Ann Reg Sci (2013) 51:119–154
DOI 10.1007/s00168-012-0539-8

SPECIAL ISSUE PAPER

Territorial patterns of innovation: a taxonomy of innovative regions in Europe

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Received: 12 January 2012 / Accepted: 6 September 2012 / Published online: 17 October 2012

Abstract The recent policy approach to innovation calls for thematically/regionally focused innovation policies in line with the place-based approach (EC – Commission of the European Communities, 2010). To achieve this goal, without incurring the unrealistic situation of having one policy action for each European region, a sound taxonomy on innovative European regions is required. The present paper claims that the existing taxonomies are somewhat unsatisfactory, since either they group European regions only on the basis of the intensity of their knowledge production, taking it for granted that knowledge equates to innovation, or they lack a priori on the conceptual links among the variables used, and the territorial conditions behind local innovation modes. The paper presents a *territorial* taxonomy of innovative regions based on a new conceptual approach which interprets, not one single phase of the innovation process, but the *alternative modes of performing the different phases of the innovation process*, highlighting the *context conditions* that accompany each "territorial pattern of innovation." The paper conceptually derives different territorial patterns of innovation and identifies them empirically for European regions.

JEL Classification R10 · R11

This paper is part of the ESPON KIT project, financed within the ESPON program, and led by the authors at the Politecnico of Milan. More on the project can be found at the website: http://www.espon.eu/main/Menu_Projects/Menu_AppliedResearch/kit.html. The authors are grateful to two anonymous referees for their useful suggestions. Usual disclaims apply.

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1 Introduction

There is an increasing awareness among policy makers that sectoral policies, like innovation policies, require a regional—place-based—approach. The EU document *Regional Policy Contributing to Smart Growth in Europe* (EC 2010) has been a first official move in this direction. The general idea is to move away from a "one-size-fits-all" policy approach to innovation like the thematically/regionally neutral and generic R&D incentives. Instead, innovation behaviors specific to each single area have to be identified so that ad hoc and targeted innovation policies can be devised.

To achieve this goal, without incurring the unrealistic situation of having one policy action for each European region, a sound taxonomy on innovative European regions is required. For this reason, a number of taxonomies of innovative regions have been proposed with the aim of identifying similarities among regions in terms of their knowledge bases. However, the large majority of the existing taxonomies are based merely on the intensity of locally produced knowledge. Very recently, OECD has proposed a taxonomy, which once again groups European regions according to their intensity of knowledge, identifying the knowledge regions, the industrial production zones, and the non-S&T-driven regions (OECD 2010). On a similar vein, Tödling and Trippl (2005) conceptually identified three types of regions, that is, peripheral regions, old industrial regions, and metropolitan regions, on the basis of their knowledge intensity, industrial specialization, and settlement structure. By focusing on the characteristics of research activities and processes, Varga et al. (2010) group regions according to their research productivity in *Edison*-type research, that is, research focused on new products with novel economic applications and on market-oriented innovation that is associated with agglomeration economies benefits, and in *Pasteur*-type research, that is, science-oriented research, governed by the specific norms, rules, and incentives of the modern scientific practice that, instead, is associated with (scientific) networking behavior.

For different reasons, the results achieved with the above-mentioned taxonomies are not totally satisfactory and leave space for further reflections. In particular, all previous taxonomies are mostly based on knowledge production only, and therefore unable to grasp important aspects of the way in which innovation processes take place, from the exploitation of knowledge spillovers, to the use of informal, non-codified knowledge, and to the development of learning by doing and by using. These aspects are in general ignored since the taxonomies mentioned are based on a specific conceptual approach that equates knowledge to innovation, as in all recent theories on regional knowledge-based growth. Whatever the scientific paradigm behind these theories, for example, economic geography theories, evolutionary theory of innovation, neo-Schumpeterian theories on local development, and evolutionary geography, they share one important feature which represents the limitation of current scientific knowledge on local knowledge and innovation processes. All these theories focus on *one particular phase* of the innovation process, often interpreted as the crucial one, and which is either knowledge creation, innovation creation, knowledge diffusion, or innovation diffusion. Some theories even interpret knowledge and innovation as overlapping processes, taking for granted that whether knowledge is created locally, this inevitably leads to innovation, or if innovation takes place, it is only due to local knowledge availability. A similar short-circuit is assumed between knowledge/innovation and performance, with a productivity increase expected in all cases in which a creative effort, a learning process, an interactive, and cooperative atmosphere characterize the local economy. Secondly, the existing taxonomies lack a link with the territorial conditions behind the modes of innovation and which enable the identification of the endogenous local elements associated with a region's innovation pattern.

An exception in the existing taxonomies based on the knowledge production come from the work developed for the DG Enterprise and Industry (namely the different editions of the *Regional Innovation Scoreboard*; Hollanders et al. 2009), which proposes a taxonomy of European regions that makes use also of innovation regional data. This is definitively a novelty as it is, in fact, one of the first attempt to empirically distinguish knowledge from innovation and to depart from the knowledge–innovation equivalence, a conceptual ambiguity clearly manifest in taxonomies using knowledge indicators such as R&D or patent intensity as proxy for innovation outputs. However, the methodologies implemented in this kind of exercise merge together indicators as diverse as innovation performance, knowledge inputs like R&D, knowledge output, like patent activities, sectoral structure, presence of spatial innovation enablers, employment indicators, with no a priori on the conceptual links among the variables used, and, ultimately, lack strong territorial roots.

It is our impression that the complexity and diversity of regional modes of innovation requires a shift away from typologies based on the intensity of knowledge production alone, lacking any linkage to the local conditions that enable specific innovation processes to take place. It is especially on these local elements that regional policies can act to create and reinforce regional innovation processes; on the identification of the specific innovation processes that each region has developed lies the difficulty of moving from innovation policies, which are typically sectoral policies, to regional innovation policies. For this reason, a sound taxonomy should interpret the different combinations of context (local) conditions and modes of performing the different phases (from knowledge creation/acquisition to innovation) of the innovation process, that is, it should highlight the different *territorial patterns of innovation*.

This paper intends to contribute to this end by proposing a taxonomy of innovative regions based on a new conceptual framework in which to read innovation potentials at regional level, and by highlighting different possible territorial patterns of innovation defined as specific combinations of context conditions and different modes of developing the various phases of the innovation process (Sect. 2). On the basis of a rich dataset for 262 NUTS2 regions of the 27 EU Member Countries, the regional taxonomy is defined by means of a cluster analysis on the intensity of both *knowledge and innovation*, thereby superseding the trivial idea that knowledge equates to innovation. The groups of regions are depicted on the basis of the *territorial conditions* behind the different modes of innovation thanks to a rich database (Sect. 3) and an appropriate choice of variables (Sect. 4). Interesting results emerge and they highlight a variety even more fragmented than conceptually envisaged (Sect. 5). Some concluding remarks are finally presented (Sect. 6).

2 Territorial patterns of innovation: a conceptual approach

2.1 A definition

The innovation process can be conceptualized in an abstract but consistent "linear model of innovation," that is, a logical sequence of phases, from knowledge creation and acquisition, to the commercialization of the new idea (innovation), to the increase in productivity that innovation output generates, even if this way of reasoning has been heavily criticized as unrealistic and rooted in the idea of a rational and orderly innovation process (Edgerton 2004).[1] Moreover, alternative modes of innovation, intended as alternative combinations of the different phases, exist in the real world; the innovation phase can in fact build (1) on knowledge internal to the region, or (2) on local creativity that, despite a lack of local knowledge, enriches thanks to knowledge developed elsewhere, or (3) on local imitation processes of innovations put in place outside the region.

Each region develops its own mode of innovation according to the presence of local conditions that allow the different phases of the innovation process to take place and to move from one mode to the other. The complex interplays between phases of the innovation process and spatial context or territorial conditions are conceptualized in the new interpretative paradigm—the so-called territorial patterns of innovation paradigm (Capello 2012). In fact, the paradigm leap in interpreting regional innovation processes today consists in the capacity to build—on the individual approaches developed to interpret knowledge and innovation creation and diffusion—a conceptual framework interpreting not just a single phase of the innovation process but the *different modes of performing the different phases of the innovation process*, highlighting the *context conditions* that accompany each innovation pattern. The result is a "spatially diversified, phase-linear, multiple-solution model of innovation," in which the single patterns represent a linearization, or a partial block linearization, of an innovation process where feedbacks, spatial interconnections, and nonlinearities play a prominent role (Capello 2012).

The new paradigm adds two new elements to previous theoretical paradigms. Firstly, it disentangles knowledge from innovation by addressing the two different (and successive) phases of the innovation process, each phase requiring specific local elements for its development, and having different locations according to the availability of the factors that support its development. This approach departs from the invention/innovation equivalence and rejects the idea that innovation takes place only within individual firms (or their territories) operating in advanced sectors, as well as the straightforward interaction between R&D/higher education facilities, on the one hand, and innovating firms on the other, due to spatial proximity.

[1] We accept the idea of a "linear model of innovation", since we strongly believe that: (1) in many cases scientific advance is a major source of innovation, as the ICT paradigm and trajectory indicate; (2) an alternative model of full complexity, where 'everything depends on everything else', does not help in conceptualizing and interpreting the systemic, dynamic and interactive nature of innovation; (3) self-reinforcing feedbacks from innovation to knowledge and from economic growth to innovation and knowledge play an important role in innovation processes.

Secondly, the concept of “patterns of innovation” requires identification of the context conditions, both internal and external to a region, that support the various innovation phases. These context conditions are key building blocks in the definition of a *territorial pattern of innovation*. Accordingly, this approach does not look for specific territorial capabilities that enable territories (in general) to perform better in individual knowledge and innovation phases. Rather, this conceptual framework looks for the *territorial specificities (context conditions)* behind the *different modes of performing the different phases of the innovation*.

A territorial pattern of innovation, therefore, is a combination of *territorial specificities (context conditions)* and *different modes of performing the different phases of the innovation process*.

