Relatedness, knowledge complexity and technological opportunities of EU regions

A framework for smart specialization

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Smart specialization is a strategic response to the important societal challenge of open innovation and economic transition. In a world where knowledge and innovation are the main drivers of sustainable growth, the smart specialization strategy aims at supporting regions to develop capabilities in new research fields and technological areas. The goal of this policy is not to make the economic structure of regions more specialized (i.e. less diversified), but instead to leverage specific strengths, to identify hidden opportunities and generate platforms upon which regions can build dynamic forms of competitive advantage. Regions should focus on their own particular skills and expertise to secure comparative advantage in high-value added activities.

Although the academic literature on this topic is growing, there remains a significant gap between current policy practice and academic knowledge on how regional economies develop new specializations. Removing this gap is critical as regions across Europe seek smart specialization diagnostics to help them select and prioritize specific fields that should be developed. We attempt to improve our understanding of how regions can identify valuable new knowledge domains, evaluate growth potentials, and guide technological transitions.

We focus attention on two key concepts that will be incorporated in our policy framework: related variety and complexity. (1) there is growing evidence that related variety in regions provides opportunities to make new combinations that give birth to new activities. That is, regions tend to diversify into new activities that are related to existing activities (Hidalgo et al. 2007; Neffke et al. 2011; Rigby 2015); (2) but besides moving into related activities, it is crucial for regions to move into more complex activities, because it will upgrade their economies and bring higher economic benefits. This idea builds on the concept of economic complexity introduced by Hidalgo and Hausmann (2009). They refer to complex economies as those that have a strong ability to combine a broad range of relevant knowledge to generate and develop a diverse mix of knowledge-intensive products. Simpler economies, instead, have a more narrow base of knowledge and therefore produce fewer and more simple products which do not require complex interactions. The more complex economies, the more capable they are to make very complex products that combine many different pieces of knowledge, which are very hard to copy or imitate by other economies. This provides an explanation of the large income gaps between rich and poor economies, and these differences are expressed in the diversity and sophistication of the products that economies specialize in. Hidalgo and Hausmann (2009) claim that countries with a higher economic complexity than expected, given their level of income, grow faster than countries that are richer, given their level of economic complexity.

Our contribution provides (1) a sound theoretical underpinning of the smart specialization policy concept, and (2) new empirical evidence on how (EU) regions develop new specializations.. We use network analysis techniques to (1) map the technological knowledge bases of all EU NUTS2 regions based on patent data from the European Patent Office (EPO), (2) identify technological fields and compute measures of the technological relatedness and knowledge complexity of those fields using recent advances in complexity theory. It should be clear from the discussion above that a smart specialization initiative requires a framework to systematically identify technological opportunities within regions. Technological opportunity can be defined as the potential to develop critical capacity in a technological field that (1) draws on the specific knowledge bases of the region and that (2) leads to technological upgrading. Technological opportunities can be identified as those technological fields in which a region does not yet possess critical development capacity, but that have a high degree of *relatedness* with the region's existing knowledge base and are characterized by high *knowledge complexity*. In this paper we use patent data from the European Patent Office (EPO) to identify technological fields and compute measures of relatedness and knowledge complexity.

To measure technological relatedness between patent classes we use the distribution of knowledge claims by International Patent Classification (IPC) class on each patent, following Boschma et al. (2015) and Rigby (2015). This is done by counting the number of patents for a given period that contain a co-class pair, say *i* and *j*, and then standardizing this count by the number of patents in total that record knowledge claims in IPC classes *i* and *j*. Relatedness is therefore a standardized measure of the frequency with which two IPC classes appear on the same patents. In this paper, we use the standardization method proposed by van Eck and Waltman (2009), as implemented in the *relatedness* function of the *EconGeo* R package (Balland, 2016). The relatedness between technologies can be further formalized as a network, the *knowledge space*. The knowledge space is an $n*n$ network where the individual nodes i (i =1,…,n) represent technological categories (IPC classes) and the links between them indicate their degree of relatedness. We compute relatedness ($\varphi_{i,j,t}$) between each pair of technology fields i and j for six different non-overlapping periods of time: 1980-1984, 1985-1989, 1990-1994, 1995-1999, 2000-2004 and 2005-2009.

