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The emergence of new technology-based sectors at the regional level : a proximity-based analysis of nanotechnology[1].

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ABSTRACT. This paper analyzes the emergence of new technology-based sectors at the regional level. We focus on the specific case of nanotechnology as representative of an industry based on a technology still in infancy whose evolution can be reliably traced on the basis of filed patent submissions. We implement a methodological framework based on the 'product-space' approach, which allows us to investigate whether the development of new technologies is linked to the structure of the existing local knowledge base. We use patent data over the period 1986-2006 to carry out the analysis at the NUTS 2 level over the EU 15 countries. The results of the descriptive and econometric analysis supports the idea that history matters in the spatial development of a sector, and that the technological competences accumulated at the local level are likely to shape the future patterns of technological diversification.

JEL Classification Codes: R11, N94, 014.

Keywords : product space, technological diversification, new industries, capabilities, EU Regions

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1 Introduction

The mechanisms by which new industries emerge and evolve over time has long attracted the interest of economics scholars. Since the works by Marshall (1890 and 1919), and the subsequent ones by Kuznets (1930) and Schumpeter (1939), the long-term evolution of industries has been characterized as a process shaped by the gradual exhaustion of technological opportunities which gives rise to efforts aimed at introducing new technologies which opens up new trajectories exploited in new industries. The issue has been then articulated at the regional level by Perroux (1955), whose "growth poles" concept provides a former account of the path-dependent nature of local industrial development. More recently, a stream of works inspired by Klepper's heritage theory proposes a view upon the mechanisms of industrial evolution. The role of cumulated technological competences in specific sectors within local contexts is there seen as a determinant of the likelihood to observe successful development patterns in terms of entry, exit and survival (Klepper, 2007 and 2011; Buenstorf and Klepper, 2009; Klepper and Simons, 2000).

The heritage theory stresses the importance of previous competences in shaping the entry of new firms in specific sectors at the local level. However, the evidence provided so far has no ambition of accounting systematically the effects of the existing industrial structure on the probability to observe the birth of new industries in the same contexts. In this perspective, a step forward is marked by the 'product-space' approach (Hidalgo et al., 2007; Hausmann and Klinger, 2007; Hausmann and Hidalgo, 2010). These authors spell-out the hypothesis that the pattern of product diversification observed in different countries is driven by the existing pattern of revealed comparative advantage. In other words, countries tend to diversify in productions that are close in the product-space to those in which they already have a comparative advantage. Recently, Boschma et al. (2012) have implemented this analysis at the regional level to investigated the emergence of new industries at the regional level in Spain. These latter studies provide a valuable framework to the empirical investigation of the emergence of new industries at a regional level, by adapting the product-space approach originally developed at the country level. Yet, being exclusively focused on products, they are not able to fully take into account technological aspects, and especially the role played by the processes of accumulation of technological competences which are instead emphasized by the 'heritage' theory.

In this paper we attempt to provide a bridge between the heritage theory and the product-space approach by analyzing the emergence of a new technology-based sector, i.e. the nanotechnology. Although many developments have some way to go before abutting into marketable products, the patenting of nanotechnology is well under way and primarily involves universities and research institutes, small firms related to academia, but also some of the largest R&D companies (Schellekens, 2010). This sector has been the object of a wide body of investigation in the last decade, but to the best of authors' knowledge there is no evidence about the path-dependent dynamics of its evolution, especially emphasizing how cumulated technological competences within a local context sustain (or not) a regular development of the sector.

This paper is aimed at analyzing the emergence of new technological fields, with a special focus on the nanotechnology sector, in the EU 15 aggregate over the period 1986-2006. By using patent data drawn from the Patstat database, we implement a 'product-space' analysis at the NUTS 2 level, but referring to a technological space where technologies are close or distant. . We investigate whether the development of revealed technology advantage (RTA) in nanotechnology is related to the structure of technological competences already developed in the region, i.e. whether a region showing RTA in technologies close to nanotechnology in the technology space have more chances to develop RTA in nanotechnology in the future. The results of both the descriptive and the econometric analysis suggest that history matters in the spatial development of technology based sectors. In general regions tend to develop new RTA in technologies that are close to those already featuring the local technology base. The results hold also when the analysis is restricted to the emergence of a brand new sector like the nanotechnology sector.

The rest of the paper is articulated as follows. Next section articulates the theoretical framework underpinning the emergence of new industries by means of technological diversification at the local level. Section 3 provides an outline of the evolution of the nanotechnology sector, while Section 4 describes the data and the methodology. In Section 5 we discuss the empirical results, which are articulated in descriptive and econometric analysis. Conclusions follow in Section 6.

2 Theoretical Framework

Since the seminal contribution by Marshall (1919), the dynamics underpinning the evolution of industries at the local level have increasingly attracted the interest of economics scholars, leading recently to a more intimate connection between industrial dynamics and economic geography. It is well known that Marshall's analysis grounds the mechanisms by which industries cluster in some specific regions on the working of agglomeration externalities. A key process in this respect is represented by the birth of new industries, as "subsidiary trades grow up in the neighbourhood, supplying it with implements and materials, organizing its traffic, and in many ways conducting to the economy of its material" (Marshall, 1919 [1890]: p. 225). The localization of industry therefore enhances the division of labour at the industry level which engenders both horizontal and vertical diversification. These arguments have been further developed by Allyn Young (1928), who grafted Adam Smith's analysis of division of labour into a dynamic Marshallian framework in which specialization leads to speciation of new industries closely intertwined with one another. Young stresses that the main effect of the growth of production is industrial differentiation, which leads to the diversification of the production of both final goods and intermediate goods. This latter phenomenon is particularly relevant in modern economies, in which "over a large part of the field of industry an increasingly intricate nexus of specializing undertakings has inserted itself between the producer of raw materials and the consumer of the final product" (Young, 1928: p. 538).

This line of reasoning has been further refined by two key authors, often represented as leaders of the post-marshallian tradition, i.e. Edith Penrose and George Richardson. Their specific focus on both the way in which and the time with which firms access complementary resources and assets is particularly relevantas it proves to play a much more important role in a firm or industry cognitive/geographical development than the resources and assets themselves. Over the years, Penrose (1959) has become an essential reference work on the role of capabilities. She depicted, with the greatest clarity, that production has to be undertaken by human organizations embodying specifically appropriate experience and skills. She gave excellent accounts of how companies grow in areas set by their capabilities and how these capabilities expand and alter. She also showed that competitive advantage required both the exploitation of existing internal and external firm-specific capabilities and newly developed ones. She had the intuition that capabilities interact with activities carried out by firms, an intuition that has been at the core of the work done by Richardson (1960, 1972). Although the link between capabilities and activities has certainly been too often overlooked, important and more recent contributions on dynamic capabilities have recurrently reaffirmed it (Foss and Loasby, 1998; Loasby, 1991; 1999; Langlois and Roberston, 1995; Teece, 1996;

Krafft, 2010). Indeed, Richardson in his 1972 article had already argued that it is convenient to think of an industry as carrying out a large number of activities, related to the discovery and estimation of future needs, to research, development and design, to the execution and coordination of processes of physical transformation, the marketing of goods, etc. He was stressing that these activities must be carried out by organizations (i.e. the firm, the market or the cooperation) with appropriate capabilities, or, in other words, with appropriate knowledge, experience and skills. He proposed a key distinction between similar and complementary activities: activities whose undertaking requires the same capability are similar activities, while activities that represent different phases in a process of production (and, consequently, do not necessarily require the same capabilities) are complementary activities. Marshallian and post-Marshallian literature has thus largely contributed to highlight a rationale for competitive advantage based on the capacity of firms to access the complementary resources and assets that are required for the development of innovations. This capacity is essentially based on how firms develop their capabilities in a changing environment, i.e. how they adapt, integrate, and reconfigure internal and external organizational skills, resources, and functional competences over time, i.e. along the entire innovation process, and also over space, i.e. in areas where the innovation process is geographically located. In more modern terms, it is referred to dynamic capabilities standing for the "ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments" (Teece et al., 1997: p. 516), that tend to appear as key determinants in more modern contributions focusing on the study of the process of cognitive/geographical development at the level of firms and industries.