The existence of a well-established literature helps the conceptual elaboration of innovation patterns in two respects. Firstly, there is a large and diversified body of scientific literature that identifies the context conditions accompanying each phase of the regional innovation process. Secondly, the existing literature helps in choosing the most interesting combinations between innovation modes and territorial elements. The literature, in fact, strongly emphasizes processes of, and territorial elements associated with, (1) local knowledge creation and knowledge spillovers (the “R” of R&D), (2) external knowledge acquisition (the “D” of R&D), (3) pure innovation imitation.

The three conceptual archetypes of territorial patterns of innovation are presented in detail in the next section.

2.2 Alternative territorial patterns of innovation

The first and most straightforward pattern is the one in which regions are endowed with local conditions for knowledge creation and for turning knowledge into innovation, so as to guarantee productivity increase and regional growth.

Figure 1 sketches the different phases of this pattern of innovation and presents the territorial preconditions, highlighted in the literature, that make it possible to move from one phase to another. An innovation pattern of this kind can be labelled an “*endogenous innovation pattern in a scientific network*.”

As to the territorial preconditions for knowledge creation, these are extensively discussed in the literature, and are in general associated with urban settings, where material and non-material elements supporting the development of scientific knowledge are more likely to concentrate, namely:

- diversity, which concerns the variety of activities and the possibilities for specialization in thin sub-sectors and specific productions opened by the size of the overall urban market (Jacobs 1969, 1984; Quigley 1998);
- large human capital pools and wide labor markets (Lucas 1988; Glaeser 1998) due to the urban size;
- the availability of advanced education facilities and research centers (Jaffe 1989; Malecki 1980);
- reduction of the risk of unemployment for households due to the thick and diverse urban labor market (Veltz 1993);

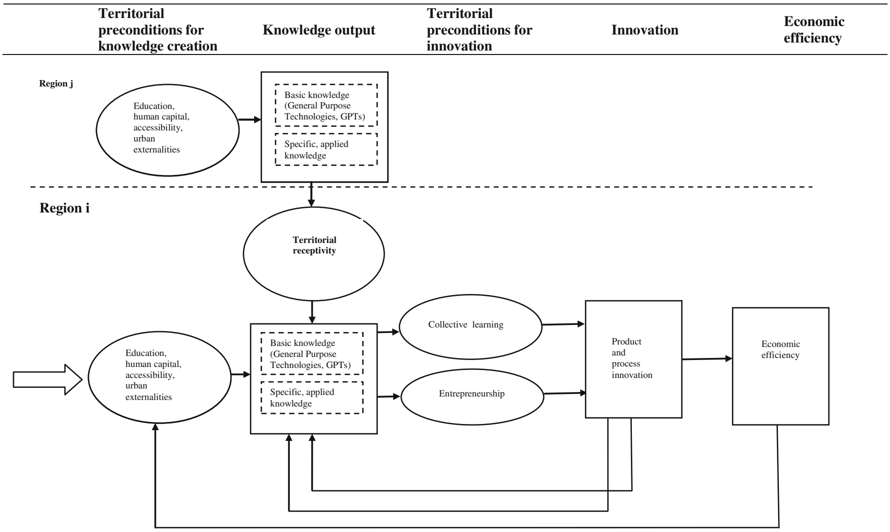

Fig. 1 Endogenous innovation pattern in a scientific network. *Source*: Capello 2012

- contacts and interaction allowing face-to-face encounters which reduce transaction costs (Scott and Angel 1987; Storper and Scott 1995);
- the synergies, complementarity, and trust due to proximity (Camagni 1991 and Camagni 1999; Haken, 1993);
- trans-territorial linkages arising from the international gateway role of large cities especially crucial in a globalizing world (Sassen 1994).

The literature has also identified territorial factors in innovation creation. In particular, the translation of knowledge into innovation is deemed to be facilitated by interaction, cooperation, and collective learning processes, as well as by the reduction of uncertainty (especially concerning the behavior of competitors and partners), of information asymmetries (thus reducing mutual suspicion among partners), and of the probability of opportunistic behavior under the threat of social sanctioning (Camagni 1991, 1999; Camagni and Capello 2002)—all of which are factors confirmed by numerous regional economics studies (Bellet et al. 1993; Rallet and Torre 1995; Cappellin 2003; Camagni and Capello 2009).

The condition for a region to acquire knowledge from outside its boundaries is *territorial receptivity*, broadly defined as the capacity of the region to interpret and use external knowledge to achieve complementary research and science advances, or more generally the absorptive capacity of a region *à la* Cohen and Levinthal (1990). More specifically, receptivity is made up of aspects which differ according to the nature of knowledge and its diffusion. If a modern view of knowledge is adopted, learning and interaction processes are put at the forefront and knowledge is considered to be a complex semipublic or cooperative good. Its diffusion is subject to strong spatial barriers, and it ensues from largely unpredictable creative processes. Knowledge creation and learning often depend on a combination of diverse, complementary capabilities of heterogeneous agents.

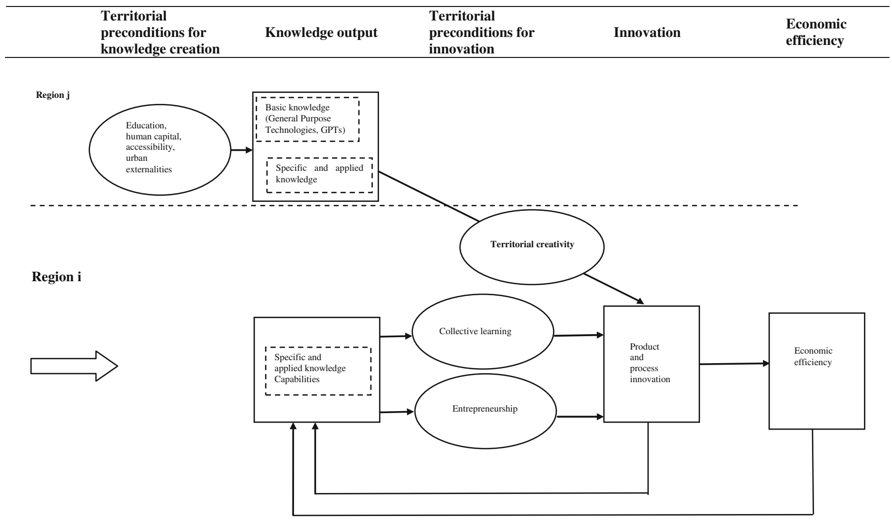

Fig. 2 Creative application pattern. *Source*: Capello 2012

Given these characteristics, receptivity is primarily dependent on a *relational capacity* required to ensure that a region is in general made up of individuals, firms, and institutions oriented toward cooperation and synergy, nourished by trust and a sense of belonging, so that collective and interactive learning processes are guaranteed.

In the literature, access to knowledge external to the region is usually considered to be moderated by physical distance, as the knowledge spillover theory has claimed. But our conceptual approach departs from the idea that knowledge exchange is only influenced by pure spatial proximity. In fact, the complex evolution of science and knowledge, together with the bounded rationality which imposes cognitive constraints on actors, induces economic agents to search in close proximity to their existing knowledge base, which provides opportunities for, and sets constraints on, further improvement (Boschma and Lambooy 1999; Boschma 2005; Rallet and Torre 1995; Cantwell 2009; Basile et al. 2012). Knowledge evolution therefore takes place in a cumulative way localized around a technological paradigm, and through cooperation among actors with a strong complementarity within a set of shared competences. For this reason, a third component of territorial receptivity is a *cognitive proximity* among regions whereby the capacity to access and to benefit from knowledge created elsewhere depends on the extent to which two regions are cognitively proximate, that is, have complementary sets of skills and competences pertaining to a common knowledge base (Capello and Caragliu 2012). This is an interpretation of the concept of “related variety” defined by Boschma (2005) at the cross-regional level.

The second abstract innovation pattern is what can be called a *creative application pattern* characterized by the presence of creative actors interested enough to search for external knowledge lacking within the region and creative enough to apply it to local innovation needs (Fig. 2).

The novelty of the second combination resides in its break with the general belief embraced by most of the literature that knowledge equates to innovation, and that if knowledge is locally available, this will automatically lead to local innovation (Capello and Lenzi 2012). Instead, it may well be the case that knowledge and innovation are disjoint at the local level and that innovation depends on knowledge spillovers, used in a creative way, and on an original recombination with the limited local knowledge.

Most of the literature takes it for granted that locally created knowledge inevitably leads to local innovation, and that local innovation takes place because of local knowledge availability since knowledge and innovation are conceptually equated. However, there are many examples showing that the knowledge/innovation equivalence whereby knowledge and innovation are viewed as necessarily overlapping processes does not hold at the spatial level (Capello and Lenzi 2012). The firms and individuals that lead an invention are not necessarily also leaders in innovation or in the diffusion of new technologies. The history of technology and innovation is full of similar examples: the fax machine, first developed in Germany, was turned into a product successful worldwide by Japanese companies. Similarly, the antilock brake system (ABS) was invented by US car makers but became prominent primarily because of German automotive suppliers (Licht 2009).

In this case, innovation stems from knowledge spillovers that reach the region more often intentionally than unintentionally (Fig. 2). This pattern recalls what the smart specialization expert group calls the "co-invention of applications" in one or several important domains of the regional economy. In such cases, innovation is achieved without embarking on expensive basic R&D activities also because of an insufficient critical mass of human and financial resources at the local level (Foray 2009; Foray et al. 2009).

As the smart specialization approach claims, the success of this second pattern of innovation lies in the capacity of the region to discover new specialization fields inside its "knowledge domain," that is, well-defined innovation niches on the basis of its present competences and human capital endowment, in which it can hope to excel in the future also thanks to synergetic policy support (Pontikakis et al. 2009). Some members of the group are explicit in this sense: "the concept of smart specialization (. . .) assumes that there are criteria to judge which specializations, and consequently which policy targets are smart" (Giannitsis 2009, p. 4). In other words, a consistent matching between investments in knowledge and human capital and the present territorial "vocations" represents a difficult and crucial challenge, impinging on a creative and by no means mechanistic decision process.