To compute knowledge complexity for technologies and regions, we simultaneously combine information on (1) which regions produce specific technologies and (2) how common specific technologies are across regions. This knowledge complexity index (KCI) is based on a seminal paper by Hidalgo and Hausmann (2009), in which they describe how the economic complexity of a country's output is reflected by the composition of its export basket, relatively to the composition of the export baskets of all other countries. This idea has been further implemented in the context of innovation and technological change by Balland and Rigby (2016). We compute knowledge complexity using an eigenvector reformulation. The starting point of the knowledge complexity index is the network that connects regions to the technological knowledge they develop, which can be represented as an n by k 2-mode adjacency matrix. The resulting network comprises $n=282$ regions (NUTS 2) and $k=33$ technological domains (2-digit level) as proposed by Schmoch (2008) . In this $n*k$ matrix, the weight of each edge $x_{c,i}$ is the number of patents produced within region r in technological category i $(r = 1,..., n; i = 1, …, k)$. As for relatedness, we divide the years for which we have patent data into six periods of five years, and we construct a 2-mode region-technology network for each of the periods: 1980-1984, 1985-1989, 1990-1994, 1995-1999, 2000-2004 and 2005-2009.

These concepts are deployed to investigate how the existing knowledge cores of regions shape future trajectories of entry and exit into and out of different technological fields. We assess to what extent EU regions are: (1) more likely to specialize in technological activities that are related to their specific knowledge bases; (2 less likely to specialize in complex technological activities; (3) more likely to experience growth in technological activities that are related to their specific knowledge bases; (4) more likely to experience technological growth in more complex technological activities.

Then, we discuss the implications of our findings for smart specialization policy. We present a framework to systematically identify technological opportunities for regions based on the relatedness density of individual technologies and what we refer to as the complexity gap. The main idea of this framework is presented in Figure 2. For every region, it is possible to map potential new technological fields in which the region does not yet possess relative technological advantage (RTA). The technological relatedness between each of these fields and the knowledge core of the region is easily measured using the density measure above. That measure provides an index of the relative ease with which a region might be able to develop RTA in a new field (X-axis). At the same time, the difference or gap in the region's overall knowledge complexity, computed with and without RTA in each new technological class, can be defined (Y-axis).

Policy-makers must then weigh the relative ease of developing a new technological field within a region in relation to the gains in knowledge complexity (and thus value) development of that field. The smartest strategy might be the one that is represented by the right-upper quadrant: those contain technologies that are not yet present in the region, but which will increase the technological complexity of the region (high benefits), and the region has potential to develop these technologies (low risks), given the high amount of local technologies (relatedness density) related to these new technologies.

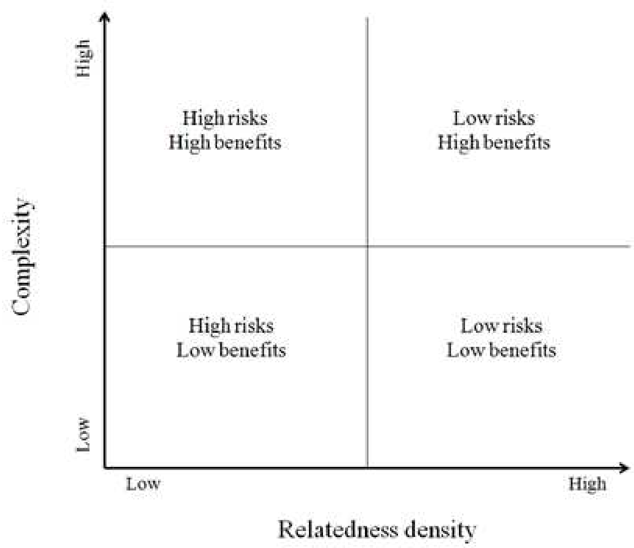

Figure 2. The smart specialization framework

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