These notions were also echoed in the domain of evolutionary theory with the concept of routines that affect the spatial evolution of economic activities (see for instance, Metcalfe, 1995; Witt, 2003; and Nelson and Winter, 1982). Routines are mainly defined as consisting of tacit knowledge, and represent the basic competencies that shape the competitiveness of economic agents. Following Schumpeter's legacy, one of the earlier attempts in relating innovation with geographical industrial development can be ascribed to François Perroux (1955) who integrated the role of technological change in his 'growth pole' theory. The economic development of regions appears to be related to the innovative potentials of the industries they are specialized in. Firms within a propulsive industry grow at faster rates, propagating the positive effects across activities directly and indirectly related to the propulsive industry. The potentials for creating new knowledge are at the basis of regional growth, and they happen to be unevenly distributed across sectors according to the relative stage of lifecycle (Perroux, 1955; Kuznets, 1930; Burns, 1934; Schumpeter, 1939)[2]. The process of industrial diversification is therefore driven by innovation dynamics, which provides the bases for the working of positive feedbacks leading to the emergence of new industries.

Much more recently Boschma and Frenken (2007) proposed a far reaching integration of these issues into an evolutionary approach combining explicitly industrial dynamics with economic geography. Routines, and hence competencies or capabilities, are developed over time as a result of costly efforts that represent a major element of dynamic irreversibilities. Regional growth thus emerges out of a process of industrial diversification, in which the introduction of new varieties is constrained by the competencies accumulated at the local level. Out of the spectrum of possible new activities, it will be more likely to observe the birth of industries that are closely related to the productions already existing in the local context, so

[2] Thomas (1975) articulated the implications of Perroux' framework on regional economic growth using a product life-cycle perspective, wherein the saturation of product markets are the main responsible for the slowdown of growth rates and the quest for innovations aims at opening new markets.

that these new activities will be able to exploit (at least in part) the already developed routines.

Similar concepts are also developed within the context of the 'heritage theory', according to which the spatial evolution of industries is shaped by the set of technological, organisational and institutional competencies accumulated at the local level. The pre-existing experience matters and affects the emergence and the performances of new industries (Buenstorf and Klepper, 2009; Klepper and Simons, 2010). Based on deep investigations into the television, automobile, and tyre industries, the authors are able to discuss the agglomeration effects often claimed in the literature. In these three industries, which are characterized either by a concentration of firms in areas where production was initially negligible, or by a progressive dispersion of firms leaving formerly highly concentrated areas, the agglomeration effect does not apply. To explain this, an hypothesis based on the ideas of organisational birth and heredity is proposed. The key role of the competencies accumulated in the past on the future development of the region points to the importance of *path dependence* in regional growth processes as well as to the need to adopt a historical approach to their analysis. In path-dependent phenomena history matters in a very peculiar way, as the phenomenology at the time t is dependent on the choices made at the time t-1. At each point in time individuals are able to make choices that are likely to influence the transition at the new state. The existence of a multiplicity of alternatives make the new state only one of the possible outcomes, and then it is not possible to fully anticipate the last outcome starting from the initial state (David, 2001; Antonelli, 2006).

The notion of path dependence is strictly linked to that of lock-in, that is a trapping region, a "basin of attraction that surrounds a (locally) stable equilibrium" (David, 2001; Colombelli and von Tunzelmann, 2011). When idiosyncratic and irreversible decisions are made, then agents are likely to base their future choices on the basis of the possessed endowment, converging towards a specific path, from which it is difficult to escape. The path-dependent emergence of new industries is therefore constrained by the capabilities developed in the past. The concept of optimal cognitive distance (Noteboom, 2007) becomes particularly relevant in this case, according to which one would expect regional growth to be more likely driven by the diversification in related domains than by the emergence of radically different activities (Frenken et al., 2007; Boschma and Iammarino, 2009; Quatraro, 2010).

On the basis of the arguments elaborated so far, we can now spell out the basic working hypotheses:

a) The process by which new industries emerges in local contexts is shaped by path-dependence in view of the constraining role played by the competencies accumulated over time;
b) The way in which path-dependence influence the process of industrial differentiation is such that new industries are more likely to be closely related to the sectors that are already available at the local level.

3 Overview of the evolution of the nanotechnology sector

The purpose of this paper is both to provide a general analysis of the path-dependent mechanisms of emergence of new sectors, and to investigate the specific evolutionary patterns of the nanotechnology sector so as to identify commonalities and peculiarities.

The focus on nanotechnology is motivated by the increasing body of empirical literature in innovation studies aimed at studying different the implications of the specific features of such technologies on innovation dynamics. Without pretending to be exhaustive, the most recent investigations include the analysis of: i) methodological issues concerning the implications for the classification systems of patents and scientific publications (Leydesdorff and Zhou, 2007;

Leydesdorff, 2008; Mogoutov and Kahane, 2007); ii) industrial organization of firms involved in nanotechnology R&D, both in terms of alliances and collaborations university-industry; (Thursby and Thursby, 2011; Mangematin et al., 2011); iii) the properties firms' knowledge base in nanotechnologies in terms of diversification and scope of applications (Avenel et al., 2007; Graham and Iacopetta, 2009; Graham, Iacopetta and Youtie, 2008); iv) the effects on the intellectual property rights system (Mowery, 2011).

The formal definition of what nanotechnologies are is obviously an uneasy task, in that a wide set of complex technologies and applications are at stake. However, the main reference as benchmark definition is the one provided in 2000 by the US National Nanotechnology Initiative:

> "Research and technology development at the atomic, molecular or macromolecular levels, in the length scale of approximately 1 - 100 nanometer range, to provide a fundamental understanding of phenomena and materials at the nanoscale and to create and use structures, devices and systems that have novel properties and functions because of their small and/or intermediate size. The novel and differentiating properties and functions are developed at a critical length scale of matter typically under 100 nm. Nanotechnology research and development includes manipulation under control of the nanoscale structures and their integration into larger material components, systems and architectures. Within these larger scale assemblies, the control and construction of their structures and components remains at the nanometer scale".

Darby and Zucker (2005) identify two key enabling technologies that allowed for the emergence of nanotechnology, i.e. the invention of scanning tunnelling microscope (STM) carried out at the IBM’s Zurich Research Laboratory and reported by the inventors Gerd Karl Binning and Heinrich Rohrer, and the subsequent invention of the atomic force microscope (AFM) by Binning, Calvin Quate and Christophe Gerber (1986) that allowed to overcome the STM drawback related to its applicability only to conducive materials.

Showing that commercialization of the relevant enabling innovations for nanotechnology occurred about five years later their introduction, the same authors conducted an analysis of both scientific publications and patent applications placing the birth of the nanotechnology sector around the end of the 1980s and the beginning of the 1990s (Darby and Zucker, 2005).

Since then nanotechnologies have been applied to a wide range of scientific domains, spanning from physics to chemistry to biology. Since this new technology emerged as a new method of inventing, its utilization across different fields make them a good example of general purpose technologies (GPTs) (Graham and Iacopetta, 2005), showing some interesting key properties. Indeed, like other GPTs, nanotechnologies foster convergence between previously distinct technology driven sectors (Rocco and Bainbridge, 2007). Moreover, they allow for the emergence of new combinations, such as the merging of microelectronics and biotechnology in nanobiotechnologies (Mangematin et al., 2011).

In view of their wide applicability, nanotechnologies not only allow for the creation of new process or products, but also the updated and improvement of existing product and processes (Bozeman et al., 2007; Rotharmael and Thursby, 2007). In this perspective, they can be thought of as both competence enhancing and competence destroying technologies (Tushman and Anderson, 1986). They show two opposite aspects of innovation, i.e. the enhancement of competences based on cumulative knowledge and experience as well as the destruction and the renewal of the existing capabilities (Linton and Walsh, 2008).

The introduction of nanotechnologies is therefore likely to represent a technological discontinuity, although it does not represent a dramatic break with the past. In view of this they represent a particularly interesting object for the analysis of the path-dependent dynamics of regional branching, in which the role of the existing competencies available at the local level is at stake. In the rest of the paper we will proceed therefore with the analysis of the emergence of new technological activities at the local level and eventually compare the general evidence with the results obtained with the specific analysis of the nanotechnology sector.

4 Methodology and data

4.1 Methodology

This paper aims at analyzing the extent to which the emergence of new industries is influenced by the local availability of related competencies. The main idea is that the existence of close competencies help such emergence process. Proximity is assessed in this direction in relation to an abstract space (Boschma, 2005), and in particular to the technological space.

