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ABSTRACT. This paper analyzes the emergence of new technology-based sectors at the regional level focusing on nanotechnology, an infant technology whose evolution can be traced on the basis of patent application filings. We employ a methodological framework based on the 'product-space' approach, to investigate whether the development of new technologies is linked to the structure of the existing local knowledge base. We conduct a 15 EU country analysis at NUTS 2 level using patent data for 1986-2006. The results of the descriptive and econometric analysis supports the idea that history matters in the spatial development of a sector, and that the .

JEL Classification Codes: R11, N94, 014.

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

1 Introduction

The mechanisms involved in the emergence and evolution of new industries over time have for long been attracting the interest of economics scholars. There is a stream of research inspired by Klepper's work highlighting the role of cumulated technological competences in specific sectors within local contexts. In this view, technological competence is seen as a determinant of successful entry, exit and survival of firms in new industries (Klepper, 2007, 2011; Buenstorf and Klepper, 2009; Klepper and Simons, 2000).

Klepper's theory stresses the importance of accumulated competences for the entry of new firms in specific sectors at the local level. However, there is no systematic evidence on the effects of the existing industrial structure on the probability of observing the birth of new industries in similar contexts. The 'product-space' approach has been proposed (Hidalgo et al., 2007; Hausmann and Klinger, 2007; Hausmann and Hidalgo, 2010) to support the hypothesis that the patterns of product diversification observed in different countries are driven by existing patterns of revealed comparative advantage. In other words, countries tend to diversify in productions which, in the product-space, are close to those in which they already have a comparative advantage. Boschma et al. (2013) implemented a regional level analysis to investigate the emergence of new industries in Spain. They propose a framework for empirical investigation of the emergence of new industries at the regional level, adapted from the country level product-space approach. However, the focus is on products and does not take account of technological aspects, and especially the role of accumulated technological competences emphasized in the 'heritage' theory.

In this paper, we attempt draw on both heritage theory and the product-space approach to analyze the emergence of a new technology-based sector focusing on the path-dependent nature of this process. There is a large theoretical literature in the economics of innovation

which originated in the seminal contribution of Paul A. David (1985), that investigates the mechanisms underlying path-dependence in different contexts and at different levels of analysis. This body of work emphasizes that history matters in economic, social and technological change processes. However, in-depth analysis of these issues is lacking, and more work is needed especially on how new technology-based sectors emerge at the regional level. The present paper is contributing to this research agenda.

We analyse the path-dependent emergence of new technological fields, with a special focus on the nanotechnology sector,[1] in the EU 15 countries in the period 1986-2006. There are several studies of nanotechnology but to the best of the authors' knowledge, there is no evidence on the path-dependent dynamics of its evolution or on how cumulated technological competences within a local context sustain (or not) the continuing development of the sector. We use patent data from the Patstat database to implement a 'technology-space' analysis at NUTS 2 level. We investigate whether the development of revealed technology advantage (RTA) in nanotechnology is related to the structure of the technological competences already developed in the region, that is, whether regions with RTA in technologies that are close to nanotechnology in the technology space are more likely to or more able to develop RTA in nanotechnology in the future. The results of the descriptive and econometric analyses 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 part of the local technology base. These results also hold if the analysis is restricted to the emergence of a new sector, such as nanotechnology.

[1]Although many developments take time to develop into marketable products, patenting of nanotechnology is underway and primarily involves universities and research institutes, small firms related to academia, and some large R&D companies (Schellekens, 2010). Note that the analysis focuses on the generation of technological knowledge in the field of nanotechnology, and not primarily on its application within the geographical areas in which it is developed.

The rest of the paper is structured as follows. Section 2 presents the theoretical framework for analyzing the emergence of new industries based on technological diversification at the local level. Section 3 discusses the evolution of the nanotechnology sector and Section 4 describes the data and the methodology. Section 5 presents the empirical results of the descriptive and econometric analyses. Section 6 concludes.

2 Theoretical Framework

Since Marshall's (1919) seminal contribution, the dynamics underpinning the evolution of industries at the local level have been studied by economics scholars, leading to an increasing overlaping between industrial dynamics and economic geography. Marshall's work looks at the mechanisms that promote the clustering of industries in some specific regions based on 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 conducing to the economy of its material" (Marshall, 1890: 225). The localization of industry enhances the division of labour at the industry level promoting horizontal and vertical diversification. Marshall's arguments were developed by Allyn Young (1928), who grafted Adam Smith's analysis of division of labour onto a dynamic Marshallian framework in which specialization leads to speciation of new closely intertwined industries. Young stressed 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.

Boschma and Frenken (2007) suggest a possible integration of these issues within an evolutionary approach to economic geography. Their starting point is the dynamics by which organizational routines affect the spatial evolution of economic activities (Nelson and Winter,

1982). Building on the work of Penrose (1959) and Richardson (1960, 1972),[2] routines are defined as consisting mainly of tacit knowledge, and represent the basic competencies that shape the competitiveness of economic agents. In this respect, dynamic capabilities stand for the "ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments" (Teece et al., 1997: 516). Routines, and hence competencies or capabilities, are developed over time as a result of costly efforts that represent a major element of dynamic irreversibilities. Thus regional development 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. From the spectrum of possible new activities, the birth of industries that are closely related to already existing local production is more likely. The new activities exploit (at least in part) already developed routines.

Similar concepts are contained in 'heritage theory', according to which the spatial evolution of industries is shaped by the set of technological, organizational and institutional competencies accumulated at the local level. Previous experience matters and affects the emergence and performances of new industries (Buenstorf and Klepper, 2009; Klepper and Simons, 2010). In studies of the television, automobile, and tyre industries, Klepper and co-authors discuss the agglomeration effects claimed in the literature. In these three industries, which are characterized either by a concentration of firms in areas where production was

[2]According to Penrose (1959), production activities require appropriate experience and skills. Companies grow along the directions set by their capabilities and the development of competitive advantages requires the exploitation of existing and newly developed internal firm-specific capabilities. Richardson (1972) suggests considering an industry as conducting several activities that are carried out by organizations with the appropriate capabilities, knowledge, experience and skills. He proposes a distinction between similar and complementary activities: activities that require the same capabilities are similar activities while activities that represent different phases in the production process (and consequently, do not necessarily require the same capabilities) are complementary activities. The dynamic capabilities literature has developed this idea (Loasby, 1991, 1999; Teece and Pisano, 1994; Langlois and Roberston, 1995; Teece, 1996; Krafft, 2010).

initially negligible or by a progressive dispersion of firms leaving formerly highly concentrated areas, the agglomeration effect does not apply. To explain this, they propose a hypothesis based on the ideas of organizational birth and heredity.

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 development 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 to the new state. The existence of a multiplicity of alternatives makes the new state only one of several possible outcomes, which makes it impossible to fully anticipate the final outcome based on the initial state. Path-dependent processes are different from past-dependent processes. The latter are a kind of processes which are strongly shaped by the initial conditions; the former are instead processes which are reshaped at each moment in time as the result of changing local conditions (David, 2001; Antonelli, 2006; Antonelli et al., 2013).

The notion of path-dependence is linked strictly to the notion of lock-in that traps the region in a "basin of attraction that surrounds a (locally) stable equilibrium" (David, 2001: p. 25). When idiosyncratic and irreversible decisions are made, agents are likely to base their future choices on existing endowments, which results in convergence towards a specific path from which it is difficult to escape (Colombelli and von Tunzelmann, 2011). The path-dependent emergence of new industries therefore is constrained by the capabilities developed in the past. The concept of optimal cognitive distance (Noteboom, 2007) is particularly relevant in this case, and regional growth can be expected to be driven more by 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 formulate our basic working hypotheses:

a) The emergence of new industries in local contexts is a persistent process.
b) The persistent process of emergence of new industries is path-dependent; it depends on the competencies accumulated over time. Path-dependence influences the process of new industry emergence such that the *new industries are likely to be closely related to the already existing local level sectors*.

Based on these working hypotheses, we analyse the path-dependent mechanisms in the emergence of new sectors, and investigate the pattern of evolution in the nanotechnology sector to identify commonalities and peculiarities.

3 Evolution of the nanotechnology sector: An overview

The focus on nanotechnology has been nurtured over the last years by the body of work on innovation investigating the implications of specific features of technologies on innovation dynamics. This work includes 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, in terms of alliances and university-industry collaborations; (Thursby and Thursby, 2011; Mangematin et al., 2011); iii) the properties of the knowledge base of nanotechnology firms and the diversification and scope of applications (Avenel et al., 2007; Graham and Iacopetta, 2009; Graham et al. , 2008); iv) the intellectual property rights system (Mowery, 2011).

It is difficult to define nanotechnology which includes a wide set of complex technologies and applications. However, the US National Nanotechnology Initiative 2000 defines it as:

> 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 remain at the nanometer scale.

Darby and Zucker (2005) identify two key enabling technologies that allow the emergence of nanotechnology, that is, the invention of the scanning tunnelling microscope (STM) in IBM's Zurich Research Laboratory by the inventors Gerd Karl Binning and Heinrich Rohrer, and the invention of the atomic force microscope (AFM) by Binning, Calvin Quate and Christophe Gerber (1986) which overcomes the shortcomings of the STM that it can be used only for particular materials.

Commercialization of the relevant enabling innovations for nanotechnology occurred about five years after their introduction. Darby and Zucker (2005) analysed scientific publications and patent applications placing the birth of the nanotechnology sector around the end of the

1980s and the beginning of the 1990s. Since then, nanotechnologies have been found a wide range of applications in scientific domains ranging 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, 2009), showing some interesting key properties. Similar to other GPTs, nanotechnologies foster convergence between previously distinct technology-driven sectors (Rocco and Bainbridge, 2007). They allow the emergence of new combinations, such as microelectronics and biotechnology in nanobiotechnologies (Mangematin et al., 2011).

The wide applicability of nanotechnologies has resulted in the creation of new processes and products and improvements to existing products and processes (Bozeman et al., 2007; Rothaermel and Thursby, 2007). Thus, they can be considered both competence-enhancing and competence-destroying technologies (Tushman and Anderson, 1986). They highlight two aspects of innovation, that is, the enhancement of competences based on cumulative knowledge and experience, and the destruction and renewal of existing capabilities (Linton and Walsh, 2008).