Besides specialization and embeddedness in the local knowledge domain, the smart specialization calls for a particular attention to the connectedness among different geographical areas and knowledge domains; cooperation linkages represent the main potential for learning, either through the integration of different knowledge bases, a general purpose, and an applied one, or through best practice of innovation application. For this reason, likely to interact in this kind of innovative pattern are regions with a similar industrial vocation; industrial distance, intended as different industrial specialization patterns, discounts the flows of informal knowledge that comes from outside the region.

The territorial precondition for this innovation pattern consists of the *territorial creativity* of entrepreneurs able to access and absorb external knowledge and use it to invent co-applications. On this particular aspect, the smart specialization

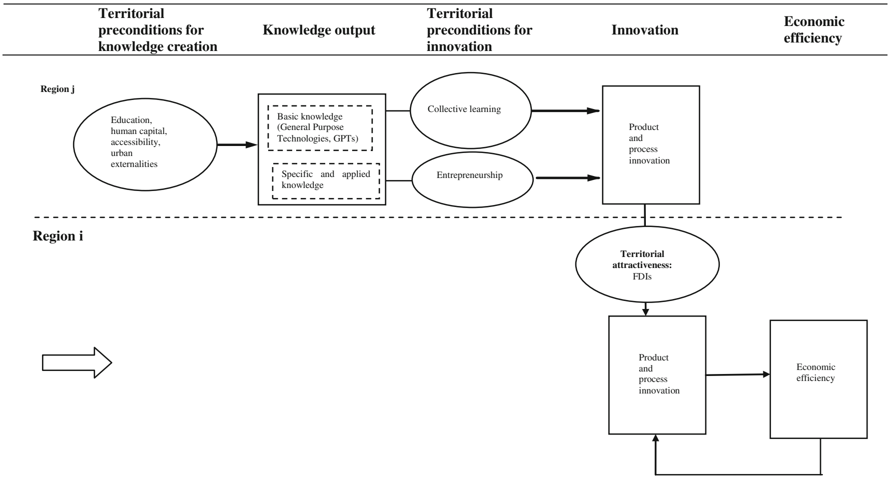

Fig. 3 Imitative innovation pattern. *Source*: (Capello 2012)

argument is very clear: the search and discovery process around the traditional specialization have to be a bottom–up process, in which local entrepreneurs are identified as the leading actors, being the main knowledge and creativity keepers, interested in efficiently exploiting existing cognitive resources and driving their re-orientation toward new innovative but related fields. For the same reasons, the smart specialization expert group warns against the use of a top–down approach for the identification of specialization, which could be disruptive for an otherwise efficient policy strategy (Camagni and Capello 2012). This can more easily happen in a context open to innovation which nourishes itself with external knowledge useful for its local purposes and needs.

This second pattern is receiving high policy attention in Europe nowadays, highlighting a strong policy debate at the EU level (Foray et al. 2009; McCann and Ortega-Argilés 2011; Camagni and Capello 2012).

Another innovation pattern which can be envisaged is an *imitative innovation pattern* whereby a region innovates by adopting external innovations. Presented in Fig. 3 is an adoption innovation pattern where, in the absence of local preconditions for knowledge and innovation creation, technological developments at the local level result from the passive attitude—in terms of invention, knowledge creation, and innovation generation—of a region which is fed by external actors with innovations already developed elsewhere (Fig. 3). This innovation pattern draws upon the large literature on "innovation adoption" which, since the seminal work of Hägerstrand (1952), has sought to interpret the spatial channels and mechanisms of innovation diffusion and adoption.

This imitative pattern is not necessarily the least efficient. Regions can be creative and rapid in the imitation phase by deepening and improving productivity in existing uses, by adapting existing uses to specific local needs, by adjusting products to local market interests, and by adapting innovation processes to local productive needs. Regions can also be more passive and imitate innovation as it was conceived.

Especially in this last case, the right innovation policy for this pattern has nothing to do with efficiency in R&D activities, or in supporting co-inventing applications. In this case, policy actions should be devoted to achieving the maximum return to imitation, and this aim is achieved through the creative adaptation of already-existing innovations, that is, through adoption processes driven by creative ideas concerning how already-existing innovations can be adopted in response to local needs.

Territorial attractiveness is the precondition for regions to acquire external innovations. A large final market (market seeking) and/or labor cost competitiveness (efficiency seeking) are likely preconditions for becoming an area attractive to Foreign Direct Investments (FDIs) (Dunning 2001, 2009; Cantwell 2009). Regions exchanging innovation through FDIs are likely to be regions with strong income differentials. The impact of international technology transfer and spillovers, in the form of FDIs as well as of traded goods, on innovative and economic performance is largely documented and debated in the literature, albeit with mixed results (Rama 2008). In fact, especially FDIs in R&D activities in host countries can sustain and stimulate local innovation, through the processes of learning and upgrading. Despite warnings about the risks of technological dependence and lock-in (Dyker 2001) or specialization in low value-added activities (Dunning 1994) and asymmetries in market and technological power (Rama 2008), the contribution of international technological and innovation can be substantial in comparison with local innovation. Several studies indeed confirm a positive impact of FDIs on regional innovative and economic performance, being inward FDIs a valuable channel of international technology transfer and an opportunity for host regions to enter more advantageously and faster into global value chains (Pavlínek 2002, 2004; Carlsson 2006; Varga and Schalk 2004).

In the rest of the paper, the aim was to determine whether the innovation patterns conceptually identified actually exist. To this end, a rich dataset including several indicators, measuring both the knowledge and innovation domains, as well as the internal and external context conditions for the generation and acquisition of knowledge and innovation, is built for 262 NUTS2 of all 27 EU Member countries (Sect. 3).

The methodology used to identify the territorial patterns of innovation was a traditional cluster analysis, a methodology which makes it possible to group observations according to their proximity among the variables on which the clusters are derived. In this case, the variables were the degree of knowledge and innovation produced in a region. The variables identifying the context conditions helped in identifying the clusters and, accordingly, in defining the actual territorial patterns of innovation (Sect. 4).

3 Data description

To identify innovation patterns across European regions, we drew on an original data set currently being collected and developed within the framework of an ESPON (European Spatial Observation Network) project—the KIT (knowledge, innovation, and territory) project—which encompasses several dimensions of knowledge and innovation creation and diffusion.

Data collection was based on EUROSTAT NUTS2 classification. The use of administrative areas in empirical analyses has long been debated. In particular, we chose

NUTS2 regions for two different reasons. The first reason was a conceptual one: NUTS3 regions are often too small to encompass functional urban areas, while NUTS1 regions tend to be too large for it to be possible to highlight local effects within their boundaries. The second reason was a practical one related to the scarcity of data, especially innovation data, at NUTS3.

The richness of our dataset derives from the fact that it encompasses all the elements that characterize the territorial patterns of innovation, namely endogenous knowledge and innovation, external knowledge and innovation potential, as well as the regional preconditions behind them. Accordingly, we can group our indicators as follows:

1. Knowledge and innovation creation;
2. Regional preconditions for knowledge and innovation creation;
3. Inter-regional knowledge and innovation flows and potentials (i.e., external knowledge and innovation);
4. Regional preconditions necessary to benefit from external knowledge and innovation.

Grouped in this way, the indicators are fully described in Tables 1, 2, 3 and 4, respectively. Most of them are traditional indicators: others are more innovative, and their construction and links with the literature require more detailed explanation.

3.1 Knowledge and innovation creation

Knowledge data mostly relied upon patent data available from the OECD REG-PAT database,[2] from which we drew selected information (Table 1).

Firstly, the size of a region's knowledge base was measured by means of a traditional indicator of the share of a region's patents in Europe in the period 1998–2001 as well as by the level of R&D expenditures on GDP in the period 2000–2002.[3]

More importantly, and differently from previous studies, we also developed a list of indicators capturing the nature and type of the knowledge created in a region—namely the degree of basic, pervasive, and original knowledge.

The degree of basic knowledge generated in a region was measured through the presence of general purpose technologies (GPTs) in the region. For each region i, we computed a technological specialization index on the basis of the number of patents applied for in GPTs. GPTs include nanotechnology, biotechnology, and ICTs, as also claimed by some studies (Foray et al. 2009). We assigned patents to these technologies on the basis of their IPC codes (see also footnote 4) following the OECD classification. The focus on these technologies was motivated by the fact that they are considered to have wider applications, large adoption and diffusion potential and, ultimately,

[2] Patents were assigned to regions according to the respective inventor's residence address as available in patent documents. Fractional count is applied. The authors are grateful to CRENoS—University of Cagliari (Italy) for granting access to, and use of, their patent database.

[3] We are aware that this measure may be affected by size effects because bigger regions may have larger shares of total EU patents. However, this is not a major concern because the correlation coefficient between the regional share of EU patents and the share of regional patents normalized by the regional population is about 0.8.