The concept of technological proximity has been empirically implemented by Jaffe (1986 and 1989), who analyzed the proximity of firms' technological portfolios. The idea is that each firm is characterized by a vector V of the k technologies that occur in its patents. Technological can then be calculated for a pair of technologies l and j as the angular separation or uncentred correlation of the vectors V_{lk} and V_{jk}. This is to say that two technologies l and j are close if they are regularly used in combination with the same third technology k.

While this approach has proved to be fertile in the analysis of proximity between pairs of technologies (Breschi et al., 2003), as well as in the featuring of the degree of internal dissimilarity of knowledge bases at different levels (Krafft et al., 2009; Colombelli et al., 2011), in this paper we will follow a different methodology which has been recently proposed to analyze the role of the existing production structure on the process of economic diversification both at the country and the regional level (Hidalgo et al., 2007; Hausmann and Klinger, 2007; Hausmann and Hidalgo, 2010; Boschma et al., 2011 and 2012).

The proximity index of Hidalgo et al. (2007) is based on a network-based conceptual representation of the product space of a country, in which each product is a node which is characterized by a specific set of linkages with the other nodes in the network. Some nodes show higher density of linkages while some other show very low density levels. These density of linkages varies across countries, so that the same product can show different values in different contexts. The density of linkages around a product is a proxy of its average proximity level. The authors show that countries are likely to diversify by developing goods that are close to what they actually produce. These dynamics are in turn possible explanations of persisting divergence between leading and lagging behind countries (Hausmann and Klinger, 2007; Hausmann and Hidalgo, 2010).

The index rests on the Balassa's revealed comparative advantage (RCA) measure, according to which a country has comparative advantage when the share of a product in its exports is larger than the share of that product in world exports. Since we are interested in the dynamics of technology-based sectors, we implement the revealed technology advantage (RTA) metric, which provides information on the relative technological strengths (or weaknesses) of a given geographic entity (Soete, 1987). This is defined as follows:

$$RTA_{s,i,t} = \left(\frac{E_{s,i,t}}{\sum_s E_{s,i,t}} \right) \Big/ \left(\frac{\sum_i E_{s,i,t}}{\sum_s \sum_i E_{s,i,t}} \right) \tag{1}$$

The RTA index varies around unity, such that values greater than 1 observed at the time *t* indicate that region *i* is relatively strong in technology *s*, compared to other regions and the same technological field, while values less than 1 indicate a relative weakness. The proximity between two technologies *s* and *z* is related to the extent to which a region shows RTA in both of them. Indeed in this case one can maintain that the two technologies are grounded on the same (or on similar) capabilities and hence they can be said to be close to each other. The proximity between each pair of technologies represents therefore a distinctive feature of local technology structure (Quatraro, 2012).

To calculate proximity between each pair of technologies *s* and *z* we have first to determine whether the regions have RTA in technology *s* according to equation (1). We do the same for each of the other technologies $z \neq s$. In what follows for the sake of simplicity we focus on technology *s*. Then we calculate the probability of having RTA in technology *s* at time *t* ($P(RTA_{s,t})$), which is the ratio between the number of regions showing the RTA>1 and the total number of regions in the dataset. We further calculate the joint probability of having RTA in technologies *s* and *z* ($P(RTA_{s,t} \cap RTA_{z,t})$), i.e. the relative frequency of regions with RTA in both technologies. Finally we calculate the conditional probability for a region to have RTA in the technology *s* given that it has RTA in the technology *z*. Conditional probability is calculated by dividing joint probability by the probability of having RTA in technology *z*:

$$P\left(RTA_{s,t} \middle| RTA_{z,t}\right) = \frac{P\left(RTA_{s,t} \cap RTA_{z,t}\right)}{P\left(RTA_{z,t}\right)} \tag{2}$$

We follow the same calculations for all the other technologies observed in the sample. This implies that for each pair of technologies *s* and *z* we end up with two conditional probabilities, i.e. the probability to have RTA in technology s given RTA in technology z and the probability to have RTA in technology z given RTA in technology s. Proximity between technologies s and z can then be defined as the minimum of the pairwise conditional probability of a region having RTA in a technology given that it has RTA in the other:

$$\varphi_{s,z,t} = \min \ \{P(RTA_{s,t} | RTA_{z,t}), P(RTA_{z,t} | RTA_{s,t})\} \quad (3)$$

In order to analyze the effect of the existing production structure on the development of new products, Hidalgo et al. (2007) elaborate a measure of average proximity of the new potential product to the existing productive structure. In our analysis this amounts to derive an index of average proximity of the technology *s* to a region's structure of technological activities. Let $x_{i,s,t}$=1 if $RTA_{i,s,t}$>1 and 0 otherwise. The average proximity, or 'density' measure can be written as follows:

$$d_{i,s,t} = \frac{\sum_k \varphi_{s,k,t} x_{i,s,t}}{\sum_k \varphi_{s,k,t}} \quad (4)$$

This measure is bounded between 0 and 1. If the region *i* happens to have RTA in all technologies at proximity higher than 0 to technology *s*, density will be equal to 1. In contrast, if the region *i* has RTA in none of the technologies related to technology *s*, then density will be equal to zero.

The analysis is articulated in two parts. We first carry out a statistical analysis of the emergence of new technologies at the regional level. To do so, we follow Hidalgo et al. (2007) and Boschma et al. (2012) by considering 5-years time lag as a reasonable lapse of time for the technology structure to affect the emergence of new technologies. Statistical analysis is based on descriptive evidence and the calculation of transition probabilities to the emergence of new RTA at t+5 given the technology structure at time t.

The second part of the analysis provides econometrics evidence of the effects of cumulated technological capabilities on the development of new RTA at the regional level. This amounts to estimate the following econometric relationship:

$$x_{i,s,t+5} = \alpha + \gamma x_{i,s,t} + \beta d_{i,s,t} + \sum_i \sum_t \delta_{i,t} + \sum_s \sum_t \delta_{s,t} + \varepsilon_{i,s,t} \quad (5)$$

Where $x_{i,s,t+5}$ takes value 1 if the region *i* has RTA in the technology *s* at time t+5, 0 otherwise. Similarly, $x_{i,s,t+5}$ takes value 1 if the region *i* has RTA in the technology *s* at time t, 0 otherwise; $d_{i,s,t}$ is the density around technology s at time t in region i calculated according to equation (4). The estimation controls for time varying region characteristics and time varying technology characteristics. Finally $\varepsilon_{i,s,t}$ is the error term.

In order to test the existence of path-dependence in the process of emergence of technology-based industries at the regional level we would only need $\gamma \neq 0$ and $\beta \neq 0$. However, our hypotheses suggest that the development of RTA in new technologies is favoured by the presence of accumulated capabilities in technological activities that are close to the new ones in the technology space. This amounts to refine our expectations the sign of the coefficients so that $\gamma > 0$ and $\beta > 0$.

The estimation of equation (5) is not straightforward. Indeed it is characterized by a dichotomous dependent variable regressed against its lagged values (t-5) and other regressors. Following the previous contributions we first estimate a simple linear probability model. This is a special case of binomial regression in which the probability of observing 0 or 1 is modelled in such a way that OLS can be used in order to estimate the parameters. However, this technique may be inefficient in presence of dichotomous dependent variables and the estimated coefficients may imply probabilities that are outside the interval [0,1] (Cox, 1970).

For this reason we also fit a Generalized Linear Model for the binomial family (McCullagh and Nelder, 1989). The presence of the lagged dependent variable in the regressors vector raise however some further concerns that lead to the implementation of a dynamic panel data regression, using the generalized method of moments (GMM) estimator (Arellano and Bond, 1991). This estimator indeed provides a convenient framework for obtaining asymptotically efficient estimators in presence of arbitrary heteroskedasticity, taking into account the structure of residuals to generate consistent estimates. In particular, we use the GMM-System (GMM-SYS) estimator in order to increase efficiency (Arellano and Bover, 1995; Blundell and Bond, 1998). This approach instruments the variables in levels with lagged first-differenced terms, obtaining a dramatic improvement in the relative performance of the system estimator as compared to the usual first-difference GMM estimator.

