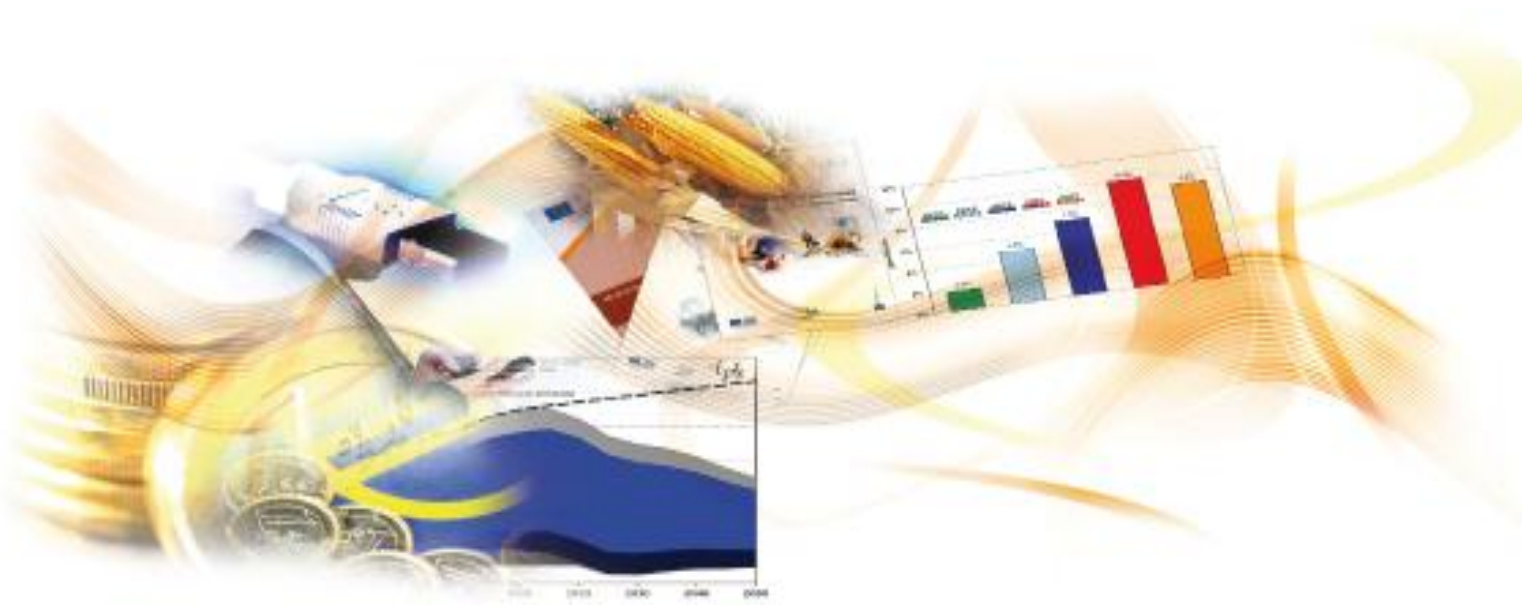


JRC TECHNICAL REPORTS



IPTS Working Papers on Corporate R&D and Innovation – No 5/2015

Key Enabling Technologies and Smart Specialization Strategies. European Regional Evidence from patent data

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2015

European Commission
Joint Research Centre
Institute for Prospective Technological Studies

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JRC95313

ISSN 1831-9408 (online)

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Abstract

The paper aims at investigating whether Key Enabling Technologies (KETs) can have a role in facilitating regional Smart Specialisation Strategies (S3). Drawing on the economic geography approach to S3, we formulate some hypotheses about the impact that KETs-related knowledge can have on the construction of new regional technological advantages (RTAs). By crossing regional data on patent applications, in KETs-mapped classes of the International Patent Classification (IPC), with a number of regional economic indicators, we test these hypotheses on a panel of 26 European countries over the period 1980-2010. KETs show a positive impact on the construction of new RTAs, pointing to a new “enabling” role for them. KETs also exert a negative moderating role on the RTAs impact of the density of related pre-existing technologies, pointing to the KETs capacity of making the latter less binding in pursuing S3. Overall, the net-impact of KETs is positive, pointing to a new case for plugging KETs in the S3 policy tool-box.

Abstract

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Keywords: Key Enabling Technologies; Smart Specialization Strategies; Revealed Technological Advantages.

JEL codes: R11; R58; O31; O33.

1 Introduction

The present paper deals with the policy concept of “Smart Specialization” and with the role that “Key Enabling Technologies” (KETs) can have for the implementation of “Smart Specialisation Strategies” (S3).

Put forward in 2008, in the new course of policy action for supporting regional development along the lines of the EU 2020 innovation plan, S3 refer to a process of regional specialization based on a bottom-up entrepreneurial discovery of what a region (or a country) is best at doing in terms of R&D and innovation (Foray et al., 2011). Taking stock of the intense debate that has accompanied its development in the meanwhile, we build on the premises that, in spite of the centrality that the concept has gained in the policy realm, its concrete application suffers from a still diffuse academic status. This is actually hampering its crystallization into consistent and recognizable strategies of smart specialisation.

Filling the gap between policy and theory in the S3 realm represents the main rationale of the paper. Its specific aim is that of evaluating whether the so-called “Key Enabling Technologies” (KETs) can help in that. Indeed, these are six technologies – industrial biotechnology, nanotechnology, micro- and nanoelectronics, photonics, advanced materials, and advanced manufacturing technologies – that the European Commission has recently set on the policy-agenda for “ensuring the competitiveness of European industries in the knowledge economy” (EC, 2009; 2012). Furthermore, their potential for the development of S3 has recently emerged in the observatory platform of S3 best-practices (Sörvik et al., 2013), referring to their generic contribution to the general spectrum of regional technological activities. Still, the exploitation of this KETs-based operational potential for S3 is affected by a possibly more pronounced gap between policy and science with respect to KETs. Indeed, a lot of policy attention is nowadays paid to these technologies, as the key-enabler of the industrial processes of the future in Europe. On the other hand, however, with the exception of the “Feasibility study for an EU Monitoring Mechanism on Key Enabling Technologies” (EC, 2011) – Feasibility Study hereafter – little can be found on the scientific rationale for giving KETs such a prominent policy role, and the proof of their relevance still seems to lay in the oven. This research-policy mismatch is even greater at the regional level, at which KETs have been recently prioritized in connection with S3, through explicit policy recommendations of monitoring (e.g. in the S3 Platform and in the Eye@RIS3 observatory) and supporting their development (e.g. in Regional Operational Plans).

In trying to solve this mismatch, and evaluate the implication of KETs for S3, in the paper we put forward a more scientifically grounded approach to the former, and to their impact on an evolutionary-geography approach to the latter (Colombelli et al., 2014; Essletzbichler 2013). More precisely, we recognize some KETs basic properties, which we claim to affect the regional capacity of developing new technological specializations, taking stock of their techno-cognitive proximity with respect to the existing ones. On this basis, we address the following research questions: Do KETs increase the regional capacity of S3, meant as this particular process of new technological specialization? Are KETs able to change the impact that the techno-cognitive proximity with respect to existing technologies has for the development of new ones? More in plain, do KETs enable regions to specialize more distantly from what they know? Or do they rather make existing technologies more binding for acquiring new specializations?

These research questions have some important policy implications. On the one hand, a positive answer to the first set of questions would indicate to regional policy makers whether KETs could actually be an additional S3 driver, able to compensate for the lack of other drivers, or to reinforce their functioning, should them be already present. In fact, KETs do not act in isolation and are only able to interact with other forces, from whose collective working the outcome of S3 will finally depend. The second set of questions could also provide important implications, suggesting whether KETs can be more possibly used to “explore” away from the existing technological base of the region, rather than to “exploit” it more deeply for obtaining new technological advantages. In other words, our analysis could also suggest which kind of smart strategy KETs could enable regions to pursue. Finally, by relating the role of KETs to the diversity of the regions in which they could be promoted, the KETs-S3 link can be more clearly disentangled.

As we said, the previous policy implications can be obtained by using an establishing approach to S3 in regional and urban studies, to which our paper also contributes in at least two directions. On the one hand, from a theoretical point of view, we try to move further a simple commodity-related relevance of KETs – as “significant [inputs] of future goods and services” (EC, 2012) – and recognise for them some more articulated characteristics that could potentially impact on the development of S3. On the other hand, from an empirical point of view, we test for this potential role by extending the patent-based data and

methodologies through which, in regional studies, S3 have been related to the construction of new RTAs (Colombelli et al., 2014; Essletzbichler 2013).

The rest of the paper is organised as follows. Section 2 provides the theoretical background of the paper and puts forward some hypotheses about a novel “key” role that the technologies at stake can be expected to have at the regional level. Section 3 presents the empirical application for testing these hypotheses, the data and the econometric strategy through which it is pursued. Section 4 comments the main results and presents their policy implications. Section 5 concludes and sets the research agenda for the future.