The introduction of nanotechnology therefore represents a technological discontinuity, although not a dramatic break with the past. This makes them an interesting object for the analysis of path-dependent dynamics in regional branching, and the role of existing competencies at the local level. In that perspective, we intend to analyse the emergence of new technological activities at the local level and compare the general evidence with the results obtained with the specific analysis of the nanotechnology sector.

4 Methodology and data

4.1 Methodology

The main idea underlying our methodology is that the emergence of new industries is influenced by the local availability of related competencies which are likely to foster their emergence. Proximity is assessed in relation to an abstract space (Boschma, 2005), and especially the technological space.

The concept of technological proximity was implemented empirically by Jaffe (1986, 1989), who analysed the proximity of firms' technology portfolios. The idea is that each firm is characterized by a vector V of the k technologies that occur in its patents. Technological proximity 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}. That is, the two technologies l and j are close if they are regularly used in combination with the same third technology k.

While this approach has been useful for the analysis of proximity between pairs of technologies (Breschi et al., 2003), and the degree of internal dissimilarity of knowledge bases at different levels (Krafft et al., 2009; Colombelli et al., 2013 and 2014), in this paper we adopt a different methodology which was proposed to analyse the role of the existing production structure on the process of economic diversification at both country and regional levels (Hidalgo et al., 2007; Hausmann and Klinger, 2007; Hausmann and Hidalgo, 2010; Boschma et al., 2012, 2013).

Hidalgo et al.'s (2007) proximity index follows a network-based conceptual representation of the product space of a country, in which each product is a node that is characterized by a specific set of linkages with the other nodes in the network. Some nodes show a high linkage density while others have less dense sets of links. This 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 current

production. These dynamics explain persisting divergences between the leading and lagging countries (Hausmann and Klinger, 2007; Hausmann and Hidalgo, 2010).

The proximity index is based on 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 RTA metrics, which provide information on the relative technological strengths (or weaknesses) of a given geographic entity (Soete, 1987). This is defined as:

$$RTA_{s,i,t} = \left(\frac{E_{s,i,t}}{\sum_{s} E_{s,i,t}} \right) \Bigg/ \left(\frac{\sum_{i} E_{s,i,t}}{\sum_{s} \sum_{i} E_{s,i,t}} \right) \tag{1}$$

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 relative weakness. The proximity between two technologies *s* and *z* is related to the extent to which a region shows RTA in both. Indeed, in this case, we can say that the two technologies are based on the same (or similar) capabilities and hence can be said to be close to each other. The proximity between each pair of technologies therefore represents a distinctive feature of the local technology structure (Quatraro, 2012).

To calculate the proximity between each pair of technologies *s* and *z* we need 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 simplicity we focus on technology *s*. Next we calculate the probability of 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 calculate the joint probability of having RTA in technologies *s* and *z* ($P(RTA_{s,t} \cap RTA_{z,t})$), that is, the relative frequency of regions with RTA in both technologies. Finally we calculate the conditional probability for a region with RTA in the technology *s* given that it has RTA in the technology *z*. The conditional probability is calculated by dividing the 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 make 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, that is, 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:

$$\varphi_{s,z,t} = \min \ \left\{P\left(RTA_{s,t} \middle| RTA_{z,t}\right), P\left(RTA_{z,t} \middle| RTA_{s,t}\right)\right\} \tag{3}$$

In order to analyse 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 deriving 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:

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

This measure is bounded between 0 and 1. If the region *i* has RTA in all the technologies at a proximity higher than 0 to technology *s*, the density will be equal to 1. In contrast, if the

region *i* has RTA in none of the technologies related to technology *s*, then the density will be equal to zero.

The analysis is carried out in two stages. First, statistical analysis of the emergence of new technologies at the regional level. We follow Hidalgo et al. (2007) and Boschma et al. (2013) and consider a five-year time lag as reasonable 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 stage in the analysis provides econometric evidence of the effects of cumulated technological capabilities on the development of new RTA at the regional level. This involves estimation of the following econometric relationship:

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

where $x_{i,s,t+5}$ takes the value 1 if the region *i* has RTA in the technology *s* at time t+5, and 0 otherwise. Similarly, $x_{i,s,t}$ takes the value 1 if the region *i* has RTA in the technology *s* at time t, and 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. $\varepsilon_{i,s,t}$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 need only $\gamma \neq 0$ 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 in the technology space to the new ones. This requires that we refine our expectations of the sign of the coefficients so that $\gamma > 0$ and $\beta > 0$.

Estimation of equation (5) is not straightforward. It is characterized by a dichotomous dependent variable regressed against its lagged values (t-5) and other regressors. In line with 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 ordinary least squares (OLS) can be used to estimate the parameters. However, this technique may be inefficient in the 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 regressor vector raises 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 is a convenient framework for obtaining asymptotically efficient estimators in the presence of arbitrary heteroschedasticity, taking into account the structure of the residuals to generate consistent estimates. In particular, in order to increase efficiency we use the GMM-System (GMM-SYS) estimator (Arellano and Bover, 1995; Blundell and Bond, 1998). This approach instruments the variables in levels with lagged first-differenced terms, providing a dramatic improvement in the relative performance of the system estimator compared to the usual first-difference GMM estimator.

4.2 The data

The implementation of a measure of RTA represents a difficult task, due to the need for a classification of technological activities into different domains. In this paper we have opted for the use of patent data in order to analyse the path-dependent dynamics of emergence of technology-based sectors. The pros and cons of the utilization of patents as a measure of innovation have been largely debated in the literature (Pavitt, 1985; Griliches, 1990).

However, in this context the use of patents seems to be particularly appropriate for at least two reasons. First, recent literature has shown that they are reliable indicators as far as regional technological activities are concerned (Acs et al., 2002). Second, patent documents provide information on technological classes, which refer to a standardized classification that can be used in order to span patents in the space of technologies (Engelsman and van Raan, 1994; Jaffe, 1986; Breschi et al., 2003). In this direction, technological classes may provide a reliable approximation for regional technological domains.

Our primary source of data consists of the Patstat database updated to October 2011. The Patstat database is a snapshot of the European Patent Office (EPO) master documentation database which has worldwide coverage and contains tables of bibliographic data, citations and family links. These data combine applications to both the EPO and national patent offices, going back to 1920 for some patent authorities. This overcomes the limitations in EPO based longitudinal analyses related to its relatively young age.

Patent applications were regionalized on the basis of inventors' addresses. Applications with more than one inventor, residing in different regions, were assigned to each of the regions on the basis of the respective share in the patent. Our study is limited to the applications from 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. Therefore, the RTA indexes, as well as the subsequent proximity and density metrics are based on 4-digit technological classes. The final dataset includes some 14,821,265 observations, amounting to 979,426 patent applications. The Table in Appendix 1

shows the regions included in the analysis, along with some key variables. Figure 1 shows the evolution of total and nanotechnology-based patent applications in the EU15 since 1977.[3]

>>> INSERT FIGURE 1 ABOUR HERE <<<

Consistent with work using United States Patent and Trademark Office (USPTO) data (Darby and Zucker, 2005), Figure 1 shows that there was marked growth in the number of nanotechnology patents in the second half of the 1980s and especially in the second half of the 1990s. Comparing with total patent applications we see a much faster growth for nanotechnology patents in the two relevant periods. Table 1 shows the distribution of patent applications across the EU 15 countries; Figure 2a shows the regional distribution of patent applications.

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

The bulk of nanotechnology-based applications are concentrated in Germany, followed at much lower levels by France and the UK: 71% of patent applications are concentrated on these three countries, with the remaining 29% spread across the other 12 countries. The map shows that, with the exception of Spain, the data are also characterized by marked within-country variance. Regional concentration of technological activities is observed for Northern Italy, Central Germany, Southern England, Southern Sweden and Southern Finland.

In relation to identification of the nanotech sector, we observed that nanotech discoveries have application used in a large number of sectors, so that defining its boundaries is difficult. A widely shared approach in the literature uses the information contained in patent applications to this purpose (Darby and Zucker, 2005; Rothaermel and Thursby, 2007; Mangematin et al., 2011). However, the relatively youth of the nanotechnology industry

[3]We used the Patstat release updated to October 2011; in order to avoid right-truncation problems we use data patent applications submitted up to 2006.

presents some difficulties and in the past querying strategies were adopted to extract nanotechnology patent applications from the EPO database (Scheu et al., 2006; Mogoutov and Kahane, 2007). However, the EPO has implemented a tagging system to identify nanotechnology-related patent applications. They were initially identified by the code Y01N, but from 1st January 2011 this code was replaced by the class B82Y, following worldwide efforts to classify nanotechnology uniformly under the IPC system.

Selection of patent applications classified as B82Y leaves 5,605 patents. Table 2 shows their country distribution. The picture for nanotechnology-based patents is similar to the picture for all patents. Most applications (about 43%) are related to Germany followed by France and the UK: nearly 73% of all nanotechnology-based application are concentrated in these three countries, with the remaining 27% shared across the remaining 12 countries.

>>> INSERT TABLE 2 ABOUT HERE <<<

Figure 2b shows the regional distribution of nano-patents which is quite similar to the distribution for all applications. There is a marked regional variety in terms of applications, with a 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 analyse the path-dependent dynamics of the emergence of new technology-based industries at the regional level. The term 'new' refers to the development of comparative advantage at the local level in technological activities where there was no comparative advantage in the past. Our main hypothesis is that the existing local technology

structure is likely to influence the emergence of RTA in new technologies. One way to investigate the historical grounds of the emergence of new technology-based industries consists of calculating the RTA for all technologies and considering that the region has comparative advantage in those technologies if RTA>1. Following Hausman and Klinger (2007) and Boschma et al. (2013) we divide the period of analysis (1986-2006) into five-year windows. This 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 calculated as 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 3 reports the relationship between technologies with RTA at time t and new technologies with RTA at t+5. Figure 3a can be considered a visual representation of the transition probability matrix. Each point on the scatter plot corresponds to one of the 225 observed regions. It is clear that the relationship between these two dimensions is positive. For example, we 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). In contrast, the Greek regions of Magnisia and Keffalonia are those with the lowest number of new technologies with RTA (both 6), and also the lowest number of technologies with RTA at time t (7 and 7.4 respectively). Overall, we 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 3 ABOUT HERE <<<

Following Antonelli et al. (2013), the transition probability matrix is split into two subperiods (1986-1996 and 1996-2006) in Figures 3b and 3c. This captures the effects of potential structural breaks on the persistent process of development of new RTAs. This type of analysis allows us to identify changes in the transition probabilities and to interpret them as clues to the effects of small external events that affect persistence. In other words, it allows us to infer the path-dependent character of RTA persistence. The diagrams reported in Figures 3b and 3c suggest that some changes can be detected in the relationship between RTA(t) and RTA(t+5). While in both cases RTA(t+5) increases at a less than proportional rate with respect to RTA, the graph in Figure 3c is flatter than the one in Figure 3b, suggesting that the response of RTA(t+5) to RTA was stronger in the first than in the second period. This can be interpreted as the outcome of a structural break that made the cumulative process less constraining.