4.2 The data

In order to analyze the path-dependent dynamics of emergence of technology-based sectors we used the Patstat database updated to October 2011. The Patstat database is a snapshot of the European Patent Office (EPO) master documentation database with worldwide coverage, containing tables including bibliographic data, citations and family links. These data combine both applications to the EPO and the application to the national patent offices, allowing to go back to 1920 for some patent authorities. This allows for overcoming the traditional limitation of EPO based longitudinal analysis due to its relatively young age.

Patent applications have been subsequently regionalized on the basis of inventors' addresses. Applications with more than one inventor residing in different regions have been assigned to each of the regions on the basis of the respective share. Our study is limited to the applications submitted in the EU 15 countries, and uses the European Classification System (ECLA), which is an extension of the International Patent Classification (IPC) maintained by the EPO, to assign applications to technological classes. The RTA indexes, as well as the subsequent proximity and density metrics, are thus based on 4-digits technological classes. The final dataset consisted of about 14,821,265 observations, amounting to 979,426 patent applications. Figure 1 shows the evolution of total and nanotechnology-based patent applications in the EU15 since 1977[3].

>>> INSERT FIGURE 1 ABOUR HERE <<<

Consistently with the previous literature based on USPTO data (Darby and Zucker, 2005), the diagram shows that a marked growth of nanotechnology patents can be observed in the second half of the 1980s and even more in the second half of the 1990s. The comparison with the line concerning total patent applications suggests that, although a general growing trend can be observed, nanotechnology patents are characterized by much faster growth rates in the two relevant periods. Table 1 shows the distribution of patent applications across the EU 15 countries, while Figure 2a shows the regional distribution of patent applications.

>>> INSERT TABLE 1 AND FIGURE 2 ABOUT HERE <<<

It is evident that the bulk of nanotechnology-based applications is concentrated in Germany, which is followed (at definitely lower levels) by France and United Kingdom. The 71% of patent applications is therefore concentrate in three countries, while the remaining 29% is spread across 12 countries. The map also shows that, with the exception of Spain, the data are also characterized by a marked within-country variance. Regional concentration of technological activities can be especially observed in Northern Italy, Central Germany, Southern England, Southern Sweden and Southern Finland.

For what concerns the identification of the nanotech sector, we have already noticed that nanotech discoveries are used in a large variety of sectors, so that defining its boundaries can

[3] As already mentioned, we used the Patstat release updated to October 2011. In order to avoid right-truncation problems we use data patent applications submitted by 2006.

be particularly difficult. A widely shared approach in the literature is based on the analysis of patent applications (Darby and Zucker, 2005; Rothaermel and Thursby, 2007; Mangematin et al., 2011). However, the relatively young age has engendered some difficulties in the past, according to which specific querying strategies have been adopted in order to extract patent applications within the nanotechnology domain from the EPO database (Scheu et al., 2006; Mogoutov and Kahane, 2007). More recently, however, the EPO have implemented a new tag system that formerly identified nanotechnology-related patent applications by assigning the code Y01N. Since the 1st January 2011 this code has been replaced by the class B82Y, following a recent effort by all patents efforts worldwide to classify nanotechnology uniformly under the IPC system.

The selection of patent applications classified with the B82Y code leaves us with 5,605 patents. Table 2 shows their country distribution. The evidence about nanotechnology-based patents seems to be very similar to the general evidence. Most of the applications (about 43%) can indeed be found in Germany, and to a much lesser extent France and UK. Also in this case nearly the 73% of all nanotechnology-based application are concentrated in three countries, while the rest is spread over 12 countries.

>>> INSERT TABLE 2 ABOUT HERE <<<

Figure 2b shows instead the regional distribution of nano-patents. Also in this case, the evidence is fairly similar to that observed in the case of the overall applications. There is indeed a marked regional variety in terms of applications, with evident concentration in Northern Italy, Southern France, Southern Sweden and Southern Finland.

5 Empirical results

5.1 Statistical evidence

The purpose of the paper is to analyze the path-dependent dynamics of emergence of new technology-based industries at the regional level. The attribute 'new' refers to the fact that comparative advantage is developed at the local level in technological activities for which no comparative advantage could be observed in the past. Our main hypothesis states that the existing local technology structure is likely to influence the emergence of RTA in new technologies. As already anticipated, we move from a simple descriptive analysis of the data. A former way to investigate the historical grounds of the emergence of new technology-based industries consists in calculating the RTA for all technologies and consider that a region has a comparative advantage in those technologies if RTA>1. Following Hausman and Klinger (2007) and Boschma et al. (2012) we divide the period of analysis (1986-2006) in 5-years window intervals. Such a time span is considered long enough to enable the emergence of new industries, and short enough to provide a sufficient number of observations for parametric and non-parametric analysis. The number of technologies with comparative advantage is an average of the years 1986, 1991, 1996, 2001 and 2006. To calculate the number of new technologies with RTA, we took the average of the number of technologies in which regions had no comparative advantage in the years 1986, 1991, 1996 and 2001 but developed comparative advantage five years later.

Figure 4 reports the relationship between technologies with RTA at time t and new technologies with RTA at t+5. Each point on the scatter plot corresponds to one of the 229 observed regions. It is clear that the relationship between these two dimension is positive. For example, we can observe that the Ile de France and the Oberbayern regions are those with the highest number of new technologies with RTA (128 and 116 respectively), and also the highest number of technologies with RTA at time t (313 and 323 respectively). On the contrary the Greek regions of Magnisia and Keffalonia are those with the lowest number of new technologies with RTA (both of them 6), and also the lowest number of technologies with RTA at time t (7 and 7.4 respectively). On the whole, we can observe that German regions are clustered in the top-right part of the diagram, along with some French and Italian regions, while peripheral regions are mostly located in the bottom-left part.

>>> INSERT FIGURE 4 ABOUT HERE <<<

In order to understand if such relationship is influenced by the regional technology structure, Figure 5 shows the relationship between the development of RTA in new technologies at time t+5 and the average density around technologies at time t. Also in this case a strong positive relationship can be observed. This suggests that regions that have cumulated competencies in technologies with higher average density are more likely to develop RTA in new technologies in the future. Indeed density is a synthetic measure of proximity, which allows for appreciating the connectedness degree of each technology. The more regions are able to incorporate technologies with high density in their portfolios, the higher the chances to develop RTA in new technologies.

>>> INSER FIGURE 5 ABOUT HERE <<<

The simple evidence provided so far provides former support to the idea that the cumulated technological capabilities are likely to shape the development of RTA in new technologies. Further information can be gained by looking at the probability of transitioning into new technologies at time t+5 for different levels of density around technologies for which there already was RTA at time t. Again, we used for the period 1986-2006 divided in 5-years intervals. We made separate calculations for the overall technology portfolio and for the nanotechnology-based patents. The results are reported respectively in Figures 6a and 6b.

>>> INSERT FIGURE 6 ABOUT HERE <<<

As is clear from both diagrams, such probability increases with the average level of density around technologies. Once again, this suggests that the existing technology structure at the regional level, which is the outcome of a cumulative learning process, is likely to shape the emergence of new technological activities. This is even more evident in the case of nanotechnologies, in which the lowest density classes show lower probabilities of transitioning than in the overall evidence.

A further method to investigate whether higher density favours the emergence of new technological activities consists of comparing the distribution over the density of technologies that remain without RTA with the distribution over the density of technologies that gain RTA. From the previous analysis, which showed that higher probability of transitioning into new technologies is higher for high values of density, we expect the bulk of technologies that remain without RTA to be concentrated on the left of the distribution, while most of the technologies that develop RTA are expected to cluster on the right of the distribution. To check these expectations we drew the kernel estimation of the probability density function for the distribution of technologies that developed RTA and for those that did not do it across different density values. The results of these estimations are reported in Figures7a and 7b. The former refers to the overall sample, while the latter focuses on nanotechnology-based activities. The dashed line refers to the technologies that remained without RTA at t+5 in the region, while the solid line represents technologies that developed RTA at t+5 in the region.

>>> INSERT FIGURE 7 ABOUT HERE <<<

The diagrams suggest indeed that most of the technologies that remained without RTA are clustered in the region corresponding to the lowest values of density. For the results concerning the overall sample (Figure 7a) this roughly corresponds to the area for which $0<d<0.03$. On the contrary the mode for the technologies that developed RTA is around d=0.25. Moreover, for values of d>1.5 the probability density distribution for technologies that developed RTA is above the density distribution for technologies that did not do it. The same evidence, although somewhat less pronounced, can be found when one focuses on the nanotechnology sector. The development of new RTA in nanotech is far more likely in regions that have cumulated competencies in high density technologies.