Table 1 Knowledge and innovation creation: indicators and measures

Indicators	Measures	Computation	Year	Source
Knowledge				
R&D	R&D expenditures	Share of R&D expenditures on GDP	Average value 2000–2002	CRENoS database
Knowledge	Share of patents	Regional share of EU total patents	Total patents in the period 1998–2001	Authors' calculation on CRENoS database
Specialization in GPTs	Index of specialization on patents in GPTs (i.e. nanotech, ICT, biotechnology)	Location quotient of regional GPTs patents	Total patents in the period 1998–2001	Authors' calculation on CRENoS database
Generality	Opposite of the Herfindal index on the technological classes of forward citations[a]	See Eq. 1	Total patents in the period 1998–2001	Authors' calculation on CRENoS database
Originality	Opposite of the Herfindal index on the technological classes of backward citations[a]	See Eq. 2	Total patents in the period 1998–2001	Authors' calculation on CRENoS database
Capabilities (knowledge embedded in human capital)	Share of managers and technicians	Factor analysis on the share of managers and technicians	Average value 1997–2001	European Labour Force Survey
Innovation				
Product and/or process innovation	Firms introducing a new product and/or a new process in the market	Share of firms introducing product and/or process innovations	One value for the period 2002–2004	Authors' estimation on CIS (Eurostat) data
Marketing and/or organizational innovation	Firms introducing a marketing and/or an organisational innovation	Share of firms introducing marketing and/or organizational innovations	One value for the period 2002–2004	Authors' estimation on CIS (Eurostat) data
Product innovation	Firms introducing a new product in the market	Share of firms introducing a product innovation	One value for the period 2002–2004	Authors' estimation on CIS (Eurostat) data

Table 1 continued

Indicators	Measures	Computation	Year	Source
Process innovation	Firms introducing a new process in the market	Share of firms introducing a process innovation	One value for the period 2002–2004	Authors' estimation on CIS (Eurostat) data
Product and process innovation	Firms introducing both a new product and a new process in the market	Share of firms introducing both product and process innovations	One value for the period 2002–2004	Authors' estimation on CIS (Eurostat) data

[a] Patent citations are here classified according to the 7 technology fields classification developed by OST (see also Table 3 footnotes for further details)

Table 2 Regional preconditions for knowledge and innovation creation: indicators and measures

Indicators	Measures	Computation	Year	Source
Regional preconditions for knowledge creation				
Scientific human capital	Share of inventors	Share of inventors on population	Average value 1999–2001	AQR calculations on CRENoS database
Highly educated human capital	Share of highly educated people	Share of people aged 15 and over with tertiary education on total population	Average value 1999–2001	CRENoS database
Accessibility	Rail and road network length by usable land	Km of rail and road network on usable land	2000	ESPON
Agglomerated regions	NUTS2 with more than 300,000 inhabitants and a population density of more than 300 inhabitants per km sq., or a population density between 150 and 300 inhabitants per km sq.	Dummy variable equal to 1 if the region is classified as agglomerated	2000	ESPON
Regional preconditions for innovation creation				
Entrepreneurship	Share of self-employment (wholesale and retail excluded)	Share of self-employed on total labor force (wholesale and retail sectors excluded)	Average value 1999–2004	Eurostat
Collective learning	Concentration in manufacturing sectors	Herfindal index on the share of employment in manufacturing sub-sectors[a]	Average value 1999–2001	Eurostat
Strategic vision on innovation	Perception of innovation as a relevant factor for growth	Factor analysis on Eurobarometer questions on innovation importance to economic performance and broadband penetration rate[b]	2005	Eurobarometer 63.4 and Eurostat

[a] Six manufacturing sub-sectors are considered, namely: food, beverages, and tobacco; textiles and leather; coke, refined petroleum, nuclear fuel, and chemicals; electrical and optical equipment; transport equipment; and other manufacturing [b] See Appendix for the list of variables used in and details about the factor analysis

Table 3 Inter-regional knowledge and innovation flows: indicators and measures

Indicators	Measures	Computation	Year	Source
Inter-regional knowledge and innovation flows				
Knowledge potential	Share of patents in GPTs of all other regions weighted by cognitive proximity	Sum of the share of patents of all regions, but the focal one, weighted by the cognitive proximity to the focal region	Total patents in the period 1998–2001	Authors' calculation on CRENoS database
Capability potential	Capabilities of all the other regions weighted by industrial proximity	Sum of the capabilities of all regions, but the focal one, weighted by industrial proximity to the focal region	Average value 1997–2001	European Labour Force Survey and Eurostat
Innovation potential	FDI penetration rate	Number of new foreigner firms in manufacturing on total population (inward FDIs)	Average values 2005-2007	FDI-Regio, Bocconi-ISLA
Proximity matrices				
Cross-regional cognitive proximity	Cross-regional common knowledge base in a digit-1 technological class multiplied by cross-regional knowledge complementarity in digit-2 technological subclasses belonging to the digit-1, summed over classes	See Eq. 3	Total patents in the period 1998–2001	Authors' calculation on CRENoS database
Industrial proximity	Cross-regional similarity in production specialization	Euclidean proximity between regional location quotients in 6 different manufacturing sectors[a]	Average values 1998-2001	Eurostat

[a] Six manufacturing sub-sectors were considered, namely: food, beverages, and tobacco; textiles and leather; coke, refined petroleum, nuclear fuel, and chemicals; electrical and optical equipment; transport equipment; and other manufacturing

Table 4 Regional preconditions for benefiting from external knowledge and innovation: indicators and measures

Indicators	Measures	Computation	Year	Source
Regional preconditions for external knowledge and innovation acquisition				
Receptivity	Capacity of the region to interpret and to use external knowledge (i.e., degree of networking)	Regional 5th Framework Program funding per capita	Average value 1998–2002	Authors' elaboration on CRENoS database
Creativity	Sensibility, interest, and openness to innovation	Factor analysis on Eurobarometer questions on sensibility, interest, and openness to innovation	2005	Eurobarometer 63.4
Attractiveness	Regional wage differential with respect to the EU average	$W_{\mathrm{Reg}\_i} - W_{\mathrm{EU\ average}}$	Average value 1999–2001	Eurostat

greater economic impact. Moreover, the lagged development and adoption of these technologies in Europe are considered to be one of the main causes of the European productivity gap with respect to the US (Foray et al. 2009). The specialization index was computed as the share of GPTs at regional level for the period 1998–2001 with respect to the European share of patents in GPTs.

Pervasiveness was captured through a *generality* index (Hall et al. 2001), that is, an adapted Herfindal index on the technological classes[4] of the citations received (i.e., *forward citations*) by the patents applied for in the period 1998–2001. More general and pervasive knowledge are used in a wider spectrum of diverse technological applications, and it is thus of greater technological value than more specific and targeted knowledge. In detail, this was computed as the opposite of the Herfindal index on the technological classes of forward citations (H_{forward}), as follows:

$$\mathrm{Generality} = 1 - H_{\mathrm{forward}} = 1 - \sum_{j=1}^{7} \left(\frac{\mathrm{cit\_forward}_{ij}}{\mathrm{cit\_forward}_{i}} \right)^2 \tag{1}$$

where $\mathrm{cit\_forward}_{ij}$ is the number of forward citations in region i in technological class j.

[4] Every patent is attributed to one or more technological classes according to the international patent classification (IPC). We reclassified patents according to a 30 technological field classification that aggregates all IPC codes into 30 technological fields, and then into 7 main technological fields. This is a technology-oriented classification, jointly elaborated by Fraunhofer Gesellschaft-ISI (Karlsruhe), Institut National de la Propriété Industrielle (INPI, Paris) and Observatoire des Sciences and des Techniques (OST, Paris). To compute the generality and the originality indexes, we used the 7-class classification.

Originality of the knowledge produced, that is, the extent to which the knowledge being developed in each region is original compared to the state of the art and recombines pieces of knowledge distributed across different technical fields, was measured by means of an *originality* index (Hall et al. 2001). More original knowledge is likely to be associated with previously unexplored technological applications and with more radical inventions. This is also an adapted Herfindal index on the technological classes of the citations made (i.e., *backward citations*) by the patents applied for in the period 1998–2001 (H_{backward}). In detail, it was computed as the opposite of the Herfindal index on the technological classes of backward citations, as follows:

$$\text{Originality} = 1 - H_{\text{backward}} = 1 - \sum_{j=1}^{7} \left(\frac{\text{cit\_backward}_{ij}}{\text{cit\_backward}_{i}} \right)^2 \qquad (2)$$

where cit_backward$_{ij}$ is the number of backward citations in region i in technological class j. with classes j available in a number of 7.

Lastly, in order to capture the knowledge not directly linked to patent activities, and which is instead embedded in human capital available in a region in the form of *technical and managerial capabilities*, an indicator was derived from a factor analysis aimed at synthesizing the information provided by two variables, that is, the share of production and specialized service enterprise managers, and physical and engineering science associate technicians on total employment. In fact, skilled and specialized human capital is an important repository of embedded and tacit knowledge and can identify the pool of capabilities locally available. One factor, extracted by the principal component method, is associated with the two variables (i.e., correlation greater the 0.75). The percentage of variance explained is 58.18.

We expected the three patterns to differ in terms of knowledge creation capacity and the nature of knowledge produced. In particular, the endogenous innovation pattern was expected to show a strong knowledge base of a pervasive and original nature. The creative application pattern was expected to have a not negligible knowledge base, although one of a relatively more applied and specific nature, as well as some degree of informal knowledge embedded in managerial and technical competencies. The third innovation pattern was expected to be relatively weaker on all these dimensions.

Innovation data were estimated by the authors on the basis of data from the community innovation survey (CIS) EUROSTAT database. In particular, innovation indicators were based on national CIS4 wave figures (covering the 2002–2004 period), next developed at the NUTS2 level. As in the case of knowledge, a general indicator of the degree of innovation was the regional share of firms introducing a product and/or a process innovation.[5]

[5] For an in-depth explanation of the estimation methodology of NUTS2 CIS data and the benchmark exercises implemented as consistency and robustness checks on our estimates, see Capello et al. (2012). Previous exercises implemented for the DG Industry and DG Regio (Hollanders et al. 2009) elaborated and used as well a dedicated estimation strategy to derive regional innovation data. Notwithstanding the use of a different methodology, our results are reasonably consistent with previous estimates.

Importantly, we distinguished between different types of innovation by making use of different questions in the CIS. This distinction is not a minor one, because different innovation strategies require a different mix of knowledge and competencies. In fact, product innovation can be associated with a technological competitiveness strategy, whereas process innovation can be associated with a price competitiveness strategy (Pianta 2001). The former involves substantial inventive and innovative efforts intended to introduce new products and to gain market shares, if not to open new markets. The latter focuses on efficiency gains obtained thanks to technological changes such as the introduction of adjustments in the production process or the adoption of new machinery, with the ultimate goal of decreasing labor costs and/or increasing production flexibility, which may lead to market shares gains (Bogliacino and Pianta 2010). In particular, we were able to compute the share of firms introducing only product innovations, the share of firms introducing only process innovations, the share of firms introducing product and process innovations (both types of innovation simultaneously, as well as all the first three main typologies altogether), and the share of firms introducing marketing and/or organizational innovations.