In order to understand whether this 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 of the technologies at time t. Again, we observe a strong positive relationship. 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 accounts for the degree of connectedness of each technology. The more regions can incorporate technologies with high density in their portfolios, the higher their chances of developing RTA in new technologies.

>>> INSER FIGURE 5 ABOUT HERE <<<

The evidence so far provides support for the idea that cumulated technological capabilities are likely to shape the development of RTA in new technologies. We can obtain further information on the probability of the transition to a new technology at time t+5 for different

levels of density of technologies in which there was RTA at time t. We again divide the period 1986-2006 into five-year intervals. The results for the overall technology portfolio and nanotechnology-based patents are reported in Figures 6a and 6b respectively.

>>> INSERT FIGURE 6 ABOUT HERE <<<

The figures show that the probability of a new technology increases with the average level of density of the technology. Again, this suggests that the existing regional level technology structure, 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, where the lowest density classes show much lower probabilities of a transition.

Another method to investigate whether higher density favours the emergence of new technological activities is to compare the probability density function of technologies with no RTA with the probability density function of technologies that gain RTA. Based on the previous analysis, which shows that the probability of a transition to a new technology is higher for high density values, we expect the bulk of the technologies with no RTA will be concentrated in the left of the distribution, while the technologies that develop RTA will be clustered mostly in the right of the distribution. To check these expectations we conduct kernel estimation of the probability density function for the distribution of technologies that developed RTA and for those that did not, for different density values. The results of these estimations are reported in Figures 7a and 7b which refer respectively to the overall sample and the sample of nanotechnology-based activities. The dashed line refers to the technologies in the region with no RTA at t+5 while the solid line represents technologies that developed RTA at t+5.

>>> INSERT FIGURE 7 ABOUT HERE <<<

The diagrams suggest that most technologies that did not gain RTA are clustered in the region corresponding to the lowest density values. In relation to the results for the overall sample (Figure 7a) this corresponds roughly to the area for which $0<d<0.03$. For technologies that developed RTA it is around $d=0.25$. 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. The evidence is similar though less pronounced for the nanotechnology sector. The development of new RTA in nanotech is more likely in regions that have accumulated competencies in high density technologies.

5.2 Econometric analysis

This section provides the results for the hypothesis that the technology structure at the regional level based on 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 results in Table 3.

>>> INSERT TABLE 3 ABOUT HERE <<<

According to the working hypotheses presented in Section 2, we formulate expectations of positive signs of 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 the density variable. As already noted, the choice of estimation technique is not straightforward. First we implemented a linear probability model, to analyse the overall sample and the nanotechnology sector sample. The results of these estimations are reported in Table 3 columns (1) and (2). Recall that these estimations take account of time varying regional effects and time varying technological effects. The results for the overall sample provide support for our hypotheses in suggesting some persistence in the development of RTA at the local level, such that development of comparative advantage at time t enhances the likelihood that this advantage will continue at

time t+5. Moreover, the architecture of the technology structure in terms of average proximity in the technology space matters. The density of the technology at the local level has a positive coefficient, suggesting that development of RTA in one technology is more likely in the case of closely connected technologies, that is, if the new technology is closely related to the technologies already developed in the region.

Table 3 column (2) shows that these results hold also for nanotechnology-based activities. The literature in this area underlines that these technologies can be regarded as competence-enhancing and competence-destroying. The econometric results suggest that the competence-enhancing effect prevails: the coefficient of the density variable is strongly significant. These results should be interpreted in the context of the wide number of applications of nanotechnologies, which reinforce the links between their development and the already existing local level technological activities.

Estimation of linear probability models are often inefficient and can create problems related to predicted values. For this reason, Table 3 columns (3) and (4) show the results of the binomial generalized linear model (GLM) estimations. The results hold for the overall sample and the nanotechnologies sample. It is evident that having comparative advantage at the beginning of the period increases the probability of comparative advantage at the end of the period. Moreover, regions tends to develop new RTA in technologies with higher levels of density, that is, those technologies that show higher proximity in the technology space to the technological competencies accumulated at the local level. The results for nanotechnologies are in line with results at the general level.

Finally, we observe that the inclusion of the lagged dependent variable in the regressor vector can lead to biased estimations. For this reason we implemented the GMM system estimator. The results are reported in Table 3 columns (5) and (6). The results are consistent with those

obtained from the other two estimation methods. The development of RTA in new technologies seems to be a path-dependent process in which competencies accumulated in the past are likely to shape future plans at the local level. Local agents cluster together based on the similarity of the capabilities needed for their implementation. This applies also to the case of new technologies such as nanotechnologies, as suggested by the results in column 6.

5.2.1 Robustness check

In order to check the robustness of our results, we follow Boschma et al. (2013) and Hausmann and Klinger (2007) and run econometric estimations using the RTA measure rather than a dummy variable that takes the value 1 at some arbitrary cut-off point. Note that including the RTA index in the econometric specifications could yield biased estimates because the index squeezes the values signalling non specialization between 0 and 1, while the values signalling specialization are between 1 and infinity. This gives rise to a skewed distribution which implies violation of the normality assumptions of the error term in the regression. For this reason it is recommended that some transformation of the index be used to make the distribution close to a normal one. In the econometric estimations reported in Table 4 we use standardized values for RTA, the distribution of which approximates normality.

>>> INSERT TABLE 4 ABOUT HERE <<<

The results appear to be in line with what we have observed so far. Table 4 columns (1) and (2) show the OLS estimations, which correspond to the linear probability model in Table 3. The coefficients of the lagged dependent variable and the density variable are still positive and statistically significant for the overall sample. This supports the idea that the emergence of technological activities at the local level shows features of a path-dependent process. The results for nanotechnology-based activities (column (2)) are somewhat different in that the coefficient of the lagged dependent variable is not statistically significant. However, the coefficient of the density variable again is positive and statistically significant, signalling that

the branching process oriented towards the development of nanotechnology-based activities is driven by the competencies accumulated in the region in the past.

Table 3 columns (3) and (4) present the results of the GMM-system estimation, which are fairly in line with the previous results. In the estimations for the overall sample both the coefficient of the lagged independent variable and the one of the density measure are positive and significant, suggesting the existence of some degree of persistence in the development of RTA, while in the estimation for nanotechnology-based activities only the latter is significant. Overall, the empirical evidence from the econometric estimation is coherent with the statistical analysis conducted in the previous section, and provides robust support for the hypothesis that the emergence of new technology-based industries at the local level appears to be path-dependent due to the dynamic irreversibilities engendered by learning and knowledge accumulation.

Another possible bias in the regression results can be engendered by the fact that the density index is based on the co-location of technologies in the same region. In order to address this issue it would be useful to substitute the density measure by using an index which is independent from the spatial distribution of technologies. For this reason we decided to calculate the average technology proximity of technology s to all other sampled technologies. This index is based on the cosine index (Jaffe, 1986 and 1989), which is obtained as follows.

Let P_{sk} = 1 if the patent k is assigned the technology s [s= 1, …, n], and 0 otherwise. The total number of patents assigned to technology s is $O_s = \sum_k P_{sk}$. Similarly, the total number of patents assigned to technology w is $O_w = \sum_k P_{wk}$. We can, thus, indicate the number of patents that are classified in both technological fields s and w as: $V_{sw} = \sum_k P_{sk} P_{wk}$. By applying this count of joint occurrences to all possible pairs of classification codes, we obtain

a square symmetrical matrix of co-occurrences whose generic cell V_{sw} reports the number of patent documents classified in both technological fields *s* and *s*.

Technologiocal proximity is proxied by the cosine index, which is calculated for a pair of technologies *s* and *w* as the angular separation or uncentred correlation of the vectors V_{sm} and V_{wm}. The similarity of technologies l and j can then be defined as follows:

$$Z_{sw} = \frac{\sum_{m=1}^{n} V_{sm} V_{wm}}{\sqrt{\sum_{m=1}^{n} V_{sm}^2} \sqrt{\sum_{m=1}^{n} V_{wm}^2}} \tag{6}$$

This index is independent of the geographical location of technologies. Then the weighted average technology proximity of technology *s* from all other technologies in the region *i* is given by:

$$TP_{i,s,t} = \frac{\sum_{w \neq s} Z_{sw} P_{iwt}}{\sum_{w \neq s} P_{iwt}} \tag{7}$$

These new estimations are reported in Table 5[4]. The results appear to be very consistent with the empirical evidence discussed so far.

>>> INSERT TABLE 5 ABOUT HERE <<<

Column (1) shows the results obtained by applying the linear probability model, while columns (2) and (3) implements GLM and GMM estimators respectively. Once again the lagged RTA variable is positive and significant, suggesting that there is a strong persistence in the patterns of technological specialization. As discussed in the Section 5.1, this persistence appears to be path dependent. The positive sign on the TP index suggests instead that the emergence of new technology based sectors is shaped also by the knowledge and competences accumulated in the region over time.

[4] Due the loss of too many observations, this check has not been done on the nanotechnology subsample.