2 Theoretical background and hypotheses

What makes of the six identified technologies “*key enabling*” ones, is for the proponent European policy-makers (see, in particular, EC, 2009 and 2012)¹ a pragmatic and prospective rationale. Pragmatically, they are claimed to “*enable*”: “the development of *new goods and services* and the *restructuring* of industrial *processes*” (our own emphasis). In a nutshell, KETs would be technological inputs for obtaining new “KETs-based products and applications”, that is “key” (in the sense specified below) innovations, according to a mechanism of knowledge production function (Griliches, 1989), whose working is notably “black-boxed”. Still pragmatically, and somehow tautologically, their common distinguishing features with respect to arguably non- or less key enabling technologies, are their being “knowledge intensive and associated with high R&D intensity, rapid innovation cycles, high capital expenditure and highly skilled employment”. Prospectively, the same technologies are deemed “*key*” as they are expected to enable (in the sense above) European industries to “*shift* to a low carbon, knowledge-based economy” (our own emphasis). As such, whether KETs are actually able to open the “doors” of “future societal challenges” can only be accounted in the framework of an economic foresight exercise.

Even with the benefits of a policy jargon, the nature and the functional boundaries (i.e. with respect to non-/less ones) of KETs are apparently quite loose, especially *vis a vis* the firm role

¹ The discussion and citations which follow, are based on these EC documents and on their synthesis reported in the relevant web-site: http://ec.europa.eu/enterprise/sectors/ict/key_technologies/index_en.htm.

they are conversely gaining in the policy realm.² This high policy attention would certainly require a sounder research base, at least in two respects: i) in disentangling a more cogent (not to say, more scientific) and extant account of the “key enabling” role of the identified technologies; ii) in ascertaining whether such a role is actually able to legitimate the inclusion of the six identified technologies in the “KETs-club”, as well as the exclusion of other than them.

In what follows, we will refrain from addressing the second question, taking for granted and postponing to our future research agenda the (EC) policy position that the six technologies at stake actually share common “key-enabling” characteristics, which other do not possibly have.³ We instead focus on the first question, and look for a sounder account of this role, by referring to a regional level of analysis and to the place KETs have recently found in the debate on S3. Indeed, also at this level of analysis, a research-policy mismatch characterises the role of KETs (Capello et al, 2014; Camagni and Capello, 2013; Foray et al, 2011; OECD, 2013). On the one hand, European policy makers recommend regions to insert the diffusion and/or application of KETs among the priority areas on which to build their smart specialisation strategies: not only through generic “best” policy practices to share with other regions – as it was initially invoked by the S3 Platform of the JRC-IPTS European Commission – but even in concrete “regional operational plans”, to be constantly monitored (such as with the Eye@RIS3 initiative) and forcefully implemented.⁴ On the other hand, the rationale for plugging KETs among the policy priorities for S3 is quite loose, and generally linked to the need of having “horizontal priorities ... in addition to technological, sectoral or cross-sectoral priority areas” (Sörvik et al., 2013). At the regional level of analysis, however, the concept of S3 has luckily found in economic geography an interesting and rigorous characterisation, with respect to which the research-policy mismatch affecting KETs could be possibly reduced.

As discussed by Boschma (2014), by adopting an economic geography perspective, the concept of smart specialisation shares the main principles of the construction of regional

² This is reflected in the recent analyses that the European Commission has requested of international industrial policies on KETS (Biorn et al., 2011), of policy practices promoting the industrial uptake and deployment of KETs (Van de Velde et al., 2012), and of international market distortions in the area of KETs (ECSIP, 2013).

³ On this position, and for a definition and an illustration of the six identified technologies, see EC (2011).

⁴ A recent report on the extent to which some KETs (namely nanotechnologies, advanced materials and advanced manufacturing and process technologies) have been reflected in the Research and Innovation Smart Specialisation Strategies (RIS3) prepared at either the national or regional level during late spring/early summer of 2014, can be found in Pattison et al. (2015).

advantages (CRA), which requires regions to identify technology based development patterns, drawing upon knowledge, variety and policy platforms (Oughton et al., 2002; Asheim et al., 2011). In turn, the CRA approach identifies “related variety” as the main driver of diversification and industrial branching at the regional level (Boschma, 2011). Proximity amongst sectors or technologies shapes regional development trajectories in such a way that competences accumulated over time are likely to create dynamic irreversibilities, engendering path-dependent diversification dynamics (Boschma et al., 2013 and 2014; Colombelli et al., 2014; Essletzbichler 2013). Differently from CRA, smart specialisation does not entail explicitly the regional dimension. As McCann and Ortega-Argiles (2011) argue, the geographical dimension should be rather integrated in the smart specialisation looking at the effects of regional features on entrepreneurs’ ability to engage in successful learning processes. In this respect, S3 should stimulate the regional diversification into particular domains yielding economic and technological opportunities. The combination of S3 and CRA allows to developing a framework in which the regional governance of S3 is driven by knowledge accumulated over time by local agents. 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.

The previous conceptual framework is of course affected by the nature of the technologies nurturing the regional system and the dynamics of its S3-CRA combination. In particular, the technologies under the KETs-heading have some characteristics that can be assumed to affect the S3 of the regions mastering the relative knowledge.⁵

The first characteristic is the *general* nature of KETs, in terms of number and variety of their possible applications. All of the six KETs are the technological building-blocks of a large array of products and industrial processes. This emerges clearly in the Feasibility Study on KETs (EC, 2011), both from their “technical” definitions and from the number of products, already or not yet commercially available, identified on their basis. All the individual KETs

⁵ In the rest of this section, we will generically refer to this circumstance by alluding to the “presence” of KETs in a region. We will be more precise about how this presence can be detected in the following section. Secondly, we will refer to characteristics that, although common to them, the different KETs can reveal to a different extent, due to their intrinsic heterogeneity: an aspect, which we will also account for in the next section.

definitions actually refer to several fields of application.⁶ Furthermore, their individual analysis (based on existing literature, web searches and experts views) leads to identify different components for them, each of which is, in turn, at the basis of different current and prospective products.⁷ Similarly to General Purpose Technologies (GPTs) – from which they differ for a lower (if not even absent) role of military and defence-related procurement (Ruttan, 2006) and for a less infrastructural nature (Lipsey et al., 2005) – KETs have many different uses and can have important spillover effects on the development of other technologies. In a regional realm, the general nature of KETs can be expected to have an impact on S3, meant as the construction of new RTAs on the basis of pre-existing technologies (see above). In a similar branching process, regions with KETs (see footnote 6) could exploit their spillovers and come to master the knowledge of other applications than an initial focal one, among the several applications relying on their use. Just to make some examples, the nanotechnology advantages a region has been able to gain in the production of carbon nanotubes could lead it to acquire a new technological specialisation in polymers films or micro fibres. Indeed, all of these applications draw on a core of nanotechnology knowledge and on the region's capacity to extend it to different fields. By the same token, a specialised knowledge of advanced materials for the production of glass and ceramics, could have spillovers on a region's capacity of specialising in advanced materials for electric or magnetic applications. All in all, for their own general nature, KETs could act as propeller of new RTAs and have a direct impact on the region's capacity of developing them. The following hypothesis can thus be put forward:

Hp1: *KETs increase the region's capacity of constructing new revealed technological advantages.*

A second KETs characteristic with important implications for the development of S3 is their *system* nature, in terms of their relationships with other technological fields. Working like

⁶ These definitions rely on specific projects documented in the Feasibility Study. Just to make an example, the definition of industrial biotechnology is taken from the HLEG project as: “the application of biotechnology for the industrial processing and production of chemicals, materials and fuels. It includes the practice of using micro-organisms or components of micro-organisms like enzymes to generate industrially useful products, substances and chemical building blocks with specific capabilities that conventional petrochemical processes cannot provide” (EC, 2011, pag. 45).

⁷ Still as an example, nanotechnology is disaggregated into as many as 10 components – Metal-foam sandwich panel structures, Quantum dot systems for optoelectronics, Carbon Nanotubes (CNT), Polymers films, Nanoalloys and composites, Microelectromechanical systems (MEMS), Micro fibres, Functional coatings, Graphene bearing Nano Powders (GNP's), and Nano catalysts – each with a variable number of based products – 17, 20, 11, 7, 7, 17, 5, 13, 2, and 4, respectively. For the sake of illustration, the 4 Nano catalysts based products are: Polyethylene catalysts, Tetraethylammonium Hydroxide (TEAH) catalysts, Catalyst micro reactors, and Split Plasma catalysts.

what Thomas Hughes called “large technological systems” (Hughes, 1987), the general extent of their potential application (see the previous characteristic) naturally entails that KETs are used in combination with other technologies, through which their application becomes more specific and then actual. Just to make an example, in order to get implemented in the realisation of electric vehicles, advanced materials and other relevant KETs will have to be linked, tailored and combined, in a systemic fashion, with more standard technologies, like mechanics and electronics, to mention a few. Following the previous economic geography approach, at the regional level, the knowledge acquired in KETs could be likely combined with other technologies, in which regions have acquired experience, if not even a specialisation. The crucial point is that, by getting combined with the extant technologies of the region, KETs could change their actual degree of exploitable relatedness and, in so doing, their relevance for the acquisition of new ones. On the one hand, KETs could widen the spectrum of opportunities along which the regional knowledge base can be newly recombined, and thus make the impact of related variety and of the cognitive proximity with respect to its constituent technologies less binding. For example, the combination of (KETs) micro-electronics with more “traditional” home technologies embodied in the region (e.g. wood and plastics assembling technologies), could make the latter less binding for the region’s capacity of obtaining new specialisations in the field, as in the case of smart domotics. On the other hand, KETs could also play an opposite role and make regional learning dependent on the deepening of the technologies to which they apply, with a more binding role for related variety. An example could be provided by the combination of (KETs) photonics with boating/shipping technologies in regions relying on fishery areas, whose impact is presumably that of making the relationship with the latter more important for the acquisition of new RTAs. In principle, each of the two outcomes illustrated above is equally possible. Indeed, not only depends it on the technical complementarities that could equally well emerge between the specific KETs and non-KETs of the regions at stake. But also on the policy-choice regions are free to make between an approach to KETs that relaxes and reinforces, respectively, the role of the existing knowledge base for regional learning. Accordingly, the following two hypotheses can be put forward, being their validity subject to empirical application:

Hp2a: *KETs negatively moderate the impact of regional related knowledge on the construction of new revealed technological advantages.*

Hp2b: *KETs positively moderate the impact of regional related knowledge on the construction of new revealed technological advantages.*

Before moving to the empirical test of the proposed hypotheses, it should be noted that the KETs characteristics identified above possibly hold true to a different extent for the six technologies the European policy makers have identified. Their intrinsic knowledge base is actually heterogeneous and makes them characterised by different degrees of generality and system properties. Accordingly, a disaggregated test of HP1 and HP2s for each and every of the six KETs appear more than desirable and can't be excluded to yield different outcomes: a circumstance that would be extremely useful in orienteering regions towards the construction of their actual KETs portfolio and to the eventual selection of specific KETs within it.

3 Empirical application

3.1 Data

In light of their EU policy relevance, the natural context for testing our hypotheses about KETs is represented by European regions. As usual, their empirical coverage is mainly determined by the availability of data for measuring the phenomenon at stake, in our case represented by the presence of KETs knowledge at the regional level and by the other regional drivers the literature has identified for the acquisition of new RTAs.

As far as the first point is concerned, we have referred to the Feasibility Study and, out of the three approaches proposed to identify KETs data in existing databases, we have opted for the so-called “technology diffusion approach” and adapted it to a regional level of analysis (EC, 2011, pag. 21).⁸ In particular, we have drawn on this approach the idea of taking the number of patent applications in KETs-mapped IPC classes as a proxy of the new knowledge produced in the respective fields.

The most critical analytical step of this approach consists of identifying KETs patents based on IPC codes. In order to address this issue, a conversion table has been put forward by the

⁸ As clarified in the Feasibility Study, this approach is actually more consistent with the kind of techno-economic analysis we are carrying out than the other two, that is: the “component approach”, which identifies KETs components and map with them companies and relevant codes of production and trade classifications; and the “value chain approach”, which identifies the underlying components of final products relying heavily on KETs technology.

Feasibility Study, which is still under revision. In the current application, we have referred to the latest available version (see Vezzani et al., 2014) and used it to access the OECD Reg Pat dataset (July 2014), which contains information on a number of patent items (e.g. International Patent Classifications (all digits); region codes; patents ID).

We have then related this information, rather than to the relevant economic sectors (in which the original approach assumes the knowledge will “diffuse”), to the regions of the relevant inventors. In so doing, we are confident to have an indication of the capability of regions in producing new technological knowledge in the field of KETs (or in one/some of them) that is relevant for industrial application and commercialisation.

As far as the other S3 drivers are concerned, regional patent data at the NUTS2 level have been crossed with those of the European Regional Database, maintained by Cambridge Econometrics,⁹ in order to build up other relevant control variables (see the next sections) at the same level of statistical territorial unit. While a more disaggregated level of analysis, such as NUTS3, could make emerge more fine-grained elements of differentiation for the issue at stake, data availability imposes the reference to NUTS2. On the other hand, previous studies have shown that NUTS2 is a relevant level of analysis both in terms of government institutions for S3 (e.g. Rodríguez-Pose et al., 2014), and for the promotion of KETs initiatives at the regional level (e.g. Pattinson et al., 2015). By merging the two datasets above, we are left with a regional dataset of 26 EU countries (excluding only Greece and Croatia from the 28 of the EU due to data constraints) over the period 1981-2010: a wide geographical account of the issues at stake, and for a quite long temporal span.

3.2 Variables

Following the economic geography approach to S3 discussed above, the focal dependent variable is the number of new RTAs of a certain region i , meant as the number of those RTAs it shows at time t , in their absence at a previous time, $t - 1$, that is:

$$New_RTA_{it} = \sum_s x_{ist} \quad (1)$$

⁹ “Cambridge Econometrics ... updates and augments the regional accounts data published by Eurostat, making use of alternative data supplied by a range of sources including other Eurostat sources and national statistical offices to produce a full time series of data ranging back to 1980 (with data for the New Member States starting in 1990) across all NUTS2 and NUTS3 regions of the EU” (<http://www.camecon.com/SubNational/SubNationalEurope/RegionalDatabase.aspx>).

where $x_{ist} = 1$, if $RTA_{ist} \geq 1$ and $0 < RTA_{ist-1} < 1$.

In turn, the Revealed Technological Advantage (RTA) of region i (out of n) in technology s (out of m) at time t is captured with a standard Balassa indicator for trade specialisation, redefined in terms of number of patents filed in the correspondent IPC class (PAT_{ist}) (Soete, 1987):

$$RTA_{ist} = \frac{\frac{PAT_{ist}}{\sum_{i=1}^n PAT_{ist}}}{\frac{\sum_{s=1}^m PAT_{ist}}{\sum_{i=1}^n \sum_{s=1}^m PAT_{ist}}} \quad (2)$$

In our sample, $m = 632$ and $n = 235$, while a lag of 1 year is considered for the emergence of a new RTA.¹⁰

According to the same approach, the dynamics of the RTAs of a region is first of all explained by the technological space that local agents have managed to command in the past, i.e. by the lagged value of the dependent variable, New_RTA_{it-1} . In the extant literature (Boschma et al., 2013; Colombelli et al., 2014), this first regressor is retained to account for the path-dependency of technological specialisation at the regional level, at which “success could breed success” and entail possible patterns of hysteresis. Its inclusion is thus fundamental, in spite of the complexity it poses in the estimate of an autoregressive kind of model (see the next section).

A second core regressor of the analysis comes from the intrinsic geographical nature of the approach we follow, namely from the role that the manifold notion of *proximity* has in it (Boschma, 2004). In particular, *technological*, or *cognitive proximity* has proven to play a key role for the process at stake. Regions should be more capable of developing a new *variety* of technological advantages by *relating* them to the existing ones, given the similarities of learning practices and heuristic principles that their “related variety” (Frenken et al., 2007) entails. This related-variety way of specialising – in brief, “specialising differently” – has been considered the core of the S3 itself (Boschma and Giannelle, 2014) and has spurred substantial research efforts to find a proper measurement of the related variety between new

¹⁰ Different lag specifications have been tried, and the results are fairly consistent.

and extant technologies at the regional level (Frenken et al., 2007; Boschma and Iammarino, 2009; Quatraro, 2010).

Among the available alternatives, we hereby stick to an approach that, while consistent with the technological focus implied by the KETs notion, appears particularly suitable to the patent-based nature of our application. Drawing on Hidalgo et al.'s (2007), and adapting their representation of the product space of a country to the technology space of a region, we look at the density of the linkages that each technology s of region i at time t (i.e. RTA_{st}) reveals with respect to those (out of the remaining $s \neq z$) it was specialised in at time $t-1$, and we then work out the average of this density for region i (Av_Dens_{it}) as described in the following.

We first calculate a proximity measure (φ) between two technologies, s and z , which is defined as the minimum of the pairwise conditional probability of a region having RTA in a technology s , given that it has a RTA in another technology z , that is:

$$\varphi_{szt} = \min \{P(RTA_{st} | RTA_{zt}), P(RTA_{zt} | RTA_{st})\} \quad (3)$$

where $P(RTA_{st} | RTA_{zt}) = \frac{P(RTA_{st} \cap RTA_{zt})}{P(RTA_{zt})}$.

For each and every focal technology z , we then calculate the (weighted) average proximity with respect to it of the different s technologies in which region i has gained a new revealed technological advantage at time t , as follows:

$$wad_{izt-1} = \frac{\sum_{s \neq z} \varphi_{szt-1} New_RTA_{ist}}{\sum_{s \neq z} \varphi_{szt-1}} \quad (4)$$

Finally, for each and every region i , we work out the regional average (or average density) of these z -specific distances at time $t-1$, by weighting them with the (relative) revealed technological advantages the region has gained in z at time t , that is:

$$Av_dens_{it} = \sum_{z \neq s} wad_{izt-1} \times \frac{New_RTA_{it}}{\sum_{z \neq s} New_RTA_{it}} \quad (5)$$

All in all, Av_Dens_{it} is thus a proxy of the extent to which the new technological advantages that a region gain at time t are, all together (that is, on average), close (in the sense specified above) to those in which it had gained an advantage in the previous period $t-1$. In brief, it is a

proxy of the idea of related variety, which a smart specialisation strategy would suggest to be positively correlated with our dependent variable, pointing to the accumulation of technological competences in ‘close’ or complementary technologies for the development of new ones.