We expected the first territorial innovation pattern to show the greatest innovation potential in all respects and to be relatively more specialized in product innovation, whereas the second and the third would be relatively more specialized in process innovation. In fact, product innovation generally requires a larger (scientific and formal) knowledge base and larger investments in knowledge advances. Differently, process innovation generally relates more to applied, informal, and tacit knowledge.

3.2 Regional preconditions for knowledge and innovation creation

Indicators on the regional preconditions for knowledge creation were relatively traditional indicators proposed in the literature (Table 2). Among all indicators, two were available: the degree of scientific human capital in the region, measured, respectively, by the share of inventors and by the share of highly educated people; and the degree of accessibility (transport infrastructure) in the region. We lacked an indicator of high-level functions, like universities and research centers, for which no reliable data exist with EU27-wide coverage at NUTS2 level. The availability of a dummy capturing the size of cities in a region (the so-called agglomerated regions) was of help in compensating for the lack of these data.

We expected especially the first territorial innovation pattern to exhibit a relatively larger endowment in terms of scientific human capital and a higher accessibility, also related to the likely location in urban settlements. Metropolitan areas, in fact, are the main sites of knowledge creation, the "incubators" of new knowledge; the principal centers of research are mostly located in cities, given their large pools of expertise and the availability of advanced services (finance and insurance) ready to carry the risk of any innovative activity.[6]

[6] The availability of financial resources such as venture capital is certainly crucial for engaging in highly risky and costly activities such as research and innovation. Moreover, the availability of financial services such as venture capital shows a prominent tendency to cluster in space and an uneven distribution at the regional level. Unfortunately, the lack of consistent, comparable and detailed data at the NUTS2 level for

As regards a region's capacity to translate knowledge into innovation, the milieux innovateurs theory and the knowledge filter theory stress the presence of collective learning and entrepreneurship as the local preconditions for knowledge to be turned into useful innovative applications (Acs et al. 2004). Entrepreneurship was measured as the share of self-employment, with the exclusion of wholesale and retail sectors that might create distortions in the indicator. Collective learning was indirectly measured through the degree of concentration in manufacturing sectors, the idea being that the higher the concentration in specific sectors, the higher the (unintended) exchange of knowledge among local firms, as claimed by the theory of milieux innovateurs (Camagni 1999) and innovative clusters (Cooke 2001; Asheim and Coenen 2005). We also added an indicator derived from factor analysis capturing the entrepreneurial and strategic vision of innovation as an element crucial for competitiveness and growth.

We expected especially the second territorial innovation pattern to show a larger endowment in terms of these variables because they represent the preconditions for "smartly" and creatively adapt external knowledge to local innovation needs.

3.3 Inter-regional knowledge and innovation flows

Regional knowledge and innovation intensity also depend considerably on the capacity of regions to attract, absorb, recombine, and adopt knowledge and innovation sourced from other regions. Specific indicators were built to measure the flows of inter-regional knowledge and innovation, that is, the external knowledge and innovation potential of a region (Table 3).

In particular, in order to capture the potential benefits that may accrue to each region i from the pool of basic (GPTs) knowledge developed by other regions (i.e., *knowledge potential*), we computed the sum of the share of all GPTs patents developed by all the N-i regions weighted by a measure of cognitive proximity between each pair of regions. In fact, the flows of basic knowledge are influenced to a limited extent by gravity-type behaviors, proxied by physical proximity, and much more by similar backgrounds, cognitive maps, and common basic knowledge shared by two regions. For this reason, the potential acquisition of basic knowledge from other regions was weighted by the degree of cognitive proximity between pairs of regions.

Cognitive proximity among actors in a region was defined in terms of related variety, that is, the presence of complementary knowledge within a set of shared and common knowledge (Boschma 2005). This idea was transferred to the inter-regional level, and it was measured as the inter-regional knowledge similarity in a specific technological macro-field i multiplied by the interregional knowledge variety in the technological subfields of macro-field i among each pair of regions.

We in fact assumed that the capacity to absorb and to use GPTs knowledge sourced from other regions depends on what we call "cross-regional cognitive proximity" between two regions. Two regions are in fact cognitive proximate if they have

Footnote 6 continued
all EU countries prevented us from including this element in the analysis, although we acknowledge the importance of this aspect when studying innovation processes. As mentioned in the main text, we indirectly controlled for this by means of the dummy variable for agglomerated regions.

complementary sets of skills and competences pertaining to a common knowledge base (Capello and Caragliu 2012). Two main elements must be measured to capture such proximity. First, it positively depends on two regions sharing a common knowledge base and cognitive frame in technological macro-fields. Second, it is more likely to occur when two regions are specialized in different, albeit related and complementary, technological subfields within a common knowledge base, that is, “cross-regional related” variety.

Common knowledge base is captured through the degree to which the distribution of patents across technological macro-fields in two regions overlaps. It is the product of the share of a region’s i patents in class d_1, that is, p_{id1}, times the share of region’s j patents in class d_1, that is, p_{jd1}, summed over classes. This is discounted by the difference between the share of patents in class d_1 of the two regions to account for the fact that common knowledge base is likely to be higher the more similar the importance of the sector in the two regions. Common knowledge base equals 1 for regions with exactly the same distribution of patents across classes, and 0 for regions with no patents in the same classes. Complementarity within a knowledge base is measured by the difference between the shares of patents in 2-digit technological classes belonging to a 1-digit class in two regions. The greater the difference between the two regional shares of patents in 2-digit technological classes, the higher the complementarity between regions. Two-digit is represented by the 30 technology fields of the OST classification, and 1-digit by the 7 OST main technological fields (see footnote 4 for further details on the OST classification).

Finally, because of the high skewness of the distribution of this variable, data were transformed using a square root transformation, a methodology largely applied in the literature (Hollanders et al. 2009).

All this is summarized in the following formula:

$$\text{Cross-regional cognitive proximity} = \sqrt{\sum_{d1=1}^{n}\left[\frac{(p_{id1} * p_{jd1})}{(|p_{id1} - p_{jd1}|)} * \left(\sum_{d2=1}^{m}(|p_{id2} - p_{jd2}|)\right)\right]} \tag{3}$$

where n represents the number of 1-digit technological classes, m the number of 2-digit technological subclasses within each n digit-1 class, p_{id2} the share of region’s i patents in digit-2 subclass d_2, p_{jd2} share of region’s j patents in digit-2 subclass d_2, p_{id1} the share of region’s i patents in digit-1 class d_1, p_{jd1} share of region’s j patents in digit-1 class d_1.

We expected a greater knowledge potential to be associated especially with the first territorial pattern, because of its stronger knowledge vocation and, accordingly, higher absorptive capacity to scout external basic knowledge and to integrate it into the local research and knowledge trajectories.

Next, in order to capture the potential benefits that may accrue to each region i from the pool of embedded knowledge available in other regions (i.e., *capability potential*), we computed the sum of the capabilities in all the n-i regions weighted by a measure of industrial proximity between each pair of regions. The exchange of capabilities is in fact higher, the closer the similarities in terms of industrial mix. In particular, industrial proximity is measured as the similarity between pairs of regions in their location quotient on the basis of employment data in six manufacturing sectors. The greater this similarity, the greater the opportunity to benefit from embedded knowledge in human capital sourced from other regions, that is, capabilities external to the region.

We expected the second territorial innovation pattern to show a greater capability potential, because of its relative specialization in more applied and less formal knowledge, frequently sourced from external regions and then rapidly adapted to local business needs.

Finally, in order to take into account the potential benefits that may accrue to each region i from the pool of innovations developed in other regions (*innovation potential*), we drew on the evidence that multinational corporations and FDIs can be considered as innovation diffusion channels and promoting learning processes (Cantwell and Iammarino 2003; Castellani and Zanfei 2006). We thus computed the number of new foreigner firms (inward FDIs) in each region in the manufacturing sector and discounted it by the regional population size.

We expected this to be prominent in the third territorial innovation pattern, which (in relative terms) lacks endogenous knowledge and innovation capacities and is more likely to draw on external innovation that may be imitated perhaps with some degree of elaboration and by making some adjustments to the original product concepts. As recent evidence shows, inward FDIs are increasingly concentrated in Central and Eastern European countries. Accordingly, we expected especially the third pattern to be more common in newly accessed countries.

3.4 Regional preconditions for benefiting from external knowledge and innovation

The knowledge and innovation potentials are likely to be enhanced by specific regional preconditions for external knowledge and innovation acquisition. Data on regional preconditions for benefiting from external knowledge and innovation are presented in Table 4.

Receptivity is defined as the capability of the region to exchange, to interpret, and to use external knowledge for complementary research and science advances. It is therefore the precondition for a region to acquire external knowledge and to use it efficiently. To capture this relational and networking capacity, we used an indicator of the 5th framework program funding per capita.

We expected relational and networking capabilities to be especially associated with the first territorial pattern of innovation. In fact, the complex and systemic nature of knowledge has increasingly made its production more dispersed. In most cases, regions reinforce and complement their internal knowledge with external knowledge through diffusive, mostly unintentional, channels based on spatial proximity, subject to strong distance decay effects, and/or through selective relations based on a spatial networks or non-spatially mediated channels (“a-spatial linkages”) that may take place at both short and long distances according to the organization of forms of transfer and exchange of information and knowledge different from pure spatial proximity.

Creativity is instead necessary for a region to achieve knowledge and turn it into local innovation, adding to internal specific capabilities not necessarily embedded in formal knowledge. Meant by "creativity" is recombination capability, the ability to identify new needs and the right basic technology of local actors, the ability to combine local knowledge and external knowledge anew, the ability to identify a gap in the application of existing technologies and to make creative efforts to overcome that gap. Creativity was therefore expected to be prominent especially in the second pattern, in which regions must develop an original and unique knowledge domain and discover the research and innovation areas in which they can hope to excel, according to their productive vocations. This discovery is made by firms and talented entrepreneurs that must achieve new combinations between technologies and various elements of the value chain, and construct very different and unpredicted competitive advantages in specific market niches. This variable was measured by means of a factor analysis on the Eurobarometer questions on sensibility, interest, and openness to innovation of the local population.[7]

By "attractiveness" is meant the capacity of a region to receive innovations developed outside the region and apply it to local needs. If innovation mainly derives from advanced multinational firms, from which the local firms system can imitate managerial, organizational, product, and process innovation, a good proxy for FDI attractiveness is low labor cost, measured by the region's wage differential from the European average. Accordingly, this was expected to characterize especially the imitative innovation pattern.