5.2 Econometric analysis

This section provides the results of the formal test of the hypothesis according to which the technology structure emerged at the regional level as an outcome of knowledge accumulation and learning dynamics affects the development of new technology-based activities at the local level. We implement econometric estimations of Equation (5) and report the output in Table 3.

>>> INSERT TABLE 3 ABOUT HERE <<<

According to the working hypotheses spelled out in Section 2, we formulated the expectations of positive signs on both the lagged value of the dependent variable (i.e. the dummy that takes value 1 if the region *i* has RTA in the technology *s*) and on the density variable. As already noticed, the choice of the estimation technique is not straightforward. We first implemented a linear probability model, both for the analysis of the overall sample and of the nanotechnology sector. The results obtained with these estimations are reported in columns (1) and (2). It is worth recalling that these estimations take into account time varying regional effects and time varying technological effects. The results at the overall level provide support to our hypotheses, by suggesting that there is some persistence in the development RTA at the local level, such that having developed the comparative advantage at time t enhances the likelihood to retain such advantage at time t+5. Moreover, the architecture of the technology structure in terms of average proximity in the technology space matters. The density around the technology at the local level shows indeed a positive coefficient, suggesting that the development of RTA in one technology is more likely when highly connected technologies are at stake, i.e. when the new technology are closely related to the ones already developed in the region.

Column (2) shows that these results hold also for what concerns nanotechnology-based activities. Previous literature analyzing the sector stressed that these technologies can be regarded as both competence-enhancing and competence-destroying. The econometric results would suggest that the competence-enhancing component is prevalent in that the coefficient on the density variable is strongly significant. Such results can also be interpreted in view of the wide scope of applications of nanotechnologies, which reinforce the links between their development and the technological activity already present at the local level.

The estimation of linear probability models can be inefficient and create some problems with the predicted values. For this reason in columns (3) and (4) we also show the results of the estimations carried out by implementing a binomial generalized linear model (GLM). The results hold both for the estimation on the overall sample and for the specific analysis of nanotechnologies. Once again it seems evident that having comparative advantage at the beginning of the period raises considerably the probability of having comparative advantage at the end of the period. Moreover, regions tends to develop new RTA in technologies with higher levels of density, i.e. those technologies that show higher proximity in the technology space to the technological competencies accumulated at the local level. Once again nanotechnologies are well in line with results obtained at the general level.

Finally, we noticed that the presence of the lagged dependent variable in the regressors' vector can lead to biased estimations. For this reason we also decided to implement the GMM system estimator. Results are reported in columns (5) and (6). The results are consistent with those obtained with the other two estimation methods. The development of RTA in new technologies seems to be indeed a path-dependent process in which the competencies accumulated in the past are likely to shape the future plans at the local level. By using the metaphor proposed by Hidalgo et al. (2007), local agents are like monkeys that prefer to climb on trees, i.e. technologies, that are close together due to the similarity of the capabilities needed to their implementation. This applies also when brand new technologies like nanotechnolgies are at stake, as suggested by the results in column 6.

In order to check for the robustness of our results, we follow Boschma et al. (2012) and Hausmann and Klinger (2007) and run econometric estimations by using directly the RTA measure rather than a dummy variable which takes value1 at some arbitrary cut-off. It is worth noting that the inclusion of the RTA index in econometric specifications may yield some biased estimates, due to the fact that the index squeezes the values signalling non specialization between 0 and 1, while values signalling specialization are between 1 and infinity. This gives rise to a skewed distribution that in turn implies the violation the normality assumptions of the error term in the regression. For this reason it is recommended to use some transformation of the index that makes its distribution close to the normal one. In the econometric estimations reported in table 4 we have taken standardized values for the RTA, the distribution of which proximate very much normality.

>>> INSERT TABLE 4 ABOUT HERE <<<

The results appear to be fairly in line with what observed so far. Columns (1) and (2) show the OLS estimations, which are the equivalent of the linear probability model in table 3. The coefficients for the lagged dependent variable are and for the density variable are still positive and statistically significant as far as the overall sample is concerned. This supports once more the idea that the emergence of technological activities at the local level shows the features of a path-dependent process. The results for nanotechnology-based activities (column (2)) are somewhat different in that the coefficient on the lagged dependent variable is not statistically significant. However the coefficient on the density variable is again positive and statistically significant, signalling that the branching process oriented towards the development of nanotechnology-based activities is driven by the competencies cumulated in the region in the past.

Columns (3) and (4) provide instead the results obtained from the GMM-system estimation, which are fairly in line with the previous one. The estimation on the overall sample indeed show positive and significant coefficients for both the lagged dependent variable, suggesting the existence of some degree of persistence in the development of RTA, and on the density measure, while in the estimation for nanotechnology-based activities only this latter is significant. All in all, the empirical evidence based on econometric estimation is coherent with the statistical analysis conducted in the previous Section, and provides robust support to the hypothesis that the emergence of new technology-based industries at the local level appears as a path-dependent phenomenon in which dynamic irreversibilities engendered by learning and knowledge accumulation play a key role.

6 Conclusions

The emergence and evolution of new industries has been at the fore of the economic speculation since the early contributions of key scholars like Alfred Marshall, Joseph Schumpeter, Simon Kuznets, Allyn Young, Edith Penrose, and George Richardson. Subsequently, François Perroux contributed to graft the onto the analysis of the dynamics of regional development. More recently, the evolutionary approach to economic geography emphasized the importance of the branching process occurring in the dynamics of regional diversification (Boschma and Frenken, 2007). These latter developments allow for appreciating the key role of routines and cumulated competencies in the process of diversification. Regional branching therefore occurs in domains that are close to the areas of local specialization. Based on these achievements, we followed Boschma et al. (2012) in applying the methodological framework developed by Hidalgo et al. (2007) to study the path-dependent dynamics of emergence of new technology-based industries at the regional level, with a special focus on nanotechnologies. The focus on these technologies is motivated by the fact that they are relatively recent and increasingly object of interest by scholars of innovation as well as by their ambiguous nature in terms of continuity with the existing technological competencies.

The analysis has been conducted by using patent information drawn from the October 2011 release of the Patstat database. Patent applications have been regionalized on the basis of inventors' addresses. We focused on the analysis of NUTS2 regions belonging to EU15 countries. Both our data and previous analyses on nanotechnologies suggested to take as a starting point the second half of the 1980s. Thus we decided to constrain our analysis to the period 1986-2006, in order to be on the safe side as far as right-censoring problems are concerned.

The empirical results, based on both statistical analysis and econometric tests, provides robust support to our main working hypothesis. The emergence of new technology-based activities is likely to be a path dependent process in which the capabilities cumulated over time may constrain the future developments at the local level. In other words, the set of activities that constitute the technological specialization of a given geographical aggregate matters in the planning of diversification strategies for the future. Regions that are specialized in technologies with higher degree of density will face lower difficulties in their diversification patterns and will be better able to jump on new specializations. Conversely, peripheral regions with comparative advantages in technologies far apart in the technological space will have more difficulties to diversify in core technologies.

The analysis bear important implications for regional technology policy. The incentives to enhance the emergence of new technology-based industries at the regional level, like in the case of nanotechnologies or in the case of 'green technologies', may not abstract for an accurate analysis of both the comparative advantages developed over time in the area and of the position of such technologies in the technological landscape. Stimulating local agents to jump on new activities that are too much far away from their cumulated competencies may prove to be inefficient and unsuccessful. This evidence is even more important in the context of the recent interest at the European level in the importance of demand for stimulating the creation of new activities. The results showed in this paper call for targeted measures able to feed the a wide and diversified set of 'demands' at the local level that take into account the history of each place, which is characterized by distinctive advantages and cumulated knowledge. This amounts to implement a plethora of local programs, rather than one big funding scheme available for every region, with no concern for the matching between future plans and previous experience. Although costly, it may provide policymakers with far higher returns on public expenditure.