The list of independent variables of the approach we are following is completed by the inclusion of a number of regional controls. Among these, an important control is represented by the “technological” size of the region. In general, this is proxied by the R&D intensity of the focal region, defined as the ratio between its R&D expenditure and its gross value added. However, when we calculate $R\&D_{t-1}$ in an internally data consistent way, that is as the lagged logarithm of the relative regional ratios from the same dataset as the other variables, we unfortunately experience a dramatic loss of observations (see Table 2). Accordingly, at least in our benchmark estimations (see Section 3), we will rather stick to an alternative proxy of regional technological size, more consistent with patent-based nature of our model, that is the number of IPC codes, in which a region has registered patent applications at time $t-1$, $CountIPC_{it-1}$. Having a lower number of observations, we insert $R\&D_{t-1}$, either instead of, or along with $CountIPC_{it-1}$, only among the robustness check estimations of the model (see Section 3.3). Indeed, their simultaneous inclusion could be motivated by the fact that, while they are both size-related variables, they have a different nature, as $CountIPC_{it-1}$ also account for the “degrees of freedom” the region has available in exploring new technological advantages over time.¹¹

As for the other controls, we included in the estimated model the (lagged logarithm of) regional gross value added and the (lagged logarithm of) regional employment.

In order to plug the role of KETs in the model and test for our hypotheses, we draw on the “technology diffusion approach” sketched above and build up two proxies for them. The first one, $KETs_File_{it-1}$, looks at the number of KETs-mapped IPC classes, in which the resident inventors of region i have filed patents at time $t-1$, irrespectively from the specific KETs in which this has occurred (a 1-year temporal lag is still retained for the sake of consistency). This indicator provides a first bit of evidence of the extent at which the inventive efforts

¹¹ It should be noticed that, at least for the time being, we are only interested in the knowledge a region acquire through the “quantity” of its patent applications, irrespectively from their quality, meant as “[their] technological and economic value, and the possible impact that [they] might have on subsequent technological developments” (Squicciarini et al., 2013).” While data availability on these aspects has recently increased, we postpone this extension to our future research.

carried out by the region makes available KETs-based knowledge, which could be used and combined with other local technologies. The second proxy we build up, $KETs_RTA_{it-1}$, tries to go beyond the “simple availability” of KETs knowledge in the region, and counts the number of cases (i.e. IPC classes) in which this availability has also turned into an actual technological specialization (as measured by the RTA index), still irrespectively from the specific KETs. In brief, unlike the former, the latter KETs proxy provides evidence of a situation in which, not only are KETs part of the regional knowledge base, but also among its superior areas of expertise. Finally, in order to test for the role of the six specific technologies within the KETs-club, both the indicators are recalculated by referring to the number of IPC classes that pertain to each of the six of them.

Table 1 summarizes the variables used in the study, the way they are defined and the data sources upon which they build.

Insert Table 1 about here

3.3 Econometric strategy

The model we use for testing our hypotheses is implicitly defined as follows:

$$\begin{aligned} New_RTA_{it} = f(& New_RTA_{it-1}, Av_dens_{it}, \\ & KETs_{it-1}, Av_dens_{it} * KETs_{it-1}, z_{it-1}, dtime, dregion, \varepsilon_{it}) \end{aligned} \quad (6)$$

where, in addition to the previous positions, z is the vector of our structural regional controls (including R&D in the robustness check estimations), $dtime$ and $dregion$ are year- and regional dummies, respectively, and ε an error term with standard properties.

In particular, the test of HP1 is related to the significance and sign of KETs, in one of its two forms, while that of HP2a and HP2b to the significance and sign of KETs as a moderating variable of the impact of Av_dens .

The econometric strategy we follow to estimate model (6) is first of all driven by the nature of our dependent variable, New_RTA , which is a count one, with a quite over-dispersed distribution (as from inspection of Figure 1 and Table 2 reporting the main descriptive statistics of our variables). Its correlation with the identified regressors is reported in Table 3.

Insert Figure 1 about here

Insert Table 2 and 3 about here

As baseline estimation, we thus apply a fixed effects Negative Binomial (NegBin) model. Dealing with longitudinal data, in a framework in which NUTS2 regions can be seen as the clusters in which year-observations are somehow nested, as a robustness check of the baseline, we resort to a Multilevel Negative Binomial (MMNegBin) model, generally used when observations are instead organized at more than one level (like NUTS2, NUTS1, etc...) (Goldstein, 1995). Accordingly, the functional form to be estimated is the following:

$$\begin{aligned}
 \text{New_RTA}_{it} = & \exp(\alpha + \beta_1 \text{New_RTA}_{it-1} + \beta_2 \text{Av_dens}_{it} + \beta_3 \text{KETS}_{it-1} + \\
 & + \beta_4 \text{Av_dens}_{it} * \text{KETS}_{it-1} + \sum_k \gamma_k z_{kit-1} + \text{dtime} + \text{dregion} + \varepsilon_{it})
 \end{aligned}
 \tag{7}$$

In augmenting the baseline, we should consider that the model specified in equation (6) regresses the dependent variable at time t against its lagged value. This introduces an intrinsic dynamics in the model, which calls for the adoption of an econometric strategy able to minimize the possible bias in the estimations. For this reason, following Cameron and Trivedi (2005 and 2010), an additional set of estimates is carried out by using a dynamic GMM model for count data. In particular, we use a Conditionally Correlated Random (CCR) effects model (Mundlak, 1978; Chamberlain, 1984) without initial conditions, which provides a compromise between fixed effects and random effects estimators.

3.4 Results

Before presenting the results of the econometric estimates, it is interesting to notice the spatial distribution of the dependent variable and of our main regressors (Fig. 2).

Insert Fig. 2 about here

In the top-left diagram of Figure 2 we show the spatial distribution of the average values of *New_RTA* over the time span 2001-2006. The map provides evidence of a marked geographical concentration of such variable, wherein Central European regions appear to be characterized by higher values, while the emergence of new technological specialization in peripheral regions seems to be much weaker a phenomenon. The top-right diagram of Figure 2 shows the distribution of the count of KETs for which the region has developed a technological specialization (average values over 2001-2006). Even in this case one can notice that the highest values are concentrated in Central European regions. The same applies also to distribution of the variables shown in the bottom-right (*CountIPC*) and in the bottom-left (*Av_density*) diagrams of Figure 2. Overall, there seem to be traces of an idiosyncratic

geographical distribution of the phenomenon at stake, which somehow mimics that of other more standard economic indicators, pointing to its apparent neutrality with respect to the need of favoring regional convergence across Europe: an issue, which is by now postpone to our future research agenda.

Let us consider now the results of the estimates, starting with those on the role of KETs in aggregate terms. The baseline (static) model provides results that are consistent with the rationale of S3 in terms of construction of new RTA, when the simplest trace of KETs-patenting in the region is considered, that is by referring to $KETs_File_{it-1}$ as proxy (Table 4).

Insert Table 4 about here

In columns (1) and (2) we report the simplest specification of the model (NegBin and MMNegBin, respectively). First of all, a previous gain of new technological advantages (New_RTA_{it-1}) contributes positively to a further gain of them in the following period. Regions having entered new technological fields in the past thus develop the capacity of doing it persistently, showing evidence of a certain hysteresis in the process already found in other studies Boschma et al., 2013; Colombelli et al., 2014). However, it must be noted that the coefficient, although statistically different from zero, is lower than one, and actually its value is very small. This implies a dynamic process in which the opportunities to develop new technological specializations in the long run are likely to get exhausted.¹²

The construction of new RTAs also builds on the knowledge locally accumulated over time, insofar as the former is to some extent related to the latter, in a cumulative perspective in which local innovative agents are likely to stand on giants' shoulders. The average proximity of the current technological portfolio to the previous one () actually yields a significant and positive coefficient. This is an interesting result, which provides evidence of a (related-) variety-friendly pattern of specialisation, recently invoked as a truly smart specialization strategy (Frenken, 2014).

¹² This is consistent with a framework in which the set of technological fields is finite and static, which is what we observe in the so-called 'normal science' periods. When paradigmatic shifts take place, one can observe the enlargement of the technological landscape through the creation of brand new technological fields (and classes). These rare events are likely to rejuvenate the prospect for the development of new technological specializations in local contexts.

In columns (3) and (4) we add the two variables that allow us to capture the impact of KETs on the entry of regions in new technological domains, i.e. *KETs_File* and its interaction with *Av_dens*.

While substantially confirmed, the previous “standard story” takes on new interesting specifications when the role of KETs is considered. First of all, the availability of generic KETs knowledge in the region increases its capacity of entering into new technological fields (*KETs_File* is significant and positive). The discovery-potential entailed by the general (purpose) nature of KETs gets thus confirmed and leads to support our HP1. As far as HP2 is concerned, *KETs_File* exerts a significant moderating role of the impact of *Av_dens* on *New_RTA*, and this is negative. In support of our HP2a, regions seem to use the systemic nature of KETs to span the boundaries of the extant technologies’ related variety. In other words, the availability of KETs knowledge (of any kind) seems to make the effect of the technological/cognitive proximity with respect to the regional knowledge base less binding in changing the regional specialisation pattern.