4 Methodological aspects

A cluster analysis was performed to combine regions into groups and to identify different patterns of knowledge and innovation across regions, the aim being to describe the variety of attitudes and knowledge and innovation behaviors across European regions. The purpose of the clustering exercise was to identify similarities and differences across regions.

In particular, we performed a *k*-means cluster analysis[8] based on the degree of knowledge and innovation in general produced by a region. In our conceptual approach, in fact, knowledge and innovation take place in different stages of the production process and can mix in a variety of ways. In particular, the cluster analysis was run with two innovation variables and one knowledge intensity variable; for the innovation variables, the share of firms introducing product and/or process innovation and the

[7] See Appendix for the list of variables used and details about the factor analysis.

[8] We opted for the *k*-means approach because, in the literature, it is preferred to hierarchical approaches (Afifi et al. 2004). The algorithm implemented by *k*-means cluster analysis assigns a case to the cluster for which its distance to the cluster mean is the smallest. Once the '*k*' number of expected clusters has been specified, the algorithm starts with an initial set of means and classifies cases based on their distances to the centers. Next, it computes the cluster means again, using the cases assigned to the cluster, and it reclassifies all cases according to the new set of means. This step is repeated until cluster means do not change much between successive steps. Finally, the means of the clusters are calculated once again, and the cases are assigned to their permanent clusters.

share of firms introducing marketing and/or organizational innovations were chosen, since they encompass the largest category of innovators and can thus take different innovation typologies into account. Used for the intensity of knowledge production was the indicator of the region's knowledge base size (i.e., the share of EU total patents).

There were both conceptual and empirical reasons for this choice. The conceptual reason was that this approach makes it possible to emphasize the role of endogenous knowledge and innovation creation capabilities. Our purpose, in fact, was to derive a taxonomy of knowledge and innovation potentials in European regions to be then read in light of specific territorial elements. The methodological reason was that running a cluster analysis on more than 20 variables would lead to a very large number of clusters of small size, and therefore with scant explanatory power and interpretability in terms of innovation patterns.

The choice of running a cluster analysis on both knowledge and innovation was not neutral vis-à-vis the results. In fact, the ranking obtained provided in some cases some counterintuitive results that go against general beliefs coming from the usual ranking based only on knowledge production, and that can be explained by the fact that some regions have prominent positions in generating knowledge but do not show the same performance in innovation activities.

We considered various statistical criteria with which to identify the appropriate number of clusters to be retained, such as the relationship between within-cluster and between-cluster variance, but also the number of firms per se. The balance between the information advantages provided by expanding the number of clusters and the interpretability of the results in terms of innovation patterns supported the extraction of five clusters; each cluster included a reasonable portion of observations, so that they could be plausibly interpreted as patterns of innovation. They statistically and significantly differed in the main variables used for the clustering exercise, as the results of the ANOVA tests presented below show. Indeed, the magnitude of the *F* values performed on each dimension is an indication of how well the respective dimension discriminated between clusters.[9]

These five clusters were highly stable. Repeating the extraction with different similarity measures and specifying different *k* random initial group centers yielded highly consistent results. Only a minor portion of regions, in fact, were assigned to a different group.

Performing an ANOVA exercise on the variables presented in Tables 1, 2, 3, and 4 provided interesting additional information that made it possible to emphasize the differences among clusters in terms of key distinctive territorial preconditions for knowledge and innovation creation and acquisition. Table 5 synthesizes the results of the ANOVA exercise and presents the mean values of the variables across the five clusters, in EU27 and (in the last column) the significance level of the ANOVA test.

The variables used for the clustering exercise reported in Table 5 at first sight simply provide a ranking of EU27 regions in terms of their endogenous knowledge and innovation performance from cluster 1 (the least knowledge and innovation intensive)

[9] The *F* test was used only for descriptive purposes because the clusters were chosen precisely to maximize the differences among cases in different clusters. The observed significance levels were not corrected for this and therefore cannot be interpreted as tests of the hypothesis that the clusters means are equal.

Table 5 Mean values by cluster and in EU and ANOVA test statistical significance (p value)

Variables	Imitative innovation area (1)	Smart and creative diversification area (2)	Smart technological application area (3)	Applied science area (4)	European science-based area (5)	EU average	ANOVA p value
Number of observation	37	86	67	52	20	262	
Variables used in the cluster exercise							
Knowledge (%)	0.01	0.13	0.40	0.48	1.53	0.35	$p < 0.01$
Product and/or process innovation (%)	18.14	27.58	38.43	46.36	63.16	35.54	$p < 0.01$
Marketing and/or organizational innovation (%)	13.94	22.05	19.61	39.33	51.07	25.99	$p < 0.01$
Knowledge							
Variables used to describe clusters							
R&D (%)	0.4	1	1.71	1.81	2.56	1.37	$p < 0.01$
Specialization in GPT	0.68	0.65	0.84	0.86	0.92	0.76	$p < 0.05$
Share of patents in GPT (%)	18.66	17.95	22.91	23.58	25.24	20.85	$p < 0.05$
Generality	0.242	0.531	0.730	0.724	0.801	0.592	$p < 0.01$
Originality	0.384	0.636	0.759	0.749	0.804	0.661	$p < 0.01$
Capabilities	−0.30	0.36	−0.04	−0.29	−0.81	−0.01	$p < 0.01$
Innovation							
Product innovation (%)	4.13	5.01	15.38	12.20	23.46	10.40	$p < 0.01$
Process innovation (%)	5.88	10.65	12.23	12.97	13.41	11.05	$p < 0.01$
Product and process innovation (%)	8.13	11.91	13.97	21.66	26.29	14.97	$p < 0.01$
Regional preconditions for knowledge creation							
Scientific human capital (%)	0.001	0.005	0.013	0.018	0.034	0.01	$p < 0.01$

Table 5 continued

Variables	Imitative innovation area (1)	Smart and creative diversification area (2)	Smart technological application area (3)	Applied science area (4)	European science-based area (5)	EU average	ANOVA p value
Highly educated human capital (%)	5.38	7.97	10.77	10.91	11.24	9.12	$p < 0.01$
Accessibility (%)	12.42	17.46	31.47	34.70	59.52	26.62	$p < 0.01$
Agglomerated	4	15	30	15	13	77	Not applicable
Regional preconditions for innovation creation							
Entrepreneurship (%)	14.39	14.83	10.73	9.24	8.61	12.04	$p < 0.01$
Collective learning	26.10	29.07	29.13	29.50	28.86	28.75	$p < 0.05$
Strategic thinking on innovation	−0.87	−0.36	−0.07	0.22	0.48	−0.14	$p < 0.01$
Regional preconditions for external knowledge and innovation acquisition							
Receptivity (thousands euro per capita)	3,799.39	16,016.29	25,015.88	30,147.05	41,220.50	21,068	$p < 0.01$
Creativity	0.39	−0.05	−0.03	−0.59	−0.96	−0.13	$p < 0.01$
Attractiveness	9.45	1.54	−1.98	−2.66	−8.23	0.25	$p < 0.01$
Inter-regional knowledge and innovation flows							
Knowledge potential	99.07	92.04	102.44	102.31	106.33	99.07	Not significant
Capability potential	−0.91	0.07	−5.13	−49.50	−92.33	−18.60	$p < 0.01$
Innovation potential	51.57	55.22	55.48	30.73	20.60	47.16	Not significant
Regional stage of development							
EU12 (Dummy variable equal to 1 if the region is located in Bulgaria, Cyprus, Czech Republic, Hungary, Estonia, Latvia, Lithuania, Malta, Poland, Romania, Slovakia, Slovenia)	30	17	6	3	0	56	Not applicable

to cluster 5 (the most knowledge and innovation intensive). However, this description may be somewhat too straightforward, and it may hide a greater variety of knowledge and innovation potentials and behaviors. The ANOVA exercise was very helpful in this regard and helps better to qualify the cluster description and identification. In fact, careful inspection of the descriptive variables of each cluster yields an extremely rich picture in terms of cases of innovation and knowledge profiles associated with territorial preconditions for knowledge and innovation creation and acquisition. Results of the cluster analysis are described in the next sections.

5 A taxonomy of innovative regions in Europe

The empirical results of the cluster analysis highlight that there exists a variety even more fragmented than that conceptually envisaged (Fig. 4). There are two clusters that can be associated with our conceptual Pattern 1, whose difference resides in the intensity of knowledge creation, but especially in the quality of knowledge created. Moreover, two patterns can be associated with Pattern 2, whose difference lies in the type of knowledge that they acquire from outside the region: one (Cluster 3) mainly looks for formal knowledge (in the form of patents in specific technologies) outside the region, and therefore it links conceptually to the "periphery" type of groups envisaged in the smart specialization; the other, instead, acquires tacit knowledge, embedded in capabilities, and is therefore have nothing to do with the "co-application" area that is envisaged by the smart specialization approach. Interestingly, the five groups exhibit sizeable differences in the variables considered in the clustering exercise. The five patterns are briefly described below in terms of their characteristics.

5.1 Cluster 1: A European science-based area

Cluster 1 consists of the regions that are the most knowledge and innovation intensive. Their innovative attitude is well above the EU average across all dimensions (i.e., product, process, marketing, and/or organizational innovation). This couples with a very strong knowledge orientation which is more directed to GPTs than in the other cases (and above the EU average) in terms of both the amount of knowledge developed and specialization profile. Interestingly, this knowledge tends to be of greater generality and originality, that is, of greater technological value and more radical than the EU average. The regions in this cluster are also well endowed with the preconditions frequently associated with a greater endogenous capacity for knowledge creation, namely the presence of a highly educated population and, more importantly, the presence of scientific human capital, here measured by the share of inventors on total population. Their accessibility is also the highest among all clusters (Fig. 5), indicating that these regions probably comprise more urban and metropolitan settings (as confirmed by the variable accounting for the number of agglomerated regions), which are traditionally more open and fertile environments for new ideas generation (Carlino et al. 2007).