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Table 1 – Distribution of Patent Applications, by Country

Country	Freq.	Percent	Cum.
Austria	24,121	2.46	2.46
Belgium	24,288	2.48	4.94
Germany	422,752	43.16	48.11
Denmark	15,506	1.58	49.69
Spain	14,086	1.44	51.13
Finland	19,633	2	53.13
France	156,904	16.02	69.15
Great Britain	120,772	12.33	81.48
Greece	1,176	0.12	81.6
Ireland	3,624	0.37	81.97
Italy	75,823	7.74	89.71
Luxembourg	1,498	0.15	89.87
Netherlands	57,353	5.86	95.72
Portugal	794	0.08	95.8
Sweden	41,096	4.2	100
Total	**979,426**	**100**	

Table 2 – Distribution of nanotechnology-based patent applications, by country

Country	Freq.	Percent	Cum.
Austria	108	1.93	1.93
Belgium	184	3.28	5.21
Germany	2,441	43.55	48.76
Denmark	56	1	49.76
Spain	78	1.39	51.15
Finland	70	1.25	52.4
France	994	17.73	70.13
Great Britain	752	13.42	83.55
Greece	12	0.21	83.76
Ireland	26	0.46	84.23
Italy	279	4.98	89.21
Luxembourg	6	0.11	89.31
Netherlands	407	7.26	96.57
Portugal	8	0.14	96.72
Sweden	184	3.28	100
Total	**5,605**	**100**	

Table 3 - Econometric results for the estimation of Equation (5)

Dependent variable $x_{i,s,t+5}$	Linear probability model		GLM		System GMM	
	Overall (1)	Nanotechnology (2)	Overall (3)	Nanotechnology (4)	Overall (5)	Nanotechnology (6)
$x_{i,s,t}$	0.202***	0.285***	1.217***	1.391***	0.071***	0.221***
	(0.003)	(0.059)	(0.023)	(0 .209)	(0.002)	(.052)
$d_{i,s,t}$	1.095***	1.678***	9.920***	8.535***	1.033***	0.617***
	(0.011)	(0. 157)	(0.227)	(0 .632)	(0.008)	(0.128)
constant	-0.104***	0.045	-4.186***	-3.523***	-0.030***	0.047*
	(0.002)	(0.056)	(0 .043)	(0 .178)	(0.001)	(0.027)
R^2	0.22	0.629				
Optimization			MQL Fisher scoring	MQL Fisher scoring		
(1/df) Pearson			0 .832	0.831		
Hansen J					1059.88	88.08
(p-value)					(0.000)	(0.000)
AR(1)					-181.50	-8.90
(p-value)					(0.000)	(0.000)
AR(2)					9.17	0.08
(p-value)					(0.000)	(0.935)
Observations	977902	1832	977902	1832	977902	1832

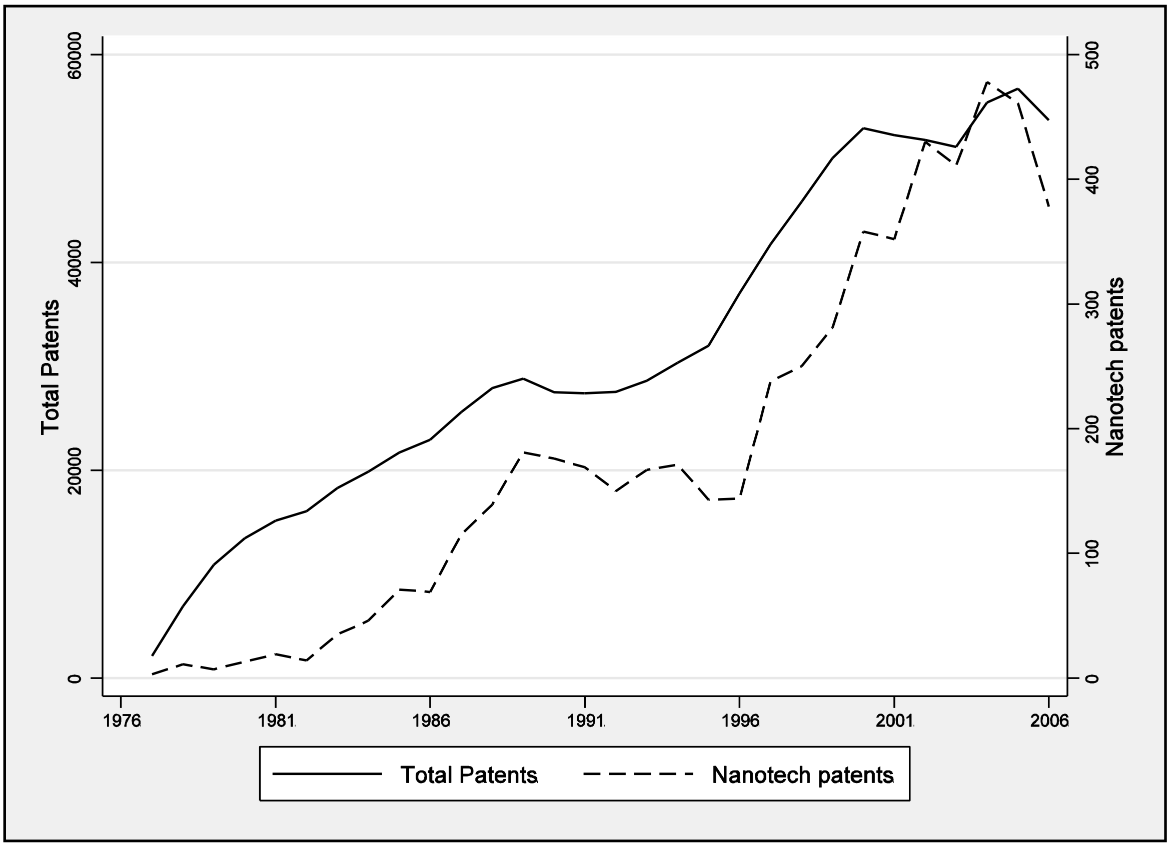
Note: regional clustered standard errors between parentheses. GLM estimation shows nonexponentiated coefficients.

Table 4 – Econometric results, estimation using the RTA index

Dependent variable $RTA_{i,s,t+5}$	OLS		System GMM	
	Overall (1)	Nanotechnology (2)	Overall (3)	Nanotechnology (4)
$RTA_{i,s,t}$	.0255**	-0.001	0 .011*	0.003
	(0 .011)	(0 .006)	(0 .006)	(0.003)
$d_{i,s,t}$	0 .769***	0 .865**	1.413***	1.087***
	(0 .040)	(0 .346)	(0 .067)	(0 .574)
constant	-0.136***	-0.206	-0.176***	-0.178**
	(0 .008)	(0 .217)	(0 .008)	(0 .085)
R^2	0.007	0.522		
Hansen J			225.09	33.36
(p-value)			(0.000)	(0.007)
AR(1)			-4.68	-1.99
(p-value)			(0.000)	(0.046)
AR(2)			-0.09	1.10
(p-value)			(0.929)	(0.270)
Observations	977902	1832	977902	1832

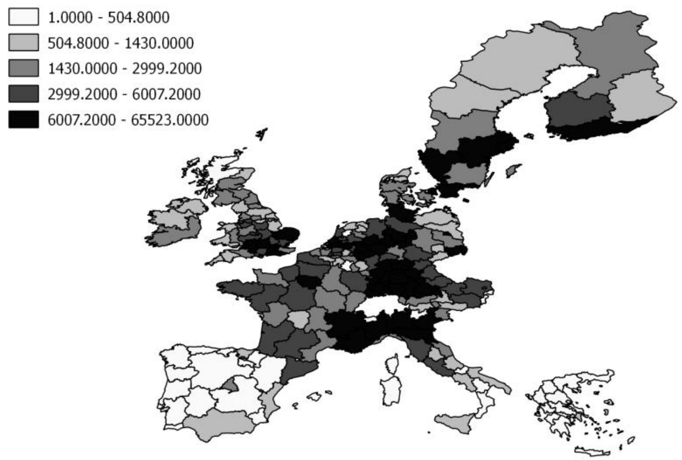
Note: regional clustered standard errors between parentheses.