In columns (5) to (10) of Table 4 we add control variables to check for regions’ size effects. Columns (5) and (6) include *Count_IPC_{it-1}* and *lnEmployment_{t-1}*. Although with low significance, and only in the NegBin specification (5), the discovery process at stake appears limited by the number of already unfolded technologies, as *Count_IPC_{it-1}* is significant and negative. This result is confirmed and strengthened when we substitute *lnGVA_{t-1}* for *lnEmployment_{t-1}* in columns (7) and (8). When a more standard proxy of innovation efforts at the regional level is included, *R&D_{it-1}* turns out significant and positive in specifications (9) and (10), signaling that higher spenders in R&D are more likely to develop technological competencies.

As for the other controls, as expected we notice that both *lnEmployment_{t-1}* and *lnGVA_{t-1}* show positive and significant coefficients. It is worth stressing that the inclusion of control variables in our estimated models does not alter the key results concerning the role of KETs and their interaction with *Av_Dens*.

The previous results about the role of KETs in general remain substantially unaltered when we consider the region’s capacity of specializing in them, i.e. with respect to *KETs_RTA* (Table 5).

Insert Table 5 about here

Table (5) reproduces the same set of specifications of Table (4), with the exception of the third and the fourth rows, where the role of KETs is captured by the variable $KETs_RTA_{it-1}$. As in Table 4, in the different columns we progressively insert the other controls of the technological and economic size of the regions, following different combinations for them. In general, the results of the baseline are confirmed, being the acquisition of new specializations positively related to both kinds of size, and still negative affected by the available degree of technological freedom ($Count_IPC$).

It must be noted that the coefficients of our focal regressors are substantially stable across the different estimations, and also when comparing Tables 4 and 5. Actually, when the impact of KETs is captured by the relative specialization of the region, the coefficient of the interaction with Av_Dens is still negative and significant. This is an interesting result, which shows that $Hp2a$ holds the true also when the regional specialisation in KETs is considered rather than its simple availability. In other words, the capacity of the region to master KETs knowledge in such a way to get a relative advantage in their development, enables the region itself to benefit from (related-) variety-freedom in getting new technological specializations.

Quite interestingly, the results obtained from the estimates of the baseline (static) model are also confirmed when a more suitable dynamic estimation strategy is followed, both in terms of $KETs_File$ and $KETs_RTA$. For the sake of brevity, in Table 6 we show only the results concerning the latter case (results on the former are available from the authors on request).

Insert Table 6 about here

We can notice that all of the coefficients show signs which are consistent with the previous estimations, and which are statistically significant. The only exception concerns the control variables. Actually in nearly all of the specifications apart from (6), $Count_IPC$ is no longer significant, and the same occurs for $lnEmpl$. Still, gross regional value added and R&D keep on showing their expected positive sign, both alone and in combination.¹³

It is worth discussing at some more length the implications of the empirical results, in particular, as far as the interaction variable is concerned. Actually, from the different sets of estimations we obtained clearly consistent results which point to a positive effect of both

¹³ Given the different econometric strategy, a comparison of the magnitude of the coefficients with the static case is of course not possible.

Av_dens and KETs on the creation of new technological specializations, no matter the way we proxy the presence of KETs in the region. The interaction variable is instead characterized by a negative and significant coefficient across the different estimations. The basic question remains as to what extent the negative coefficient of the interaction variable can offset the positive coefficients of the other focal regressors. In brief, do KETs play a positive net-effect on the region’s capacity to develop new technological specializations?

In this direction, it can be useful to evaluate the marginal effects at means of each variable of interest. It is worth recalling that when estimating a negative binomial model like the one reported in Table 5, the coefficients tell us to what extent the difference in the logs of expected counts of the dependent variable is expected to change for a one unit change in the predictor variable, all other things being equal. Moving from equation (6), we can therefore calculate the overall effects of KETs, by taking the derivative of the dependent variable with respect to *KETs_RTA_{it-1}*. If we set $y = \ln[E(New_RTA)]$, we then obtain:

$$\frac{\partial y}{\partial KETs_RTA_{it-1}} = \beta_3 + \beta_4 Av_dens_{it} \quad (8)$$

The first row of Table 7 provides the results of the calculation, along with a z-test indicating if the overall effect is statistically different from zero.

Insert Table 7 about here

Actually, the overall effect appears to be positive and significant. The creation of new specialization in KETs is likely to positively contribute the prospective creation of further new specializations in the future, even by discounting the dumping role KETs play on the specialization potential of related variety.

The second battery of results concerns the estimates of the same model as above (see Eq.(6)), but by “exploding” each and every of the six technologies *j* (with *j* = BIOTECH, NANOTECH, NANOELCT, PHOTO, ADVMAT, and ADVTECH) separately considered. Given the robustness of the results across the two ways of capturing the role of KETs, in the following we will just present those obtained in terms of KETs specialization (i.e. *KETs(j)_RTA_{it-1}*).¹⁴ For the same token, given the robustness of the aggregated results to the inclusion of R&D, in order to keep a satisfactory number of observations, we will limit this

¹⁴ Those in terms of patent applications (i.e. *KETs(j)_File_{it-1}*) are available from the authors on request.

last part of the analysis to the benchmark specifications of Table 4, that is by excluding the regional R&D intensity among the regressors.

Starting with the estimates of the baseline (static) model, let us observe that the basic mechanisms underlying the construction of new RTAs are confirmed when individual KETs specialisations are considered (Table 8).

Insert Table 8 about here

Furthermore, as in the case of KETs in aggregate terms, the previous disaggregated results appear in general robust with respect to a dynamic specification of the model (Table 9). This is a first set of reassuring results about the functional boundaries of the KETs club. When their additive and their moderating role for the creation of new technological advantages are considered, each and every of the six KETs share the same features we have identified for KETs in general. Whether these same features are not shown by other non-KETs technologies, thus setting an actual boundary with respect to the former, is instead an open issue, which we postpone to our future research agenda.

Insert Table 9 about here

As for the overall effect of *RTA_KETs*, we can use equation (8) to provide an evaluation of the overall contribution of the single KETs group to the creation of new technological specializations. Rows (2) to (7) of Table 7 provide the results of the calculations using the margins at means. First of all, we must notice that two KETs groups seem not to have statistically significant net-effects of *NEW_RTAs*, i.e. *Nanotech* and *Advtech*. For these two specific technologies, and for these two only, the two “enabling” roles (additive and moderating) we have singled out with our model somehow seems to cancel out, making them not significant in developing new technological advances. Whether they could identify a subset of less effective KETs is of course no more than a suggestion, which is in need of future check by looking at the inner characteristics of these technologies and at their diffusion at the regional level in Europe. On the other hand, the net-effect of the significant KETs is quite heterogeneous: *Biotech* shows the highest coefficient, followed by *Advmat* and *Photo*, which are characterized by nearly similar coefficients, and finally *Nanoelect*. The possibility that these four technologies could exert different degrees of “enabling power” is also no more than a suggestion, which require further scrutiny of their knowledge-bases and applications.

4 Conclusions

Increasingly more invoked by European policy makers as the main driver of a new wave of knowledge-based structural changes, which regions should implement with their help in a new wave of specialisation patterns, KETs have so far attracted the sole attention of technical reports and feasibility studies, which take their role for granted. In the light of such a high policy potential, this is of course quite unfortunate, and urges more profound research work in order to establish whether the six technologies identified by the European Commission are actually enabling, and eventually of what.

By making use of regional patent data, in this paper we have moved a first step in this direction and plugged KETs in the economic geography approach to smart specialization strategies. In particular, by identifying some pivotal characteristics of these technologies, we have tried to test whether their alleged enabling role could be seen (also) in their capacity of allowing regions to acquire new technological specialisations on the basis of their pre-existing ones.

The results we have obtained are quite reassuring in this last respect. Irrespectively of their specificities, all of the six technologies “enable” European regions to increase their portfolio of new technologies over time, confirming such a role at the aggregated level. Quite interestingly, and still consistently with their aggregate pattern, all of the KETs also enable regions to search for new technologies more distantly from their pre-existing knowledge base, by attenuating the binding effect that the latter has in the same respect. Finally, with the exceptions of only two of them, the dumping role that KETs play on the related variety of the regions is more than compensated by the inner variety potential assured by their general and systemic nature. All in all, KETs actually guarantee regions a higher capacity to master new technological advantages.

These results convey to KETs a policy potential that can be finally deemed actual, and not only potential. Furthermore, they also enable to make this policy impact more specific. First of all, in spite of the attention so far reserved to the so-called “deployment” or “use” of KETs, the development of KETs-related knowledge appears as much important in fostering smart specialisation patterns. Accordingly, the support to the creation of KETs knowledge and KETs research strongly candidates for entering the S3 policy-mix. Secondly, while drawing on pre-existing knowledge, KETs also enable regions to make it less binding. Accordingly, KETs also appear the leverage for turning S3 from exploitative to explorative and to span the

boundaries of the regions' related variety. In this last respect, we should however notice that, as we said, this kind of explorative S3 outcome that the data make emerge as general, could not be among the priorities of regional development for all the regions, as some of them might instead find more in line with their entrepreneurial capacity a deeper exploitation of the existing knowledge base. Should this be the case, according to our results, KETs should paradoxically not be prioritized, even in spite of their potential of adding new technological specializations to the existing ones. Which regions could benefit from one or the other of two S3 patterns we have identified, possibly in relation to their relative level of development, represents a complementary analysis to the present one, which we postpone to our future research.