6 Conclusions

The emergence and evolution of new industries has been at the forefront of economic speculation since the contributions of scholars such as Alfred Marshall, Joseph Schumpeter, Simon Kuznets, Allyn Young, Edith Penrose and George Richardson. The more recent evolutionary approach to economic geography emphasizes the importance of the branching process that occurs in regional diversification dynamics (Boschma and Frenken, 2007; Boschma et al. 2013). These developments highlight the role of routines and cumulated competencies in the process of diversification. Thus, regional branching occurs in domains that are close to the local areas of specialization. Based on these achievements, we applied the methodological framework developed by Hidalgo et al. (2007) to study the path-dependent dynamics of the emergence of new technology-based industries at the regional level, with a special focus on nanotechnologies. The focus on these technologies was motivated by their being relatively recent and of interest to scholars of innovation because of their ambiguous nature in terms of continuity with the existing technological competencies.

The analysis was conducted on patent information drawn from the October 2011 release of the Patstat database. Patent applications were regionalized on the basis of inventors' addresses. We focused on the NUTS2 regions in the EU15 countries. Both our data and previous analyses of nanotechnologies suggested the second half of the 1980s as the starting point. Our analysis covers the period 1986-2006 in order to avoid right-censoring problems.

The empirical results of our statistical analysis and econometric tests provide robust support for our working hypotheses. The emergence of new technology-based activities is likely to be a path-dependent process in which the capabilities cumulated over time may constrain future

developments at the local level. In other words, the set of activities that constitutes the technological specialization of a given geographical aggregate matters for planning future diversification strategies. Regions that are specialized in technologies with higher degrees of density will find it easier to diversify and adopt new technologies. Conversely, peripheral regions with technological comparative advantages that are not close in the technological space will find it more difficult to diversify in core technologies.

It should be noted that the path-dependent nature of the emergence of new technology-based sectors does not imply an endless process of cumulative causation *à la Myrdal* (1957). On the contrary, in path-dependent processes the final outcome is highly unpredictable. At any moment in time, unexpected events and changing local conditions can modify the economic agents' trajectories. Also, at each moment in time, the set of attainable multiple equilibrium points changes. This makes the final outcome definitely uncertain (David, 1994, 1997; Colombelli and von Tunzelmann, 2011). As a consequence, the dynamic irreversibilities due to local technological specialization can represent a strength or a weakness, depending on the nature of the search processes underlying the introduction of the new technologies. The introduction of radically new technologies or new technological standards to replace old ones can render initial technological advantage an obstacle rather than a resource.[5]

The analysis has important implications for regional technology policy. Actions to encourage the emergence of new technology-based industries at regional level, such as nanotechnologies or 'green technologies', should be based on the accurate analysis of both the comparative advantages developed over time in the area and of the relative position of such technologies in the technological landscape. Stimulating local agents to jump to new activities far away from

[5]An example of these dynamics is provided in Nelson (1993), who observed that no firm managed the double transition from valves to transistors and transistors to integrated circuits. Once the future of high tech was obviously along Route 128, created by researchers and entrepreneurs from MIT; no-one thought about Californian drop-outs.

their cumulated competencies can be inefficient and unsuccessful. This evidence is especially important in the context of recent interest at European level in stimulating new activities. The results in this paper call for targeted measures to promote the process of local technological differentiation that take account of the history of the region and its distinctive advantages and cumulated knowledge.

The scope for application of the methodology developed in this paper to investigate the emergence dynamics of new technology-based sectors goes beyond analysis of the path-dependent character of this persistent process. Recent research shows that the properties of knowledge bases in terms of coherence, variety and cognitive distance affect economic and technological performances at different levels of aggregation (Colombelli et al., 2013, 2014; Antonelli and Colombelli, 2013; Quatraro, 2010). Future research should study the effects of the properties of local knowledge bases on the differential patterns of emergence of new technological activities at the local level.

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7 References

Acs, Z.J., Anselin, L. and Varga, A., 2002. Patents and innovation counts as measures of regional production of new knowledge. Research Policy 31, 1069–1085.

Antonelli, C., 2006. Path dependence, localized technological change and the quest for dynamic efficiency, in Antonelli, C., Foray, D., Hall, B. and Steinmueller, E. (eds.), Frontiers in the economics of innovation. Essays in honor of Paul David. Edward Elgar, Cheltenham.

Antonelli, C. and Colombelli, A., 2013. Knowledge cumulability and complementarity in the knowledge generation function. LEI&BRICK Working Paper 03/2013, Department of Economics, University of Torino.

Antonelli, C., Crespi, F. and Scellato, G., 2013.Internal and external factors in innovation persistence. Economics of Innovation and New Technology, forthcoming, doi: 10.1080/10438599.2012.708135.

Arellano, M. and Bond, S.R., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Review of Economic Studies 58, 277-297.

Arellano, M. and Bover, O., 1995. Another look and the instrumental-variable estimation of error-components models. Journal of Econometrics 68, 29-52.

Avenel, E., Favier, A.V., Maa, S., Mangematin, V., Rieu, C., 2007. Diversification and hybridization in firm knowledge bases in nanotechnologies. Research Policy 36, 864-870.

Blundell R.W and Bond S.R., 1998.Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics 87, 115-143.

Boschma, R.A., 2005. Proximity and innovation: A critical assessment. Regional Studies 39, 61-74.

Boschma, R.A.,Frenken, K. 2007. A theoretical framework for economic geography: industrial dynamics and urban growth as a branching process. Journal of Economic Geography 7, 635-649.

Boschma, R.A., Iammarino, S., 2009. Related variety, trade linkages and regional growth. Economic Geography 85, 289-311.

Boschma, R., Minondo, A., Navarro, M. (2012), Related variety and regional growth in Spain. Papers in Regional Science 91, 241-256.

Boschma, R.A., Minondo, A., Navarro, M., 2013. The emergence of new industries at the regional level in Spain. A proximity approach based on product-relatedness. *Economic Geography* 89, 29-51.

Bozeman, B., Laredo, P., Mangematin, V., 2007. Understanding the emergence and deployment of ‘‘Nano’’ S&T. Research Policy 36, 807–812.

Breschi, S., Lissoni, F., and Malerba, F., 2003. Knowledge relatedness in firm technological diversification. Research Policy 32, 69-97.

Buenstorf, G., Klepper, S., 2009. Heritage and agglomeration: The Akron tyre cluster revisited. Economic Journal 119, 705-733.

Burns A. F., 1934. Production trends in the United States since 1870. NBER, Boston.

Colombelli A., von Tunzelmann G.N., 2011. The persistence of innovation and path dependence in Antonelli C. (ed.) Handbook on the Economic Complexity of Technological Change. Edward Elgar, Cheltenham, pp. 105-120.

Colombelli, A., Krafft, J., Quatraro, F., 2013. Properties of knowledge base and firm survival: Evidence from a sample of French manufacturing firms. Technological Forecasting and Social Change 80, 1469-1483.

Colombelli, A., Krafft, J., Quatraro, F., 2014. High Growth Firms and Technological Knowledge: Do gazelles follow exploration or exploitation strategies? Industrial and Corporate Change, 23, 261-291.

Cox, D.R., 1970. Analysis of Binary Data. Methuen.

Darby, M.R., Zucker, L.G., 2005. Grilichesian Breakthroughs: Inventions of Methods of Inventing and Firm Entry in Nanotechnology. Annales D'Économie et de Statistique 79-80, July-December 2005.

David, P.A. 1985. Clio and the economics of QWERTY. American Economic Review 75, 332-337.

David, P.A. 1994. Positive feedbacks and research productivity in science: Reopening another black box, in Granstrand, O. (ed.), *The economics of technology*, Elsevier North Holland, Amsterdam.

David, P.A. 1997. Path dependence and the quest for historical economics: One morechorus of ballad of QWERTY, Oxford University Economic and Social History Series020, Economics Group, Nuffield College, University of Oxford.

David, P.A., 2001. Path Dependence, its Critics and the Quest for “Historical Economics”, in Garrouste, P. and Ioannidis, S. (eds), Evolution and Path Dependence in Economic Ideas: Past and Present. Cheltenam, Elgar.

Engelsman, E.C. and van Raan, A.F.J., 1994. A patent-based cartography of technology. Research Policy 23, 1-26.

Foss, N.J. and Loasby, B.J. (eds), 1998. Economic Organization, Capabilities and Co-ordination. London, Routledge.

Frenken, K., von Oort, F., Verburg, T., 2007.Related Variety, Unrelated Variety and Regional Economic Growth. Regional Studies 41, 685-97.

Graham, S., Iacopetta, 2009. Nanotechnology and the Emergence of a General Purpose Technology. Les Annales d'Economie et de Statistique, Available at SSRN: http://ssrn.com/abstract=.

Graham, S., Iacopetta, M., Youtie, J., 2008. Assessing the Nature of Nanotechnology: Can We Uncover an Emerging General Purpose Technology? Journal of Technology Transfer 33, 315-329.

Griliches, Z., 1990. Patent statistics as economic indicators: a survey. Journal of Economic Literature 28, 1661–1707.

Hausmann, R. and Hidalgo, C.A., 2010. Country diversification, product ubiquity, and economic divergence. CID Working Paper No. 201.

Hausmann, R. and Klinger, B., 2007. The Structure of the Product Space and the Evolution of Comparative Advantage. CID Working Paper No. 146.

Hidalgo, C.A., Klinger, B., Barabasi, A.L. and Hausman, R., 2007. The product space conditions the development of nations. Science 317, 482-487.

Jaffe, A.B. 1986. Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value. American Economic Review 76, 984–1001.

Jaffe, A., 1989. Real Effects of Academic Research. American Economic Review 79, 957-70.

Klepper, S., 2011. Nano-economics, spinoffs, and the wealth of regions. Small Business Economics 37, 141-154.

Klepper, S., 2007. Disagreements, Spinoffs, and the Evolution of Detroit as the Capital of the U.S. Automobile Industry. Management Science 53, 616-631.

Klepper, S., Simons, K.L., 2000. Dominance by birthright: entry of prior radio producers and competitive ramifications in the U.S. television receiver industry. Strategic Management Journal 21, 997–1016.

Krafft, J., 2010. Profiting in the Info-Coms Industry in the Age of Broadband: Lessons and New Considerations. Technological Forecasting and Social Change 77(2), 265-278.