Figure 1 – Evolution of patent applications in the EU 15 regions over time

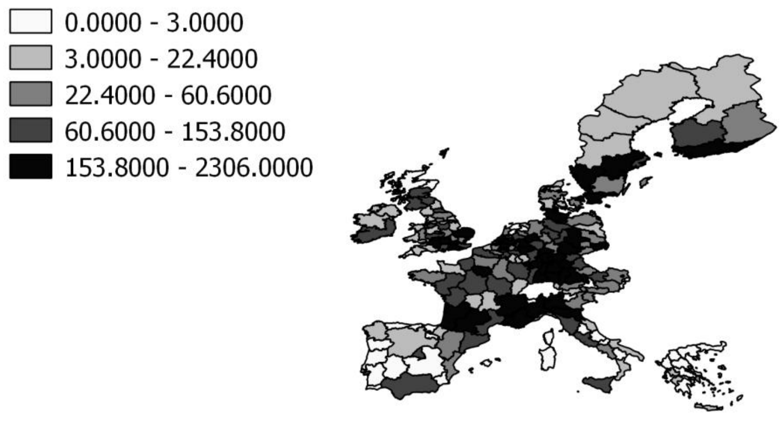


Note : Total Patents applications on the left y-axis. Nanotechnology-based patents applications on the right y-axis

Figure 2 – Regional distribution of patent applications

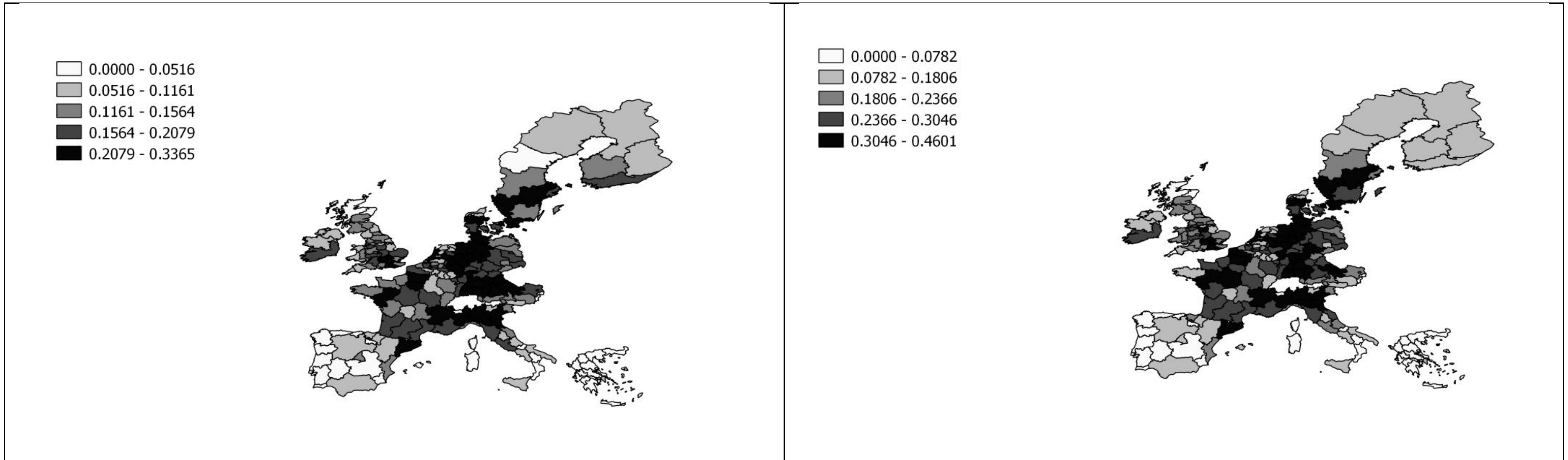


a) Overall



b) Nanotechnology

Figure 3 – Average density, by region (t=2001)



a) Overall

b) nanotechnology

Figure 4 – Relationship between technologies with RTA at time t and new technologies with RTA at time t+5 in European regions (1986-2006 average; 5-years interval)

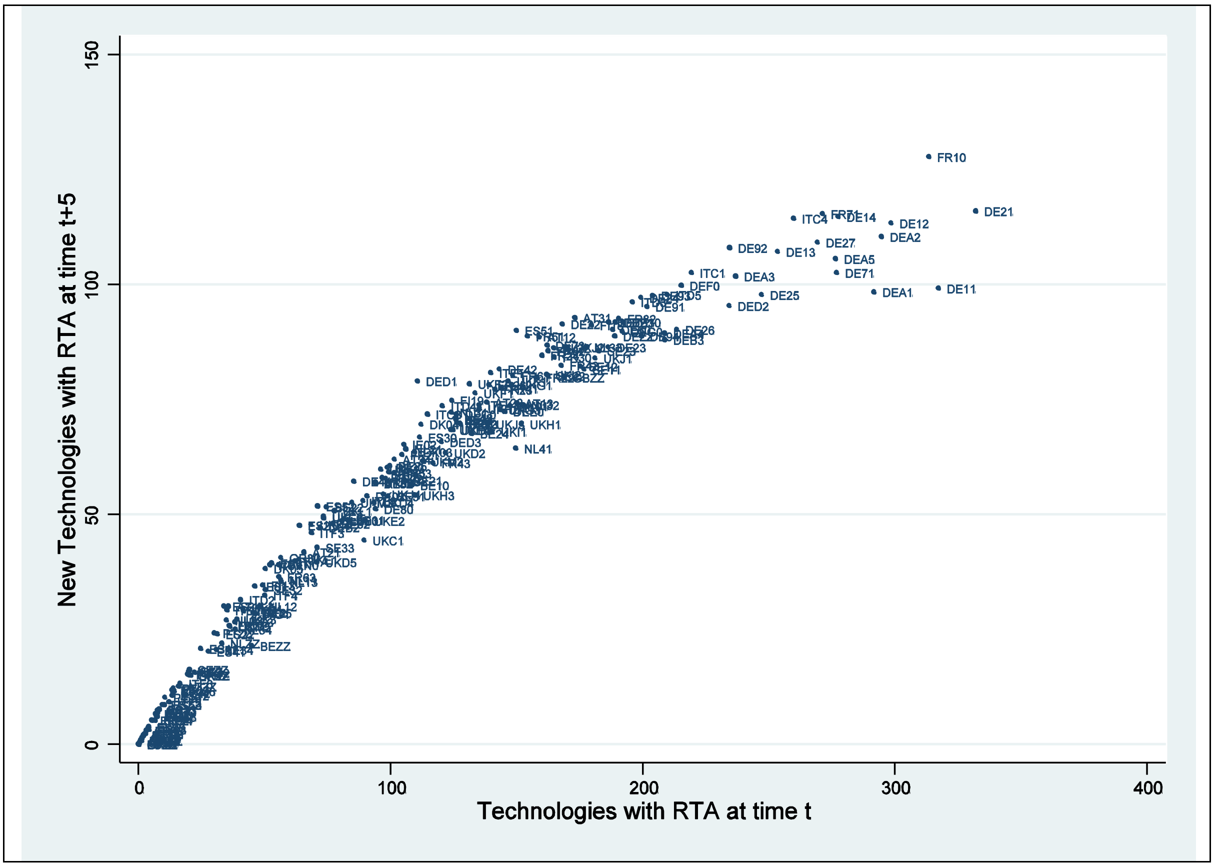


Figure 5 - Relationship between the average density of technologies with RTA at time t and new technologies with RTA at time t+5 in European regions (1986-2006 average; 5-years interval)