Future research should also be addressed to solve some limitations, from which the paper inevitably suffers. First of all, the kind of patent data we have used represents only one of the possible perspectives through which the generation of KETs knowledge can be measured, with all the caveats patent data require. Secondly, other aspects more connected to the use and exploitation of this KETs knowledge would require consideration, to see whether the enabling role of the technologies at stake could be confirmed. Last but not least, other forms of proximity in addition to that we have accounted for with our density variable could be plugged into the analysis. Actually, the development of new technological specialisations by a focal region could be affected by that of geographically closer ones, as their *spatial proximity* could allow for inter-regional knowledge spillovers that affect the capacity of acquiring new RTAs (Fisher and Varga, 2003; Fritsch and Franke, 2004; Paci et al., 2014). This eventuality should thus be carefully controlled for in the structure of the observable data, and its detection possibly recommends the use of proper spatial econometrics techniques, on which our future research will focus. This last kind of analysis will also enable us to ascertain the extent to which the internal development of KETs should actually be a priority in general, or whether regions could rely on their KETs absorptive capacity from neighboring regional KETs poles.

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Figure 1 - Kernel Density Distribution of New_RTAs

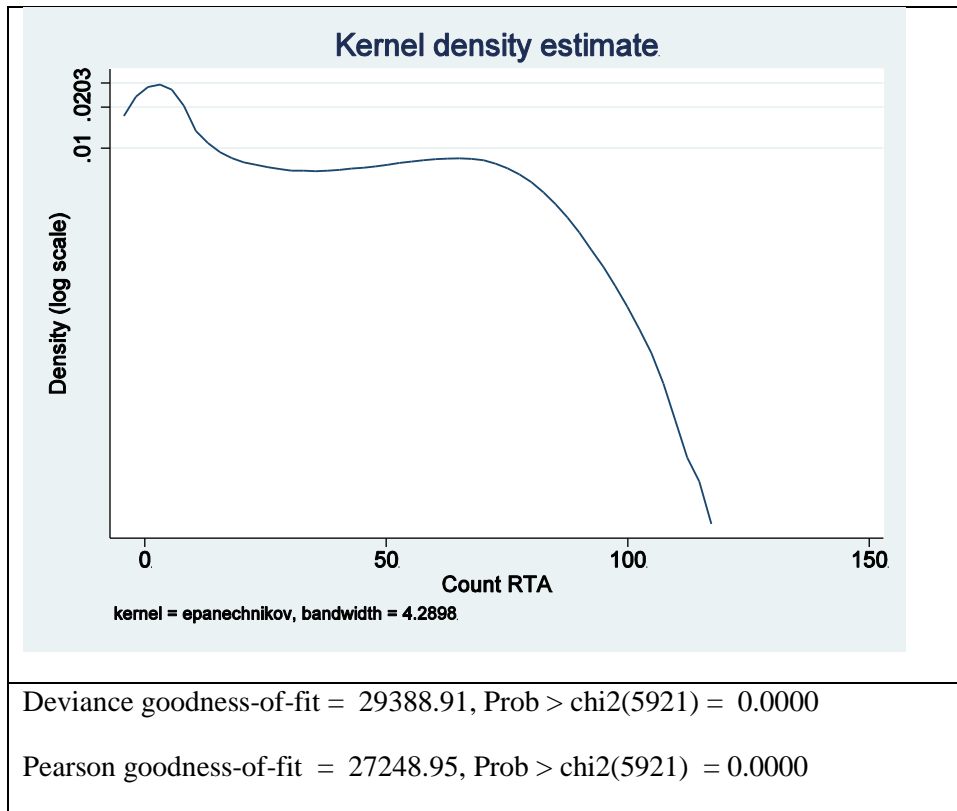


Figure 2 - Spatial Distribution of Relevant Variables

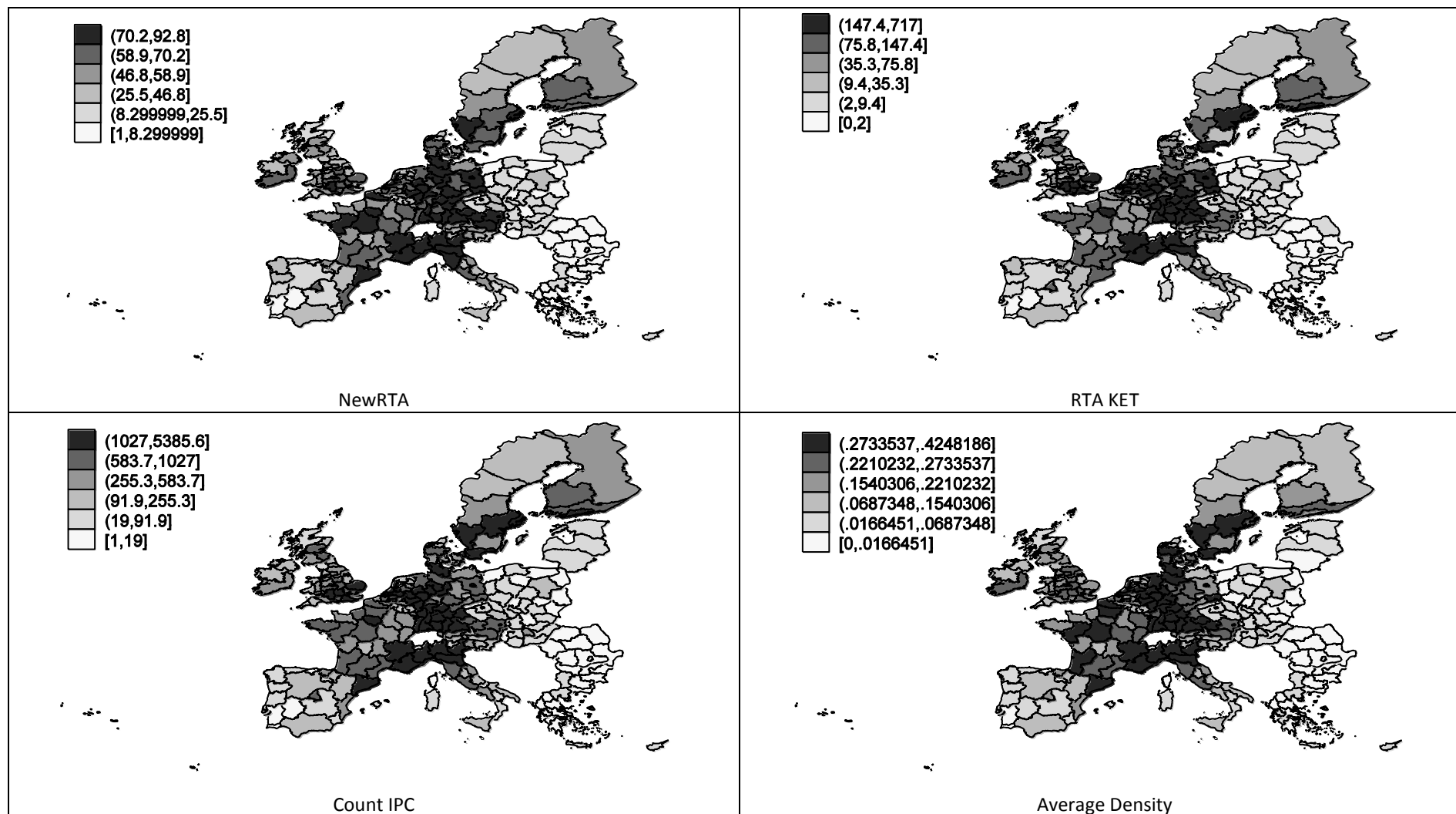


Table 1 - Variables Definition

Variable	Definition	Source
NewRTA_{i,t}	Number of technological specializations in region <i>i</i> , which were observed at time <i>t</i> but were not at time <i>t-1</i>	Elaborations on OECD RegPat Database (July 2014).
Av_dens_{i,t}	Average proximity of all technologies observed at time <i>t</i> in region <i>i</i> to all other technologies observed in the same region at time <i>t-1</i>	Elaborations on OECD RegPat Database (July 2014).
KETs_file_{i,t}	Number of technologies flagged as KET observed at time <i>t</i> in region <i>i</i> .	Elaborations on OECD RegPat Database (July 2014); EC (2011).
KETs_RTAs_{i,t}	Number of KETs for which the region <i>i</i> has developed a specialization at time <i>t</i> .	Elaborations on OECD RegPat Database (July 2014); EC (2011).
R&D_{i,t}	Logarithm of the ratio between regional R&D expenditure and gross value added	Elaborations on Eurostat and Cambridge Econometrics Databases
CountIPC_{i,t}	Number of different technologies observed in the patent portfolio of region <i>i</i> at time <i>t</i> .	Elaborations on OECD RegPat Database (July 2014).
lnGVA_{i,t}	Natural logarithm of Gross Value Added of region <i>i</i> at time <i>t</i> .	Cambridge Econometrics (December 2014)
lnEmployment_{i,t}	Natural logarithm of employment level in region <i>i</i> at time <i>t</i> .	Cambridge Econometrics (December 2014)