Krafft, J., Quatraro, F. and Saviotti, P.P., 2009. Evolution of the knowledge base in knowledge intensive sectors. LEI-BRICK Working Paper no 06/2009.

Kuznets S., 1930. Secular Movements in Production and Prices.Houghton Mifflin, Boston.

Langlois, R., P. Robertson, 1995. Firms, markets and economic change: a dynamic theory of business institutions. London: Routledge.

Leydesdorff, L., 2008. The delineation of nanoscience and nanotechnology in terms of journals and patents: A most recent update. Scientometrics 76, 159-167.

Leydesdorff, L., Zhou, P., 2007. Nanotechnology as a Field of Science: Its Delineation in Terms of Journals and Patents. Scientometrics 70, 693-713.

Linton, J. D., Walsh, S. T., 2008. Acceleration and extension of opportunity recognition for nanotechnologies and other emerging technologies. Beschleunigung und Erweiterung der Wahrnehmungunternehmerischer Gelegenheiten fu¨r Nanotechnologie und andereneue Technologien 26, 83–99.

Loasby, B.,1991. Equilibrium and evolution: an exploration of connecting principles in economics, Manchester University Press: Manchester and New York.

Loasby, B., 1999. Knowledge, institutions and evolution in economics, Routledge: London.

Mangematin, V., Errabi, K., Gauthier, C., 2011. Large players in the nanogame: dedicated nanotech subsidiaries or distributed nanotech capabilities?. Journal of Technology Transfer 36, 640-664.

Marshall, A., 1890. Principles of Economics. London: Macmillan and Co., Ltd.

Marshall, A., 1919. Industry and Trade. A Study of industrial technique and business organization; and of their influences on the condition of various classes and nations. London: Macmillan and Co., Ltd.

McCullagh, P., and J. A. Nelder. 1989. Generalized Linear Models. 2nd ed. London, Chapman & Hall/CRC.

Metcalfe, S., 1995.Technology systems and technology policy in an evolutionary framework, Cambridge Journal of Economics 19(1), 25-46.

Mogoutov, A., a nd Kahane, B., 2007. Data search strategy for science and technology emergence: A scalable and evolutionary query for nanotechnology tracking. Research Policy 36, 893–903.

Mowery, D.C., 2011.Nanotechnology and the US national innovation system: continuity and change. Journal of Technology Transfer 36, 697-711.

Myrdal, G. (1957), Economic Theory and Underdeveloped Regions. London: University Paperbacks, Methuen.

Nelson, R.R., 1993. National Innovation Systems. A comparative analysis. Oxford, Oxford University Press.

Nelson, R.,S. Winter, 1982. An evolutionary theory of economic change, Cambridge, MA: Belknap Press of Harvard University Press.

Nooteboom, B., 2007. Organization, Evolution, Cognition and Dynamic Capabilities. The IUP Journal of Managerial Economics 0(4), 31-55.

Pavitt, K., 1985. Patent statistics as indicators of innovative activities: possibilities and problems. Scientometrics 7, 77–99.

Penrose, E., 1959. The theory of the growth of the firm, Oxford University Press.

Quatraro, F., 2012. The Economics of Structural Change in Knowledge. London and New York, Routledge.

Quatraro, F., 2010. Knowledge Coherence, Variety and Productivity Growth: Manufacturing Evidence from Italian Regions. Research Policy 39, 1289-1302.

Richardson, G. B., 1960. Information and Investment. Oxford: Oxford University Press.

Richardson, G.B., 1972. The organisation of industry, Economic Journal, 82.

Richardson, G.B.,1990. Information and Investment: a study in the working of competitive economy, Cambridge: Cambridge University Press.

Rocco, M., & Bainbridge, W. S. (Eds.)., 2007. Nanotechnology: Societal implications. Dorsdrescht: Springer.

Rothaermel, F. T., Thursby, M. , 2007. The nanotech versus the biotech revolution: Sources of productivity in incumbent firm research. Research Policy 36, 832–849.

Scheu, M., Veefkind, V.,Verbandt, Y., Molina Galan, E., Absalom, R., Forster, W., 2006. Mapping nanotechnology patents: The EPO approach. World Patent Information 28, 204-211.

Schellekens, M.H.M., 2010. Patenting nanotechnology in Europe: Making a good start? An analysis of issues in law and regulation. Journal of World Intellectual Property 13, 47-76.

Schumpeter, J. A.,1939. Business Cycles. A Theoretical, Historical and Statistical Analysis of the Capitalist Process. New York and London, McGraw Hill.

Soete, L. 1987. The impact of technological innovation on international trade patterns: The evidence reconsidered. Research Policy 16, 101-130.

Teece, D., 1996. Firm organization, industrial structure, and technological innovation, Journal of Economic Behavior and Organization 31(2), 192 225.

Teece, D., G. Pisano, 1994. The dynamic capabilities of firms: an introduction. Industrial and Corporate Change 3(3), 537 555.

Teece, D., Rumelt, R., Dosi, G. and Winter, S., 1994. Understanding Corporate Coherence: Theory and Evidence. Journal of Economic Behavior and Organization 23, 1–30.

Thomas M. J., 1975. Growth pole theory, technological change and regional economic growth. Papers in Regional Science 34, 3-25.

Thursby, J., Thursby, M., 2011.University-industry linkages in nanotechnology and biotechnology: evidence on collaborative patterns for new methods of inventing. Journal of Technology Transfer 36, 605-623.

Tushman, M. L. and Anderson, P., 1986. Technological discontinuties and organizational environments. Administrative Science Quarterly 31 , 439-65.

Young, A., 1928. Increasing Returns and Economic Progress. Economic Journal 38, 527-542.

Witt, U., 2003. The Evolving Economy: Essays on the Evolutionary Approach to Economics. Cheltenham: Edward Elgar.

Table 1 – Distribution of Patent Applications, by Country

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

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

Country	Freq.	Percent
Austria	108	1.93
Belgium	184	3.28
Germany	2,441	43.55
Denmark	56	1
Spain	78	1.39
Finland	70	1.25
France	994	17.73
Great Britain	752	13.42
Greece	12	0.21
Ireland	26	0.46
Italy	279	4.98
Luxembourg	6	0.11
Netherlands	407	7.26
Portugal	8	0.14
Sweden	184	3.28
Total	**5,605**	**100**

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

Dependent variable $x_{i,s,t+5}$	Linearprobability 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

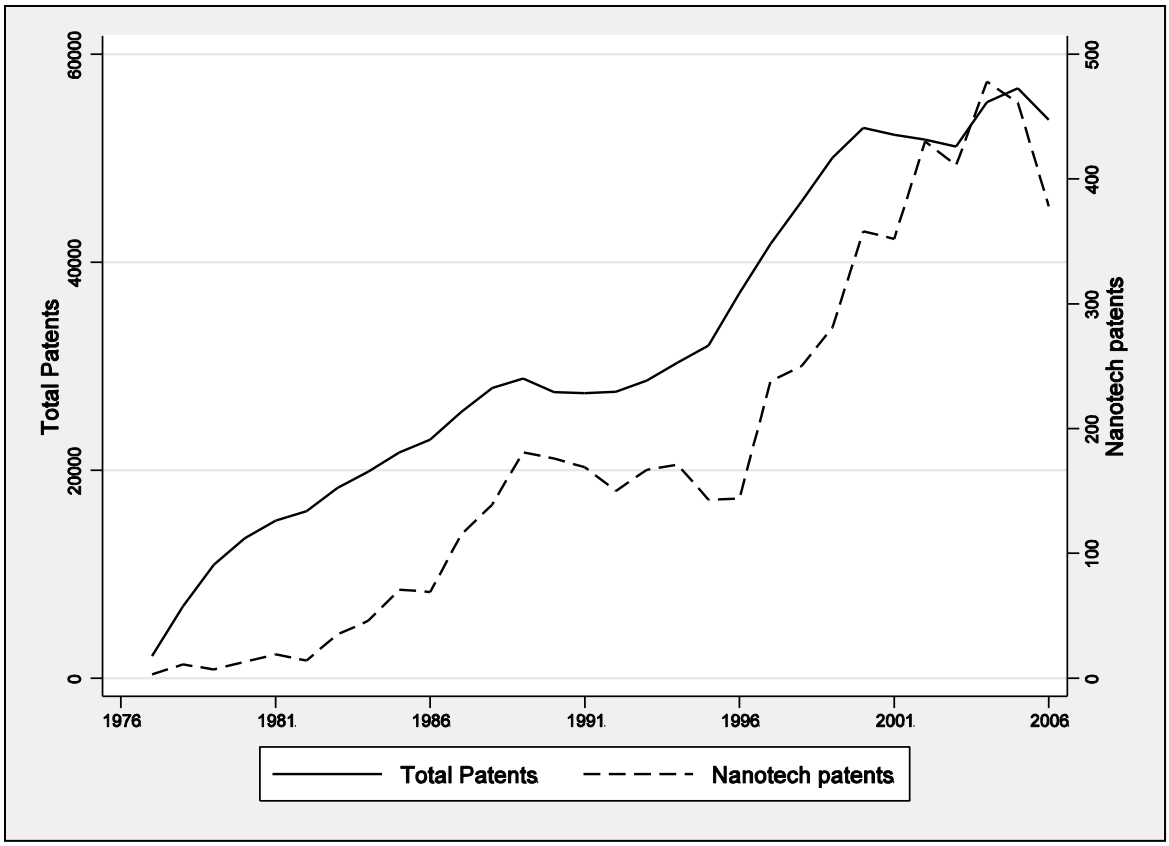
Note: regional clustered standard errors between parentheses.