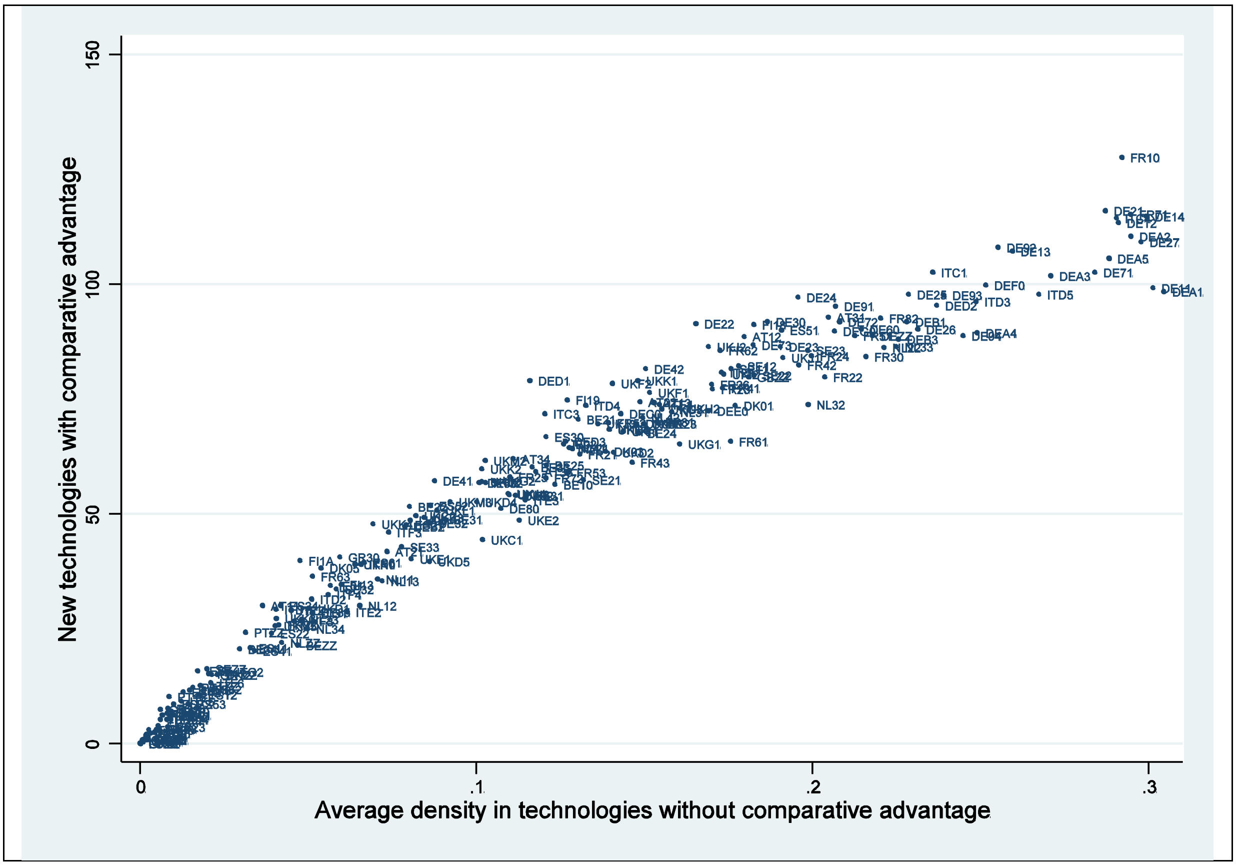
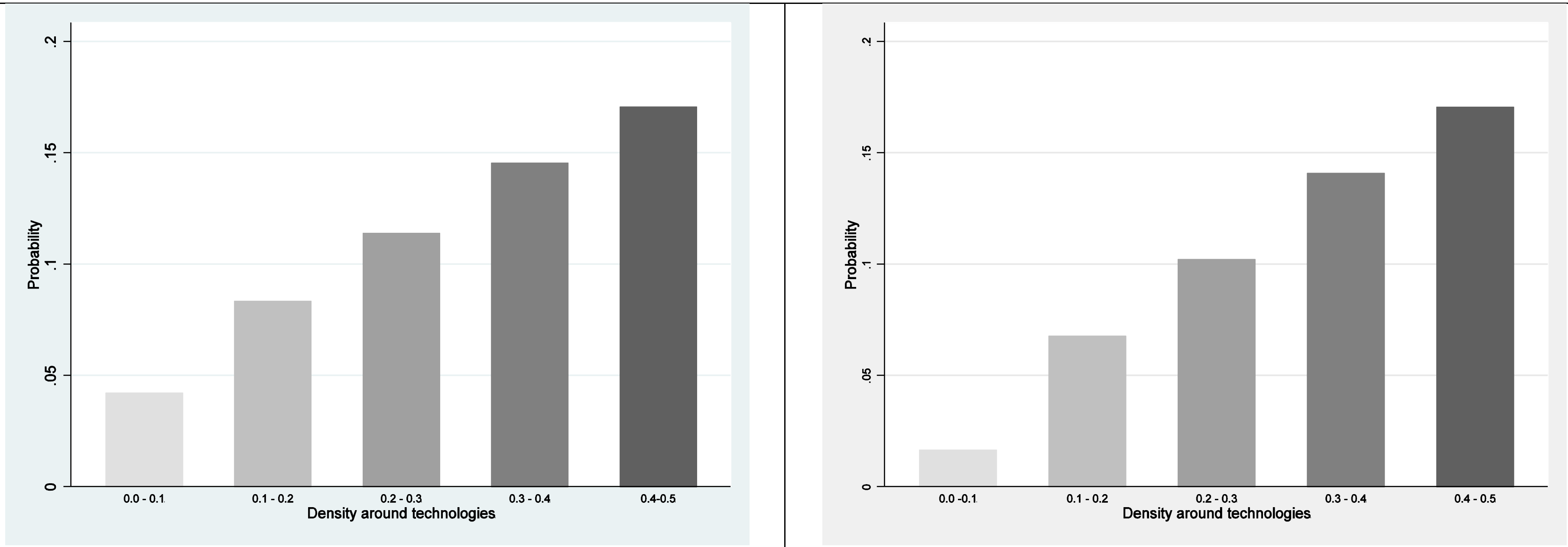


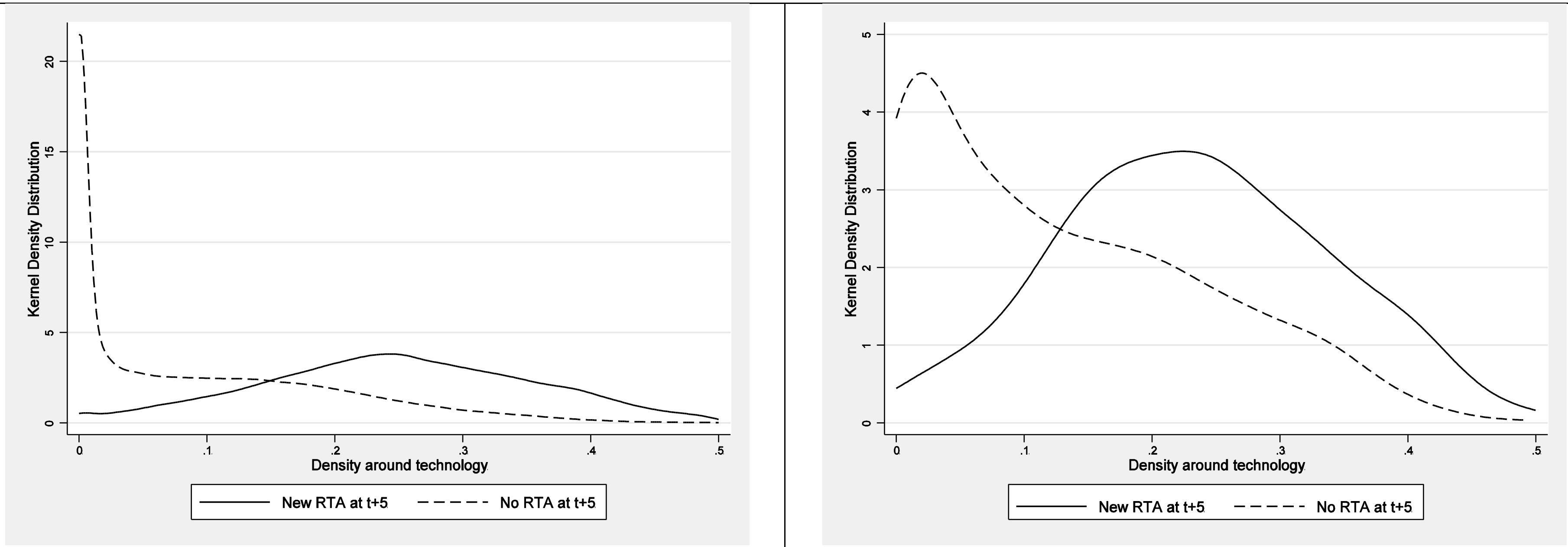
Figure 6 - Probability of transitioning into new technologies in European regions (period 1986-2006; 5-years interval)



a) Overall

b) Nanotechnologies

Figure 7 – Kernel density estimation for new technologies with RTA at t+5 and for technologies with no RTA (period 1986-2006; 5-years interval).



a) Overall

b) Nanotechnologies