The indicators of regional preconditions for innovation creation, on the other hand, do not show the highest values across EU27. In particular, these regions are less entrepreneurial than the EU average. However, the variable accounting for collective

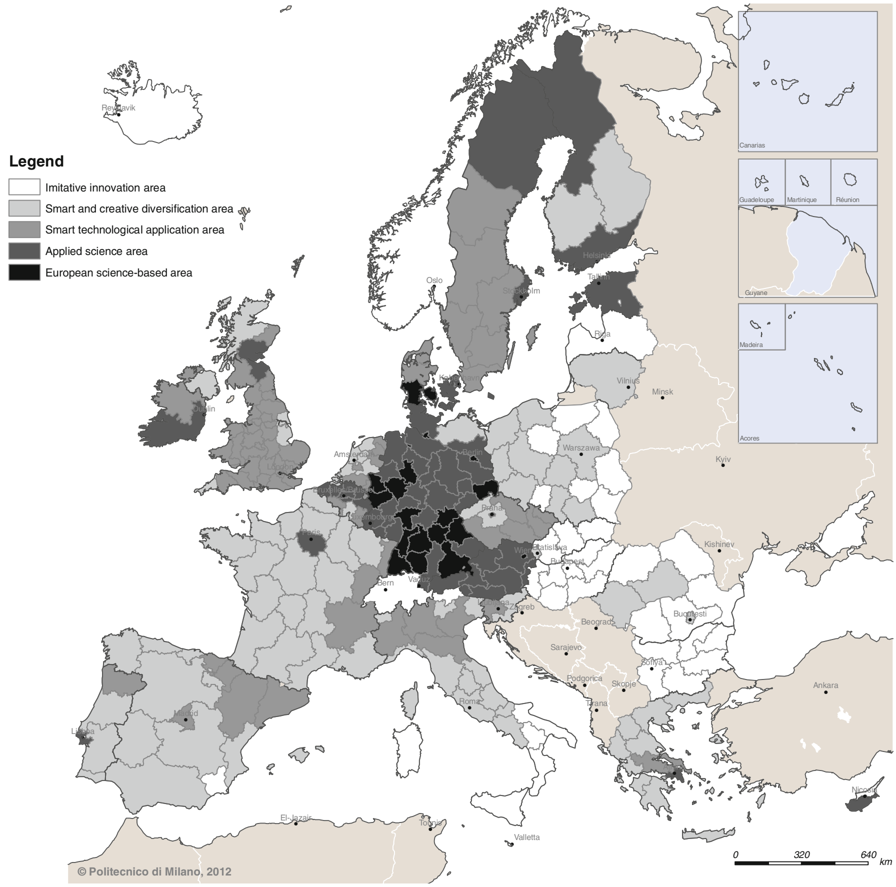

Fig. 4 Territorial patterns of innovation in Europe

learning shows a value comparable to the EU average and, interestingly, the regions in this cluster seem to have a more strategic attitude to the role of innovation in performance, competitiveness, and economic growth. As regards the variables relative to the preconditions for knowledge and innovation acquisition, these regions outperform the others in terms of their propensity to network (i.e., *receptivity*), whereas they seem less creative and attractive than the EU average (Fig. 6). Lastly, their capability and innovation potentials are below the EU average, whereas their knowledge potential is above it.

Overall, these observations suggest that these regions have a strong knowledge and innovation orientation which is primarily linked to their endogenous capacity to create new knowledge and to translate it efficiently into new products and processes, as well as into managerial and/or organizational changes. This marked orientation suggests that these regions can potentially host the *European science-based area* and be part of what has been termed the "European Research Area" (Foray et al. 2009; Pontikakis et al. 2009). These regions are mostly located in Germany, with the addition of Vienna, Brussels, and Syddanmark in Denmark.

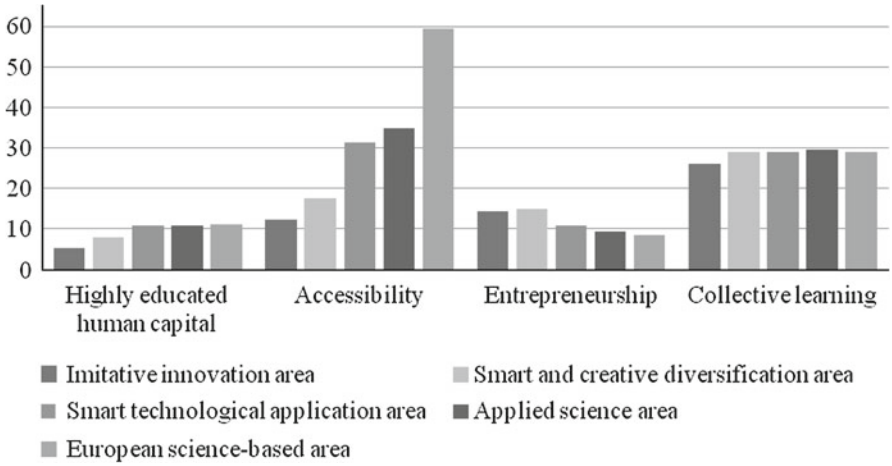

Fig. 5 Regional preconditions for knowledge and innovation creation (shares), by cluster

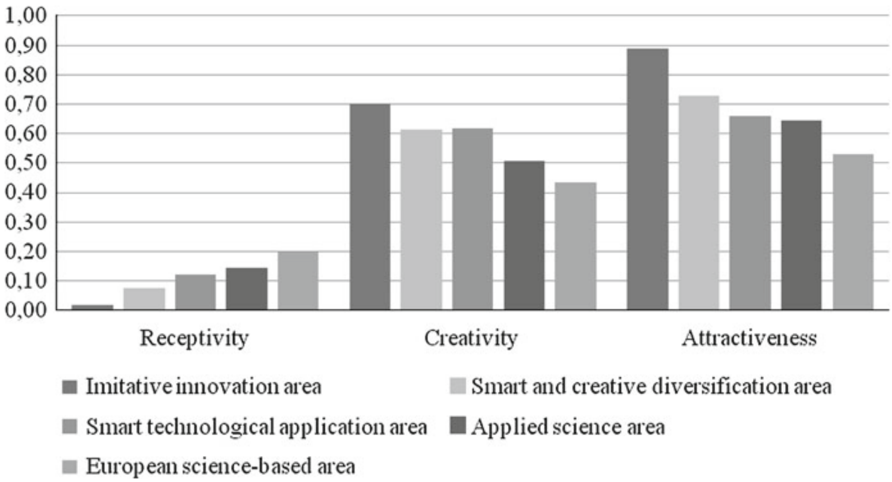

Fig. 6 Regional preconditions for external knowledge and innovation acquisition (normalized values), by cluster

It may come as a surprise that important knowledge centers like Paris, London, Helsinki, the Dutch (especially Eindhoven), and the Milan (Lombardy) regions are not included in this group (Fig. 4). In this respect, it is worth pointing out that, even if these regions are among the top regions in terms of total patent applications, from one side they are not specialized in general purpose technology, and from the other side they are mainly specialized in knowledge-intensive services, thus having a lower propensity to introduce product innovations. As mentioned above (Sect. 4), based on both knowledge and innovation, our taxonomy generates a different picture with respect to the ones based on simple raking of knowledge production.

5.2 Cluster 2: An applied science area

Cluster 2 includes a wider group of regions with characteristics similar to those of regions in cluster 1, although most of the variables show lower mean values. In particular, this is the case of the share of EU total patents, which is almost halved, as well as the share of scientific human capital and R&D expenditures. Interestingly, the importance of GPTs is lower both in terms of share of GPTs patents developed and in terms of specialization profile. Importantly, these regions appear more entrepreneurial, creative, attractive, and with larger capability potential than regions in cluster 1, although it is below the EU average. These regions thus maintain a rather strong knowledge and innovation intensity, that is, form a knowledge area; but differently from the ones in cluster 1, they are less focused on GPTs, and, accordingly, more specialized in a wider spectrum of applied technologies.

Figure 4 shows that these regions are mostly agglomerated and located in central and northern Europe, namely in Austria, Belgium, Luxembourg, France (i.e., Paris), Germany, Ireland (i.e., Dublin) Denmark, Finland, and Sweden, with some notable exceptions in the East such as Prague, Cyprus, and Estonia, and in the South, such as Lisbon and Attiki (Fig. 4). These are strong knowledge producing regions that distinguish themselves from the European science-based area by their applied knowledge production profile.[10] From the normative point of view, these regions can strengthen their positions by specializing in the production of applied knowledge, making use of the basic knowledge produced by the science-based area. If they do so, this group may become the "*applied science area*" of Europe.

5.3 Cluster 3: A smart technological application area

Regions in cluster 3 are rather different from those in clusters 1 and 2. They have knowledge bases of smaller size than in the previous two clusters and a lower intensity and importance of GPTs. By contrast, they show a greater endowment of embedded knowledge in human capital (i.e., capabilities). Despite their lower knowledge intensity, they are strongly oriented to product innovation, while they are somewhat weak in terms of process innovation (although more innovative than the EU average also according to this dimension), marketing and/or organizational innovation.

Their weak knowledge creation is associated with low regional preconditions for knowledge and innovation creation, while their strong product innovation capacity is linked to the fact that they have more favorable preconditions for knowledge and innovation acquisition, namely creativity and attractiveness, than in the previous clusters (Fig. 5 above).

Overall, these regions have the greatest advantage in terms of product innovation, accompanied by a high degree of knowledge potential flows and internal preconditions to translate external knowledge into innovation thanks to high creativity. These results

[10] Lisbon and Attiki's position in this cluster may be affected by a general overestimation of CIS data at national level encountered for Greece and Portugal, a common risk of all survey data based on respondents' self-reported evaluation, that can be considered as a limitation of the CIS data collection strategy and of its final national figures.

suggest that these regions are able efficiently to translate internal and external knowledge into new specific commercial applications. Cluster 3 can easily represent our conceptual Pattern 2, the creative application pattern, where co-invention of applications results from internal creativity and external basic knowledge. It includes mostly agglomerated regions in EU15, such as the northern part of Spain and Madrid, Northern Italy, the French Alpine regions, the Netherlands, Czech Republic, Sweden, and the United Kingdom (Fig. 4). Normative interventions should strengthen these specificities and push this group into being the "*smart technological application area*" of Europe.