Table 5 - Econometric results, estimation using the TP index

Dependent variable $x_{i,s,t+5}$	Linearprobability model	GLM	System GMM
	(1)	(2)	(3)
$x_{i,s,t}$	0.168***	0.717***	0.035***
	(0.006)	(0.027)	(0.005)
$TP_{i,s,t}$	0.126***	0.633	0.738***
	(0.038)	(0.163)	(0.073)
constant	0.297***	-0.936***	0.253***
	(0.007)	(0.030)	(0.0114)
R^2	0.040		
Optimization		MQL Fisher scoring	
(1/df) Pearson		0.999	
Hansen / Sargan test (p-value)			877.465 (0.000)
AR(1) (p-value)			-77.70 (0.000)
AR(2) (p-value)			1.429 (0.152)
Observations	209576	209576	132077

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

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

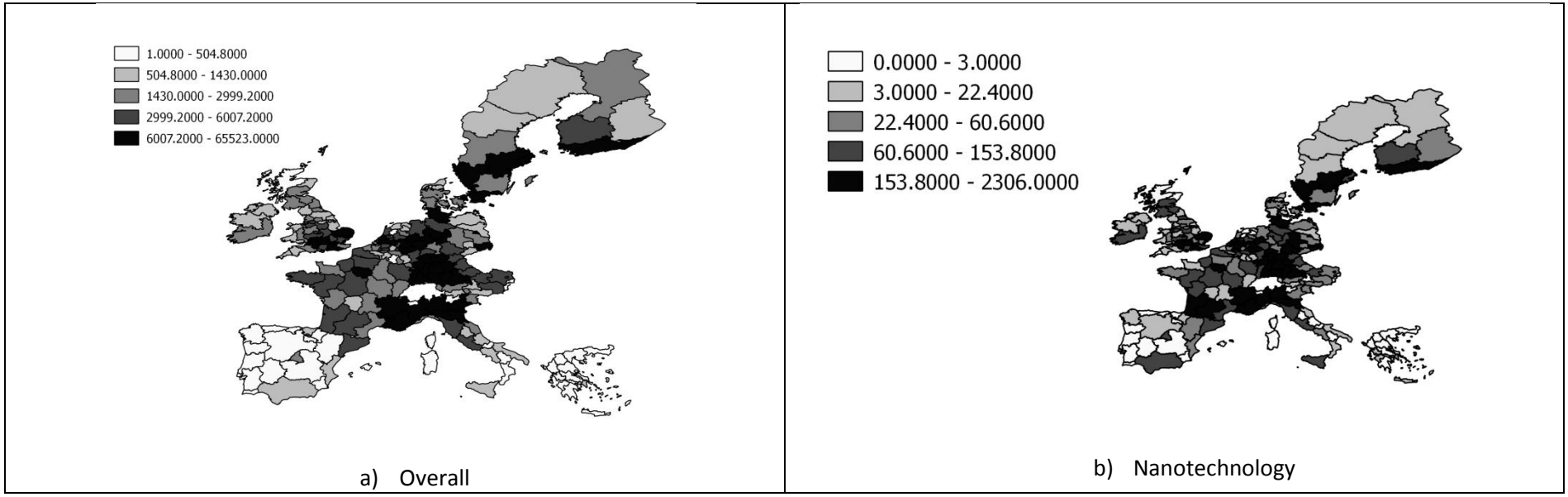
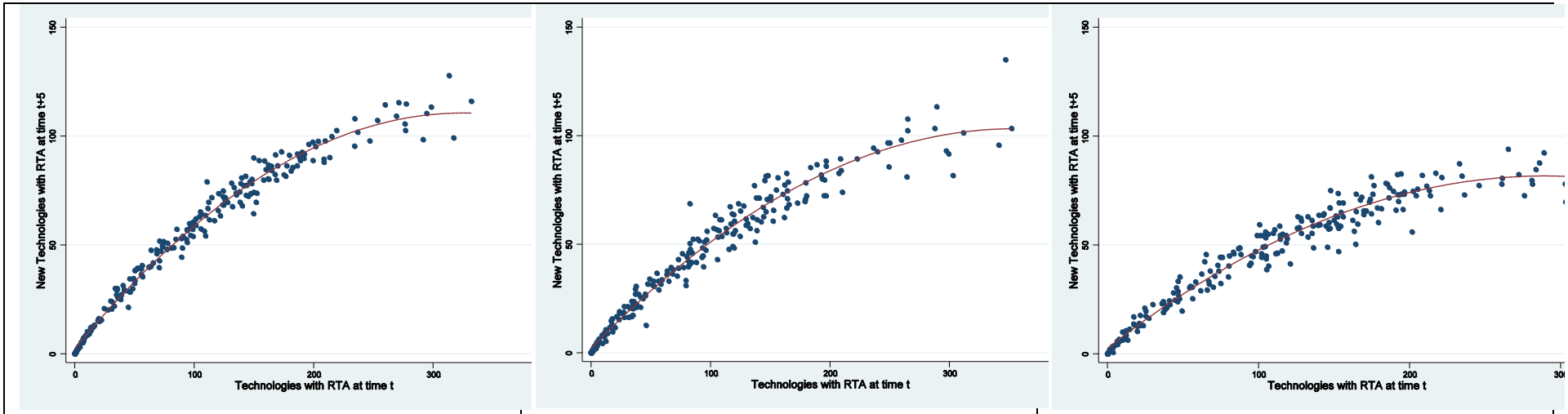


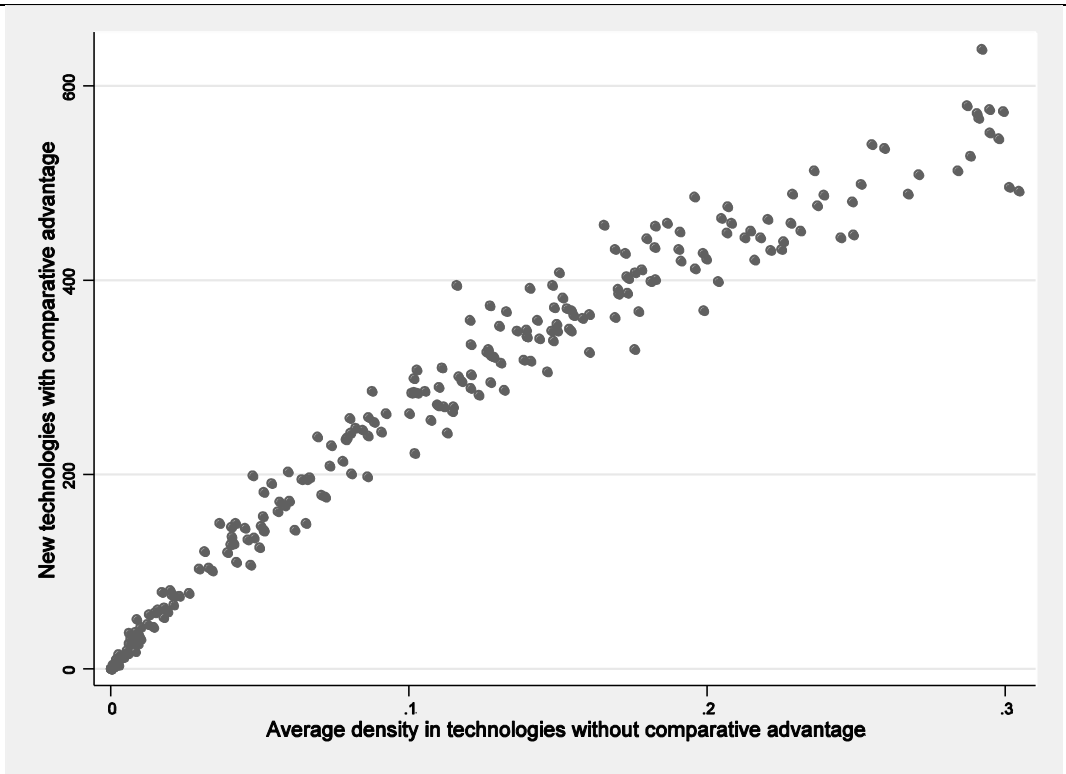
Figure 3 - Relationship between technologies with RTA at time t and new technologies with RTA at time t+5 in European regions (average values; 5-years interval)



a) Overall period | b) Before 1996 | c) After 1996

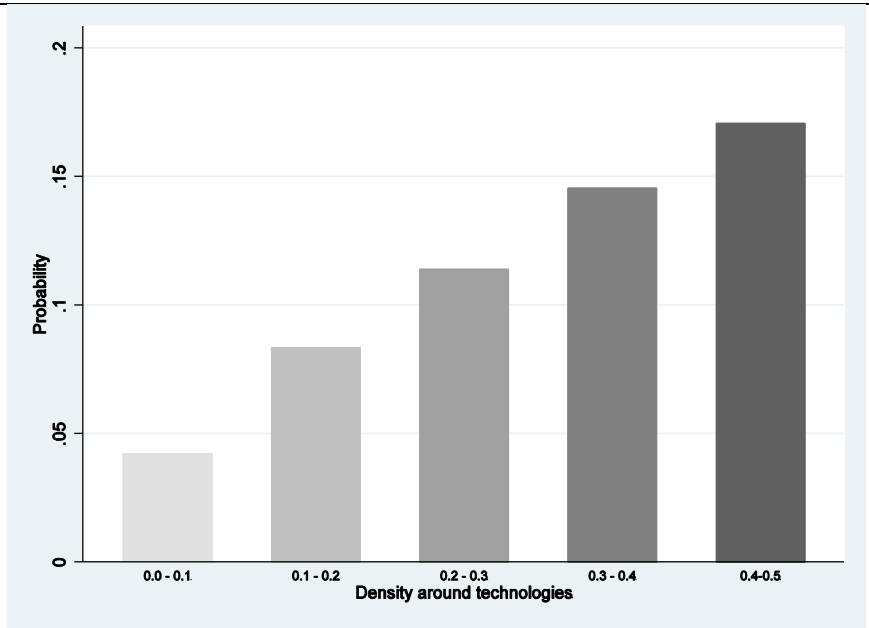
Note : each circle in the scatter plot represents a sampled region.
A region has a comparative advantage in a given technology if the calculated RTA > 1.