Table 2 - Descriptive Statistics

Variable	N	max	min	mean	sd	skewness	kurtosis
New_RTA	7942	117.000	0.000	38.385	27.767	0.156	1.787
Av_dens	6797	0.533	0.000	0.137	0.112	0.434	2.147
KETS_file	8370	1976.000	0.000	123.266	354.883	5.845	46.395
KETS_RTA	9290	906.000	0.000	58.343	106.540	3.379	17.018
Av_dens* KETs_RTA	6475	320.655	0.000	19.163	36.466	3.390	16.637
R&D	3157	0.00023	0.136	0.0151	0.0127	1.882	8.689
Count_IPC	9290	6914.000	1.000	446.853	771.337	3.568	18.889
LnEmplt	6486	8.685	0.000	6.408	0.814	-0.940	7.284
lnGVA	6486	13.045	0.000	10.018	0.992	-1.076	12.227

Table 3 - Correlation Matrix

	1	2	3	4	5	6	7	8	9
1 New_RTA	1								
2 Av_dens	0.9028*	1							
3 KETS_file	0.8960*	0.8840*	1						
4 KETS_RTA	0.8950*	0.8831*	0.9999*	1					
5 Av_dens* KETs_RTA	0.9053*	0.9415*	0.9614*	0.9609*	1				
6 Count_IPC	0.9226*	0.9148*	0.9732*	0.9722*	0.9723*	1			
7 LnEmplt	0.4393*	0.4144*	0.4471*	0.4459*	0.4486*	0.4673*	1		
8 lnGVA	0.7771*	0.7715*	0.7808*	0.7800*	0.7959*	0.8093*	0.7685*	1	
9 R&D	0.6418*	0.6487*	0.7327*	0.7333*	0.7300*	0.7305*	0.2487*	0.5594*	1

Table 4 - Baseline estimation

	(1) NegBIN	(2) MMNegBin	(3) NegBIN	(4) MMNegBin	(5) NegBIN	(6) MMNegBin	(7) NegBIN	(8) MMNegBin	(9) NegBIN	(10) MMNegBin
New_RTAt _{t-1}	0.0076*** (0.0003)	0.0233*** (0.0005)	0.0067*** (0.0003)	0.0196*** (0.0005)	0.0054*** (0.0004)	0.0165*** (0.0005)	0.0046*** (0.0004)	0.0145*** (0.0005)	0.0021*** (0.0005)	0.0167*** (0.0006)
Av_dens _t	0.8994*** (0.0906)	1.5036*** (0.1072)	1.6128*** (0.1056)	2.9308*** (0.1139)	1.4744*** (0.1181)	3.1815*** (0.1154)	1.3592*** (0.1106)	2.9070*** (0.1122)	0.6406*** (0.1582)	2.8888*** (0.1425)
KETs_File _{t-1}			0.0012*** (0.0001)	0.0031*** (0.0002)	0.0015*** (0.0002)	0.0034*** (0.0002)	0.0011*** (0.0002)	0.0032*** (0.0002)	0.0010*** (0.0002)	0.0026*** (0.0002)
Av_dens _t * KETS_File _{t-1}			-0.0061*** (0.0005)	-0.0123*** (0.0005)	-0.0052*** (0.0005)	-0.0120*** (0.0006)	-0.0037*** (0.0005)	-0.0108*** (0.0005)	-0.0024*** (0.0006)	-0.0103*** (0.0006)
Count_IPC _{t-1}					-0.0001** (0.0000)	-0.0000 (0.0000)	-0.0001*** (0.0000)	-0.0001*** (0.0000)		
lnEmplt _{t-1}					0.1537*** (0.0384)	0.0067 (0.0081)				
lnGVA _{t-1}							0.5428*** (0.0319)	0.1574*** (0.0086)		
R&D _{t-1}									3.3241*** (1.0102)	3.5775*** (0.6420)
Cons	2.8518*** (0.0486)	2.3002*** (0.0269)	2.8629*** (0.0516)	2.2371*** (0.0254)	2.1498*** (0.2485)	2.3272*** (0.0551)	-2.4522*** (0.3277)	0.9289*** (0.0826)	4.0184*** (0.1178)	2.3489*** (0.0270)
lnalpha		-1.9398*** (0.0250)		-2.1018*** (0.0264)		-2.3596*** (0.0309)		-2.4546*** (0.0316)		-2.4431*** (0.0407)
<i>N</i>	6472	6472	6472	6472	5103	5103	5103	5103	3106	3106
<i>AIC</i>	43628.7230	52651.2054	43448.4925	51999.4869	34610.6650	41108.9501	34355.9796	40777.2465	19549.4926	24837.9999
<i>BIC</i>	43811.6545	52840.9251	43644.9745	52202.7580	34813.3301	41318.1528	34558.6447	40986.4492	19664.2734	24958.8217
chi2	2130.1643	16886.0536	2292.6299	20097.7279	1546.5749	16839.5829	1969.3246	18188.9192	184.8963	11083.1060
ll	-	-26297.6027	-21695.2462	-25969.7435	-17274.3325	-20522.4751	-17146.9898	-20356.6233	-9755.7463	-12398.9999
	21787.3615									

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5 - RTA in KETs

	(1) NegBIN	(2) MMNegBin	(3) NegBIN	(4) MMNegBin	(5) NegBIN	(6) MMNegBin	(7) NegBIN	(8) MMNegBin
New_RTAt-1	0.0066*** (0.0003)	0.0194*** (0.0005)	0.0053*** (0.0004)	0.0162*** (0.0005)	0.0046*** (0.0004)	0.0143*** (0.0005)	0.0021*** (0.0005)	0.0165*** (0.0006)
Av_dens _t	1.7178*** (0.1076)	3.0494*** (0.1142)	1.5598*** (0.1204)	3.2644*** (0.1150)	1.4332*** (0.1127)	2.9822*** (0.1120)	0.6883*** (0.1626)	2.9996*** (0.1427)
KETs_RTAt-1	0.0015*** (0.0002)	0.0035*** (0.0002)	0.0018*** (0.0002)	0.0035*** (0.0002)	0.0013*** (0.0002)	0.0033*** (0.0002)	0.0012*** (0.0002)	0.0030*** (0.0002)
Av_dens _t * KETs_RTAt-1	-0.0074*** (0.0006)	-0.0140*** (0.0006)	-0.0062*** (0.0006)	-0.0141*** (0.0006)	-0.0045*** (0.0005)	-0.0128*** (0.0006)	-0.0028*** (0.0007)	-0.0120*** (0.0007)
Count_IPC _{t-1}			-0.0001*** (0.0000)	0.0000 (0.0000)	-0.0001*** (0.0000)	-0.0000 (0.0000)		
lnEmpl _{t-1}			0.1516*** (0.0383)	0.0070 (0.0081)				
lnGVA _{t-1}					0.5385*** (0.0319)	0.1548*** (0.0085)		
R&D _{t-1}							3.2750*** (1.0127)	3.5383*** (0.6421)
_cons	2.8511*** (0.0516)	2.2301*** (0.0253)	2.1515*** (0.2482)	2.3202*** (0.0547)	-2.4174*** (0.3276)	0.9488*** (0.0822)	4.0003*** (0.1181)	2.3429*** (0.0269)
lnalpha		-2.1171*** (0.0265)		-2.3759*** (0.0310)		-2.4685*** (0.0317)		-2.4612*** (0.0410)
<i>N</i>	6472	6472	5103	5103	5103	5103	3106	3106
<i>AIC</i>	43429.3233	51936.7806	34595.8547	41055.9546	34344.5047	40732.2859	19547.4343	24804.7187
<i>BIC</i>	43625.8053	52140.0518	34798.5198	41265.1573	34547.1698	40941.4886	19662.2150	24925.5406
chi2	2310.0281	20407.9782	1559.3238	17092.9524	1980.2319	18407.6702	186.5275	11259.0888
ll	-21685.6617	-25938.3903	-17266.9273	-20495.9773	-17141.2523	-20334.1430	-9754.7171	-12382.3594

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6 – GMM Dynamic Count Data Model

	(1) GMM	(2) GMM	(3) GMM	(4) GMM	(5) GMM	(6) GMM
New_RTAt-1	0.0149*** (0.0007)	0.0130*** (0.0007)	0.0120*** (0.0006)	0.0130*** (0.0007)	0.0129*** (0.0007)	0.0117*** (0.0006)
Av_dens _t	2.7556*** (0.1636)	2.8996*** (0.1484)	2.6368*** (0.1435)	2.8637*** (0.1689)	2.8513*** (0.1687)	2.4960*** (0.1563)
KETs_RTAt-1	0.0030*** (0.0004)	0.0032*** (0.0004)	0.0030*** (0.0004)	0.0029*** (0.0004)	0.0029*** (0.0004)	0.0026*** (0.0004)
Av_dens _t * KETs_RTAt-1	-0.0114*** (0.0015)	-0.0115*** (0.0014)	-0.0105*** (0.0013)	-0.0106*** (0.0013)	-0.0105*** (0.0013)	-0.0088*** (0.0011)
Count_IPC _{t-1}	0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)	-0.0001** (0.0000)
lnEmplt _{t-1}		0.0145 (0.0175)			0.0201 (0.0199)	
lnGVA _{t-1}			0.1172*** (0.0163)			0.1328*** (0.0179)
R&D _{t-1}				1.9049*** (0.7323)	2.0535*** (0.7497)	2.4909*** (0.7376)
Cons	2.4993*** (0.0351)	2.4833*** (0.1123)	1.4973*** (0.1665)	2.5455*** (0.0421)	2.4250*** (0.1283)	1.3357*** (0.1824)
<i>N</i>	6475	5103	5103	3106	3106	3106

