a region to diversify in new future specializations.

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Regional sustainable growth is very much influenced by the renewal capacity of the region in order to adapt to a changing environment, i.e. to develop new trajectories. According to the Smart Specialization strategy, policy makers make have a great influence in the development of these new trajectories, but they have to be selective and select a limited number of technological areas to specialize. However, how can policy makers choose the areas they should support? This paper aims to fill this gap. It proposes a policy framework to asses all the possible trajectories for a region, thus policy makers can take better informed decisions. On the one hand, it looks at the similarity between the knowledge bases of the region and the required skills for the new technological area, i.e. the higher their similarity (relatedness), the higher the chance to succeed. On the other hand, it looks at the upgrading potential of the technology, i.e. the higher the potential (knowledge complexity) the more rewarding will be the effort. The paper illustrates how the framework works by applying it to several regions in Europe.

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