Figure 4 - 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)

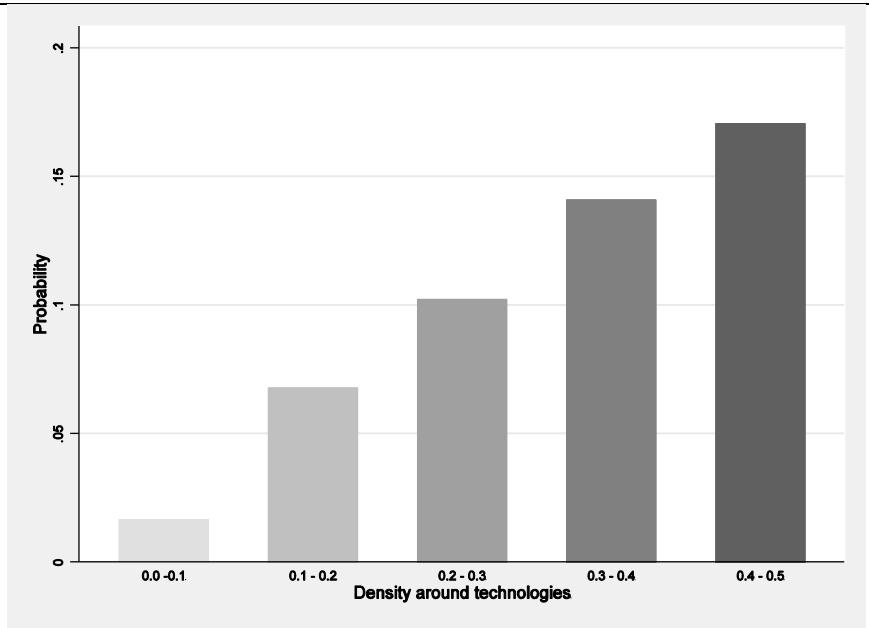


Note : each circle in the scatter plot represents a sampled region.
A region has a comparative advantage in a given technology if the calculated RTA > 1.

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

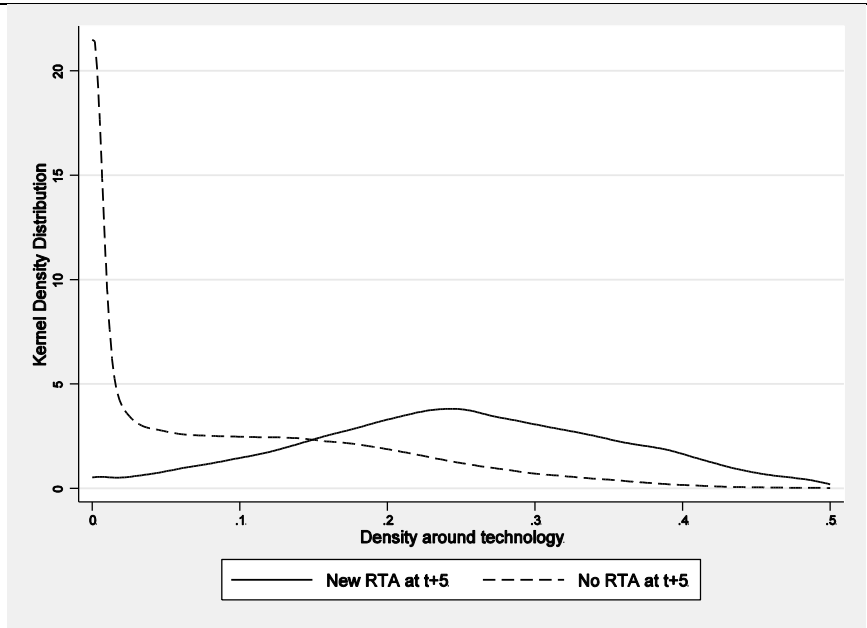


a) Overall

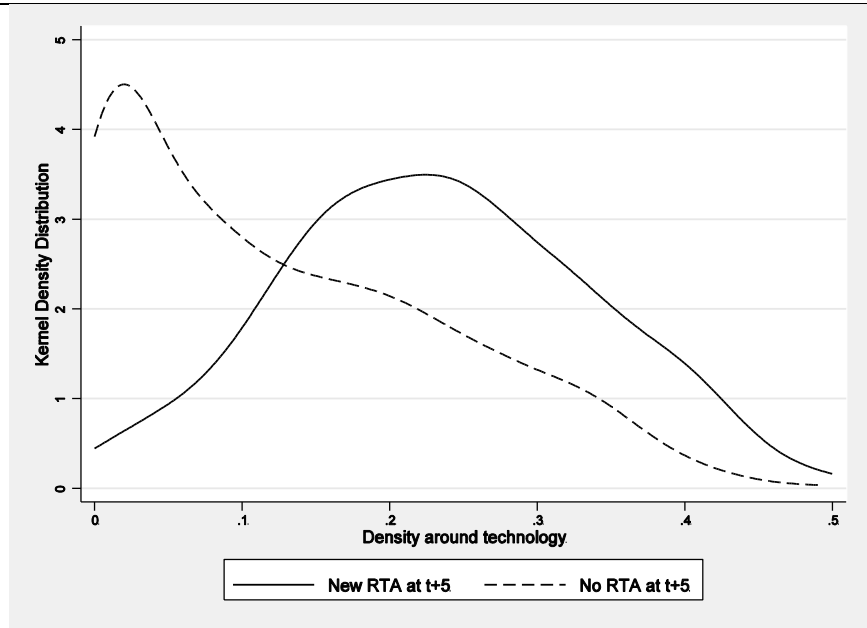


b) Nanotechnologies

Figure 6 – 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

Note: A region has a comparative advantage in a given technology if the calculated RTA > 1.

Appendix 1- Regions included in the analysis (average values)

Nuts Code	Region	R&D Expenditure[a] (Share of GDP)	Employment[a] (thousands)	Patents Count[b]
AT11	Burgenland (AT)	0,597	111,933	34,266
AT12	Niederösterreich	0,970	660,250	391,600
AT13	Wien	3,437	899,183	490,502
AT21	Kärnten	2,267	256,717	94,499
AT22	Steiermark	3,370	575,733	297,413
AT31	Oberösterreich	1,940	687,017	431,001
AT32	Salzburg	0,990	286,033	115,388
AT33	Tirol	2,143	352,350	168,939
AT34	Vorarlberg	1,320	169,617	215,844
ATZZ	Extra-Regio NUTS 2	NA	NA	17,095
BE10	Région de Bruxelles-Capitale	1,234	655,083	294,810
BE21	Prov. Antwerpen	2,250	719,400	538,857
BE22	Prov. Limburg (BE)	0,930	305,550	133,810
BE23	Prov. Oost-Vlaanderen	1,840	519,517	335,095
BE24	Prov. Vlaams-Brabant	3,090	402,517	477,143
BE25	Prov. West-Vlaanderen	1,000	481,283	212,000
BE31	Prov. Brabant Wallon	6,850	128,017	244,048
BE32	Prov. Hainaut	1,030	400,283	148,048
BE33	Prov. Liège	1,510	357,150	209,095
BE34	Prov. Luxembourg (BE)	0,520	86,583	45,381
BE35	Prov. Namur	1,060	150,550	74,667
BEZZ	Extra-Regio NUTS 2	NA	NA	60,667
DE11	Stuttgart	5,075	2105,517	3635,915
DE12	Karlsruhe	3,920	1383,817	2835,570
DE13	Freiburg	2,345	1048,867	1795,774
DE14	Tübingen	3,960	872,567	1428,328
DE21	Oberbayern	4,715	2318,533	3752,210
DE22	Niederbayern	NA	570,033	360,972
DE23	Oberpfalz	NA	536,700	540,871
DE24	Oberfranken	1,240	534,117	518,565
DE25	Mittelfranken	2,775	899,883	1259,559
DE26	Unterfranken	1,985	649,850	919,561
DE27	Schwaben	1,145	859,150	1054,471
DE30	Berlin	3,915	1549,050	993,941
DE41	Brandenburg - Nordost (NUTS 2006)	0,620	432,200	139,688
DE42	Brandenburg - Südwest (NUTS 2006)	1,580	588,300	251,358
DE50	Bremen	2,440	384,883	134,932
DE60	Hamburg	1,890	1049,833	675,133
DE71	Darmstadt	3,100	1992,333	3642,735
DE72	Gießen	1,885	463,333	588,431
DE73	Kassel	0,940	588,150	321,328
DE80	Mecklenburg-Vorpommern	1,335	717,967	108,185
DE91	Braunschweig	7,300	761,217	676,478
DE92	Hannover	2,155	1018,433	907,004
DE93	Lüneburg	0,625	644,917	565,583
DE94	Weser-Ems	0,565	1113,367	548,551
DEA1	Düsseldorf	1,615	2533,700	3423,704
DEA2	Köln	2,960	2083,000	2999,385
DEA3	Münster	0,935	1138,000	1076,655
DEA4	Detmold	1,325	991,950	817,424
DEA5	Arnsberg	1,410	1696,633	1589,248

Nuts Code	Region	R&D Expenditure[a] (Share of GDP)	Employment[a] (thousands)	Patents Count[b]
DEB1	Koblenz	0,625	668,233	623,227
DEB2	Trier	0,640	229,450	99,670
DEB3	Rheinhessen-Pfalz	2,810	883,167	2200,433
DEC0	Saarland	1,065	506,017	290,341
DED1	Chemnitz (NUTS 2006)	1,385	673,483	153,177
DED2	Dresden	3,355	752,617	589,057
DED3	Leipzig (NUTS 2006)	1,775	487,633	115,385
DEE0	Sachsen-Anhalt	1,155	1009,983	222,274
DEF0	Schleswig-Holstein	1,130	1233,000	788,446
DEG0	Thüringen	1,825	1018,200	444,585
DEZZ	Extra-Regio NUTS 2	NA	NA	403,095
DK01	Hovedstaden	NA	940,333	738,738
DK02	Sjælland	NA	329,000	184,548
DK03	Syddanmark	NA	583,667	194,349
DK04	Midtjylland	NA	636,333	227,151
DK05	Nordjylland	NA	281,667	72,786
DKZZ	Extra-Regio NUTS 2	NA	NA	21,524
ES11	Galicia	0,823	1034,867	21,190
ES12	Principado de Asturias	0,697	397,633	16,150
ES13	Cantabria	0,535	232,833	8,000
ES21	País Vasco	1,428	1001,217	102,190
ES22	Comunidad Foral de Navarra	1,460	303,100	43,600
ES23	La Rioja	0,663	138,467	6,875
ES24	Aragón	0,738	581,817	43,238
ES30	Comunidad de Madrid	1,748	2900,417	255,190
ES41	Castilla y León	0,875	1020,550	42,190
ES42	Castilla-la Mancha	0,408	717,000	22,611
ES43	Extremadura	0,602	369,417	4,125
ES51	Cataluña	1,267	3285,317	510,476
ES52	Comunidad Valenciana	0,848	1892,700	104,238
ES53	Illes Balears	0,252	450,183	9,650
ES61	Andalucía	0,755	2679,983	56,143
ES62	Región de Murcia	0,662	504,600	13,667
ES70	Canarias (ES)	0,567	751,017	9,737
ESZZ	Extra-Regio NUTS 2	0,000	NA	10,143
FI13	Itä-Suomi (NUTS 2006)	1,582	260,967	70,868
FI18	Etelä-Suomi (NUTS 2006)	3,543	1260,733	1077,602
FI19	Länsi-Suomi	3,462	568,517	433,042
FI1A	Pohjois-Suomi (NUTS 2006)	4,547	256,983	163,112
FI20	Åland	0,145	17,233	4,000
FIZZ	Extra-Regio NUTS 2	NA	NA	9,611
FR10	Île de France	3,243	5404,850	5418,524
FR21	Champagne-Ardenne	0,710	528,283	180,714
FR22	Picardie	1,355	667,217	395,000
FR23	Haute-Normandie	1,455	700,200	393,143
FR24	Centre (FR)	1,538	986,983	519,952
FR25	Basse-Normandie	0,970	566,517	172,810
FR26	Bourgogne	0,980	646,717	312,524
FR30	Nord - Pas-de-Calais	0,698	1440,900	382,333
FR41	Lorraine	1,115	844,817	347,810
FR42	Alsace	1,520	726,700	679,143
FR43	Franche-Comté	1,993	452,467	245,143
FR51	Pays de la Loire	0,943	1392,083	362,476