It might sound as a strange result that the Rhône-Alpes and the Milan (Lombardy) regions belong to this cluster, since they were used to be among the top regions in terms of patent activities in Europe. In the case of Milan, this strange result is corroborated by a case study analysis highlighting that local firms in the ICTs sector in Lombardy, once fully capable of bringing new products to the market by exploiting local GPTs, and innovative capacity, must now look for scientific knowledge that is sourced from outside the region in order to innovate. The causes of this shift of innovation pattern has been identified in the insufficient innovation investments and poor governance of the ICTs sector in Lombardy, which nowadays registers attempts to launch new policies, in particular with regard to interesting and promising experiences concerning the production of vouchers for cooperative behavior in innovation activities by the regional board (ESPON 2012).

5.4 Cluster 4: A smart and creative diversification area

Cluster 4 exhibits some distinctive features that clearly discriminate regions in this group from the others. In particular, the knowledge and innovation variables show values below the EU average. However, these regions exceed in capabilities, which suggests that the not negligible innovation activities carried out in regions belonging to this cluster mainly rely upon tacit knowledge embedded in human capital.

Moreover, regions in this cluster appear highly entrepreneurial (this variable takes the highest mean value in this cluster) and, importantly, are strongly endowed with those characteristics such as creativity and attractiveness that help to absorb and to adopt innovations developed elsewhere. Additionally, whereas the knowledge potential does not seem prominent, the capability and innovation potentials are well above the EU average. Thus, the key advantages of these regions reside in their embedded human capital and the entrepreneurial and creative attitudes that can be wisely exploited to upgrade innovative strategies.

In these regions, a different type of Pattern 2 emerges with respect to cluster 3. In these regions, internal innovation capacity is largely fed by external knowledge, as is the case for cluster 3, but the type of knowledge is neither basic nor applied formal knowledge. These regions gain significant advantages from external knowledge embedded in technical and organizational capabilities, in technicians and managers (Cooke 2005). On the basis of the high degree of local creativity, these regions are able to take advantage of specific capabilities available in regions with similar sectoral profiles and to innovate in different industries (Fig. 7).

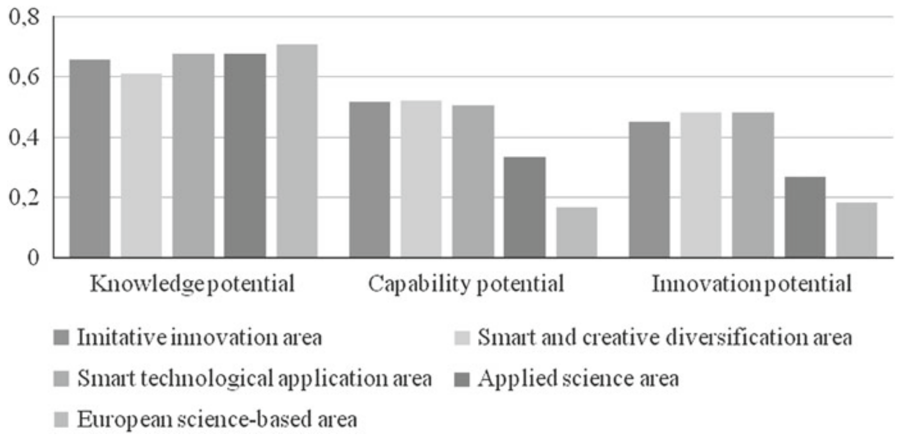

Fig. 7 Inter-regional knowledge and innovation flows (normalized values), by cluster

For this reason, the group of regions can be called *a smart and creative diversification area* in order to highlight a possible innovative strategy associated with these regions, namely a creative and appropriate diversification of existing specialization and an upgrading of their quality. These regions are mainly located in Mediterranean countries (i.e., most of the Spanish regions, Central Italy, Greece, and Portugal), in EU12 agglomerated and capital regions in Slovakia and Slovenia, Poland and Czech Republic, few regions in northern Europe, namely in Finland, and the United Kingdom (Fig. 4). Normative interventions should strengthen this innovative attitude and push these regions into becoming the "*smart and creative diversification area*" of Europe.

5.5 Cluster 5: An imitative innovation area

Finally, the last group (i.e., cluster 5) can be associated with Pattern 3. In fact, it consists of regions with rather narrow knowledge and innovation profiles and which are the worst performers in both respects. However, some key distinctive features characterize this cluster. In particular, entrepreneurship, creativity, attractiveness, capabilities, and innovation potentials show values above the EU average. Especially, attractiveness is stronger than in the other clusters (Fig. 7). These dimensions can be enhanced and supported creatively to embrace new adoption, imitation, and innovation strategies. For this reason, these group of regions can form an "*imitative innovation area*" in Europe. Most of these regions are rather peripheral and rural, mostly in EU12, such as all regions in Bulgaria and Hungary, Latvia, Malta, several regions in Poland, Romania, and Slovakia, but also in Southern Italy (Fig. 4).

The high levels of creativity, entrepreneurship, and collective learning present in this cluster are potential assets with which to turn, from an evolutionary perspective, this area into a smart and creative diversification area through normative intervention that helps exploit creativity and entrepreneurship in order to increase endogenous innovation activities, and not only for imitative innovation.

6 Conclusions

The main idea put forward by this study is that, since the pathways to innovation and modernization are differentiated among regions according to local specificities, ad hoc policy interventions are needed in the field of innovation, even at the regional level. Required to achieve this goal, without incurring the unrealistic situation of having one policy action for each European region, is a sound taxonomy of innovative European regions.

Departing from the existing taxonomies that conceptually equate knowledge to innovation, or, as in the case of RIS, that mix knowledge input and output, sectoral specificities of regions, and enablers of innovation with no clear a priori on the conceptual links among the variables used, and, ultimately, lacking strong territorial roots, we have presented a taxonomy based on a new conceptual approach which interprets, not one single phase of the innovation process, but the *different modes of performing the different phases of the innovation process*, highlighting the *context conditions* that accompany each "territorial pattern of innovation."

The empirical results show that the geography of innovation is much more complex than the simple core/periphery model proposed in the smart specialization debate (Foray et al. 2009). The capacity to turn knowledge and innovation into regional growth differs among regions, and the identification of regional specificities in innovation patterns is essential for building targeted normative strategies to achieve a cohesion policy goal. The maximum return to R&D investments may be the right goal for a region specialized in knowledge creation, but it cannot at the same time be the right policy goal for regions that innovate by exploiting external knowledge, or for regions that imitate innovation processes. For the former, the ad hoc policy goal is the maximum return to co-inventing applications, which happens when the region promotes changes in response to external stimuli (such as the emergence of a new technology). A maximum return to imitation, pushing toward creative imitation, is instead the right policy aim for regions that rely on external innovation processes. Each region must be able to discover its territorial innovation pattern, and only through its awareness of its original and unique territorial innovation pattern can a region hope to excel in exploiting innovation efficiency.

Moreover, each pattern comprises regions more advanced and efficient than others because of good policy strategies and actions, or because of particularly dynamic economic actors. For these regions, evolutionary policies can be conceived as aimed at the achievement of more advanced innovation patterns. The complementary actions of static and evolutionary innovation policies—targeted on each innovation pattern—would certainly be the right policy mix with which to implement the "smart specialization policies" in the field of innovation called for by the EU in its official document *Regional Policy Contributing to Smart Growth in Europe* (EC 2010)—and to achieve a "smart Europe" in the years to come (Camagni and Capello 2012).

Appendix: Eurobarometer survey

To extract the factor "Strategic thinking on innovation," we used the following questions from the Eurobarometer Survey 63.4 (Table 6):

Table 6 Factor loadings

Variable	Strategic thinking on innovation	Creativity
Q389	0.265	**0.741**
Q390	0.205	**0.827**
Q392	0.484	**0.577**
Q394	−0.051	**0.861**
Q395	0.157	**0.670**
Q396	**0.635**	0.312
Q397	**0.813**	0.204
Q398	**0.869**	0.160
Q401	**0.880**	0.257
Qbb	**0.659**	−0.029

Factor loadings greater than 0.55 are in bold

– Innovation simplifies everyday life (% of people mentioning this statement), Q396;
– A company that sells an innovative product or service improves the image of all its products or services (% of people mentioning this statement), Q397;
– A company which does not innovate is a company that will not survive (% of people mentioning this statement), Q398;
– Innovation is essential for improving economic growth (% of people mentioning this statement), Q401;
– Broadband penetration rate (% of households with broadband access) from Eurostat, Qbb.

To extract the factor "Creativity," we used the following questions from the Eurobarometer Survey 63.4 (Table 6):

– In general, to what extent are you attracted toward innovative products or services, in other words new or improved products or services? (% of people that are very or fairly attracted to new products), Q398;
– Compared to your friends and family, would you say that you tend to be more inclined to purchase innovative products or services? (% of people that are more inclined than the average to buy innovative products), Q390;
– In general, when an innovative product or service is put on the market and can replace a product or service that you already trust and regularly buy, do you quickly try the innovative product or service at least once? (% of people that shift easily consumption patterns toward innovative products), Q392;
– Innovative products or services are most of the time gadgets (% of people not mentioning this statement), Q394;
– Innovative products or services are a matter of fashion (% of people not mentioning this statement), Q395;
– The advantages of innovative products or services are often exaggerated (% of people not mentioning this statement), Q400;

We extracted the two factors by means of principal component analysis and applied a varimax rotation method with Kaiser normalization. The percentage of variance explained is 62.54. In this analysis, within each component, we considered the variables with a factor loading greater than 0.55. Table 6 reports the factor loadings; factor loadings greater than 0.55 are in bold.

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