Nuts Code	Region	R&D Expenditure[a] (Share of GDP)	Employment[a] (thousands)	Patents Count[b]
FR52	Bretagne	1,643	1211,817	398,143
FR53	Poitou-Charentes	0,810	655,567	175,524
FR61	Aquitaine	1,610	1185,917	326,619
FR62	Midi-Pyrénées	3,653	1076,567	478,667
FR63	Limousin	0,780	285,117	67,952
FR71	Rhône-Alpes	2,590	2440,317	2227,238
FR72	Auvergne	2,445	525,267	224,524
FR81	Languedoc-Roussillon	2,090	853,350	274,810
FR82	Provence-Alpes-Côte d'Azur	1,888	1785,233	713,905
FR83	Corse	0,293	100,600	4,441
FR91	Guadeloupe (FR)	0,000	135,717	3,733
FR92	Martinique (FR)	0,000	125,067	2,197
FR93	Guyane (FR)	0,000	50,400	1,738
FR94	Réunion (FR)	0,000	207,917	5,590
FRZZ	Extra-Regio NUTS 2	142,838	NA	47,476
GR11	Anatoliki Makedonia, Thraki	0,365	237,900	2,000
GR12	Kentriki Makedonia	0,590	753,733	15,662
GR13	Dytiki Makedonia	0,155	103,817	2,400
GR14	Thessalia	0,285	295,567	4,556
GR21	Ipeiros	0,615	128,850	2,778
GR22	Ionia Nisia	0,105	91,883	1,000
GR23	Dytiki Ellada	0,690	280,567	6,780
GR24	Sterea Ellada	0,125	218,883	3,875
GR25	Peloponnisos	0,200	252,517	2,822
GR30	Attiki	0,760	1661,500	58,857
GR41	Voreio Aigaio	0,390	71,267	1,000
GR42	Notio Aigaio	0,105	122,617	1,833
GR43	Kriti	0,860	268,433	8,474
GRZZ	Extra-Regio NUTS 2	NA	NA	2,667
IE01	Border, Midland and Western	1,166	459,567	71,143
IE02	Southern and Eastern	1,198	1409,533	219,952
IEZZ	Extra-Regio NUTS 2	NA	NA	14,714
ITC1	Piemonte	1,663	1948,083	958,030
ITC2	Valle d'Aosta/Vallée d'Aoste	0,367	58,383	11,947
ITC3	Liguria	1,230	645,900	169,048
ITC4	Lombardia	1,120	4471,000	2359,619
ITD1	Provincia Autonoma Bolzano/Bozen (NUTS 2006)	0,377	244,467	46,619
ITD2	Provincia Autonoma Trento (NUTS 2006)	1,083	226,700	45,333
ITD3	Veneto (NUTS 2006)	0,620	2210,267	803,810
ITD4	Friuli-Venezia Giulia (NUTS 2006)	1,153	564,950	262,444
ITD5	Emilia-Romagna (NUTS 2006)	1,170	2045,450	1057,905
ITE1	Toscana (NUTS 2006)	1,100	1633,767	385,238
ITE2	Umbria (NUTS 2006)	0,813	368,517	63,857
ITE3	Marche (NUTS 2006)	0,587	698,367	135,810
ITE4	Lazio (NUTS 2006)	1,803	2352,050	401,476
ITF1	Abruzzo	1,057	501,683	91,571
ITF2	Molise	0,440	116,833	6,579
ITF3	Campania	1,123	1823,133	104,952
ITF4	Puglia	0,637	1295,750	66,095
ITF5	Basilicata	0,523	210,533	13,737
ITF6	Calabria	0,387	632,500	16,994
ITG1	Sicilia	0,833	1485,950	80,857

Nuts Code	Region	R&D Expenditure[a] (Share of GDP)	Employment[a] (thousands)	Patents Count[b]
ITG2	Sardegna	0,650	598,500	25,315
ITZZ	Extra-Regio NUTS 2	NA	NA	54,524
LU00	Luxembourg	1,625	297,350	132,143
NL11	Groningen	1,680	209,900	81,938
NL12	Friesland (NL)	0,690	227,733	69,634
NL13	Drenthe	0,725	167,083	74,340
NL21	Overijssel	1,420	427,750	216,508
NL22	Gelderland	1,770	756,817	462,912
NL23	Flevoland	4,688	109,283	48,198
NL31	Utrecht	1,880	541,983	334,358
NL32	Noord-Holland	1,678	1169,150	540,985
NL33	Zuid-Holland	1,650	1390,050	817,844
NL34	Zeeland	0,775	135,800	58,248
NL41	Noord-Brabant	2,900	994,500	1671,849
NL42	Limburg (NL)	1,918	422,033	333,858
PT11	Norte	0,567	1728,733	17,333
PT15	Algarve	0,230	204,017	3,111
PT16	Centro (PT)	0,655	1203,300	19,875
PT17	Lisboa	1,155	1447,633	22,000
PT18	Alentejo	0,790	312,683	4,800
PT30	Região Autónoma da Madeira (PT)	0,278	120,150	2,143
PTZZ	Extra-Regio NUTS 2	NA	NA	36,524
SE11	Stockholm	4,250	1048,533	1003,376
SE12	Östra Mellansverige	4,025	682,617	518,518
SE21	Småland med öarna	0,970	395,950	143,737
SE22	Sydsverige	4,285	600,017	633,401
SE23	Västsverige	5,600	879,067	680,160
SE31	Norra Mellansverige	1,315	367,317	194,500
SE32	Mellersta Norrland	0,690	173,933	62,617
SE33	Övre Norrland	2,490	228,767	92,668
SEZZ	Extra-Regio NUTS 2	0,000	NA	23,143
UKC1	Tees Valley and Durham	0,950	491,083	156,333
UKC2	Northumberland and Tyne and Wear	1,060	611,800	156,238
UKD1	Cumbria	0,630	225,583	49,667
UKD2	Cheshire (NUTS 2006)	4,225	473,900	384,905
UKD3	Greater Manchester	1,025	1160,950	271,286
UKD4	Lancashire	2,635	655,400	139,952
UKD5	Merseyside (NUTS 2006)	1,690	564,233	215,000
UKE1	East Yorkshire and Northern Lincolnshire	0,540	405,150	101,571
UKE2	North Yorkshire	1,650	374,267	148,095
UKE3	South Yorkshire	1,055	570,417	87,667
UKE4	West Yorkshire	0,715	992,000	243,048
UKF1	Derbyshire and Nottinghamshire	2,170	943,417	300,238
UKF2	Leicestershire, Rutland and Northamptonshire	1,645	790,083	295,048
UKF3	Lincolnshire	0,395	312,950	42,286
UKG1	Herefordshire, Worcestershire and Warwickshire	1,815	615,150	311,857
UKG2	Shropshire and Staffordshire	0,510	724,033	150,286
UKG3	West Midlands	1,300	1107,233	261,524
UKH1	East Anglia	5,140	1076,333	765,762
UKH2	Bedfordshire and Hertfordshire	3,490	822,383	550,333
UKH3	Essex	3,390	799,950	346,143

Nuts Code	Region	R&D Expenditure[a] (Share of GDP)	Employment[a] (thousands)	Patents Count[b]
UKI1	Inner London	1,135	1341,717	454,048
UKI2	Outer London	0,755	2153,700	564,286
UKJ1	Berkshire, Buckinghamshire and Oxfordshire	3,160	1134,050	907,810
UKJ2	Surrey, East and West Sussex	1,305	1263,750	653,619
UKJ3	Hampshire and Isle of Wight	3,695	910,467	473,524
UKJ4	Kent	2,405	753,317	281,714
UKK1	Gloucestershire, Wiltshire and Bristol/Bath area	3,015	1123,750	542,619
UKK2	Dorset and Somerset	0,875	566,550	140,905
UKK3	Cornwall and Isles of Scilly	0,265	228,450	43,000
UKK4	Devon	0,780	511,650	74,905
UKL1	West Wales and The Valleys	0,680	786,417	117,000
UKL2	East Wales	1,660	494,167	157,476
UKM2	Eastern Scotland	2,285	933,083	237,619
UKM3	South Western Scotland	0,930	1026,350	144,143
UKM5	North Eastern Scotland	1,625	251,700	90,857
UKM6	Highlands and Islands	0,785	192,967	21,810
UKN0	Northern Ireland (UK)	1,045	724,633	62,143

Notes : a) Own elaborations on Eurostat Data (average 1996-2006)
b) own elaborations on PATSTAT Data (average 1986-2006)