Regional Clustered Standard errors in parentheses

Conditionally correlated random (CCR) effects model (Mundlak (1978) and Chamberlain (1984))

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7 – Overall effect of RTA_KETS

	Coef.	Std. Err.	z	P>z
Overall effect	0.000823	0.00016	5.11	0.000
Biotech	0.004594	0.000496	9.26	0.000
Nanotech	0.000621	0.007025	0.09	0.930
Nanoelct	0.00117	0.000409	2.86	0.004
Photo	0.002685	0.000678	3.96	0.000
Advmat	0.002221	0.000244	9.10	0.000
Advtech	9.51E-05	0.000281	0.34	0.735

Note: Linear combination of margins at means

Table 8 - RTA Breakdown (1/3)

	(1) New_RTAt	(2) New_RTAt	(3) New_RTAt	(4) New_RTAt	(5) New_RTAt	(6) New_RTAt	(7) New_RTAt	(8) New_RTAt	(9) New_RTAt	(10) New_RTAt	(11) New_RTAt	(12) New_RTAt
New_RTAt _{t-1}	0.0068*** (0.0003)	0.0054*** (0.0004)	0.0046*** (0.0003)	0.0068*** (0.0003)	0.0053*** (0.0004)	0.0045*** (0.0004)	0.0072*** (0.0003)	0.0056*** (0.0004)	0.0048*** (0.0003)	0.0072*** (0.0003)	0.0055*** (0.0004)	0.0048*** (0.0003)
Av_dens _t	1.5460*** (0.1049)	1.4846*** (0.1150)	1.4551*** (0.1081)	1.5504*** (0.1047)	1.3976*** (0.1155)	1.3928*** (0.1087)	0.9135*** (0.0907)	0.8094*** (0.0987)	0.8370*** (0.0925)	0.9719*** (0.0916)	0.8050*** (0.0983)	0.8503*** (0.0925)
BIOTECH _{t-1}	0.0103*** (0.0009)	0.0102*** (0.0009)	0.0089*** (0.0009)	0.0108*** (0.0009)	0.0101*** (0.0009)	0.0089*** (0.0009)						
Av_dens _t * BIOTECH _{t-1}	-0.0393*** (0.0032)	-0.0367*** (0.0033)	-0.0319*** (0.0031)	-0.0374*** (0.0033)	-0.0334*** (0.0034)	-0.0289*** (0.0031)						
NANOTECH _{t-1}							0.0431*** (0.0130)	0.0645*** (0.0170)	0.0471*** (0.0161)	0.0508*** (0.0132)	0.0589*** (0.0170)	0.0414** (0.0161)
Av_dens _t * NANOTECH _{t-1}							-0.2944*** (0.0472)	-0.3529*** (0.0576)	-0.2713*** (0.0531)	-0.2998*** (0.0479)	-0.3195*** (0.0580)	-0.2370*** (0.0538)
lnEmpl _t	No	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES	
lnGVA _t	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES
Count_IPC _{t-1}	NO	NO	NO	YES	YES	YES	NO	NO	NO	YES	YES	YES
_cons	2.7882*** (0.0497)	2.0435*** (0.2467)	-2.6178*** (0.3212)	2.8793*** (0.0524)	1.9485*** (0.2524)	-2.6740*** (0.3223)	2.9427*** (0.0499)	2.1576*** (0.2502)	-2.5615*** (0.3271)	2.9922*** (0.0517)	2.0541*** (0.2554)	-2.6302*** (0.3277)
N	6472	5103	5103	6472	5103	5103	6472	5103	5103	6472	5103	5103
AIC	43481.4080	34627.2508	34354.7931	43441.7822	34599.5842	34320.9622	43534.8551	34655.5243	34383.7303	43516.8769	34641.2463	34364.7043
BIC	43677.8900	34823.3783	34550.9206	43645.0394	34802.2493	34523.6273	43731.3371	34851.6518	34579.8578	43720.1341	34843.9114	34567.3694
chi2	2266.0920	1535.1575	1979.2355	2308.2549	1566.4153	2011.6750	2232.4127	1523.1566	1949.8933	2250.4184	1540.7158	1963.9936
ll	-21711.7040	-17283.6254	-17147.3965	-21690.8911	-17268.7921	-17129.4811	-21738.4275	-17297.7621	-17161.8651	-21728.4384	-17289.6232	-17151.3522

Standard errors in parentheses
 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8 - RTA Breakdown (2/3)

	(1) New_RTAt	(2) New_RTAt	(3) New_RTAt	(4) New_RTAt	(5) New_RTAt	(6) New_RTAt	(7) New_RTAt	(8) New_RTAt	(9) New_RTAt	(10) New_RTAt	(11) New_RTAt	(12) New_RTAt
New_RTAt-1	0.0073*** (0.0003)	0.0059*** (0.0004)	0.0050*** (0.0003)	0.0073*** (0.0003)	0.0058*** (0.0004)	0.0050*** (0.0003)	0.0071*** (0.0003)	0.0057*** (0.0004)	0.0049*** (0.0004)	0.0071*** (0.0003)	0.0057*** (0.0004)	0.0048*** (0.0004)
Av_dens _t	1.1670*** (0.0974)	1.0693*** (0.1073)	1.0343*** (0.1002)	1.2058*** (0.0973)	1.0197*** (0.1069)	1.0105*** (0.1001)	1.2927*** (0.0985)	1.1830*** (0.1075)	1.1368*** (0.1013)	1.3072*** (0.0983)	1.1325*** (0.1077)	1.1010*** (0.1014)
NANOELCT _{t-1}	0.0038*** (0.0007)	0.0037*** (0.0008)	0.0024*** (0.0008)	0.0046*** (0.0008)	0.0036*** (0.0008)	0.0024*** (0.0008)						
Av_dens _t * NANOELCT _{t-1}	-0.0185*** (0.0027)	-0.0160*** (0.0028)	-0.0111*** (0.0025)	-0.0184*** (0.0027)	-0.0139*** (0.0029)	-0.0094*** (0.0026)						
PHOTO _{t-1}							0.0083*** (0.0012)	0.0080*** (0.0013)	0.0057*** (0.0012)	0.0095*** (0.0012)	0.0083*** (0.0013)	0.0062*** (0.0012)
Av_dens _t * PHOTO _{t-1}							-0.0389*** (0.0042)	-0.0343*** (0.0044)	-0.0245*** (0.0039)	-0.0382*** (0.0043)	-0.0315*** (0.0045)	-0.0218*** (0.0040)
lnEmpl _t	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO
lnGVA _t	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES
Count_IPC _{t-1}	NO	NO	NO	YES	YES	YES	NO	NO	NO	YES	YES	YES
_cons	2.8423*** (0.0495)	2.2384*** (0.2445)	-2.6306*** (0.3258)	2.9152*** (0.0519)	2.0882*** (0.2519)	-2.7054*** (0.3259)	2.8506*** (0.0497)	2.2097*** (0.2447)	-2.4962*** (0.3261)	2.9106*** (0.0520)	2.1001*** (0.2504)	-2.6124*** (0.3269)
<i>N</i>	6472	5103	5103	6472	5103	5103	6472	5103	5103	6472	5103	5103
<i>AIC</i>	43572.5866	34712.4949	34436.2800	43542.8540	34689.0037	34405.4753	43528.5196	34677.5198	34414.5901	43509.4760	34662.7453	34389.9812
<i>BIC</i>	43769.0686	34908.6224	34632.4075	43746.1112	34891.6688	34608.1404	43725.0016	34873.6473	34610.7176	43712.7332	34865.4104	34592.6463
<i>chi2</i>	2182.5421	1453.1585	1895.7712	2214.4558	1481.2778	1921.8039	2222.8979	1484.4741	1911.6029	2245.2125	1503.0804	1932.9937
<i>ll</i>	-21757.2933	-17326.2474	-17188.1400	-21741.4270	-17313.5019	-17171.7376	-21735.2598	-17308.7599	-17177.2950	-21724.7380	-17300.3726	-17163.9906

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8 - RTA Breakdown (3/3)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	New_RTAt	New_RTAt	New_RTAt	New_RTAt	New_RTAt	New_RTAt	New_RTAt	New_RTAt	New_RTAt	New_RTAt	New_RTAt	New_RTAt
New_RTAt _{t-1}	0.0068*** (0.0003)	0.0056*** (0.0004)	0.0048*** (0.0003)	0.0067*** (0.0003)	0.0054*** (0.0004)	0.0047*** (0.0003)	0.0066*** (0.0003)	0.0052*** (0.0004)	0.0046*** (0.0004)	0.0066*** (0.0003)	0.0052*** (0.0004)	0.0046*** (0.0004)
Av_dens _t	1.4885*** (0.1040)	1.3687*** (0.1119)	1.3049*** (0.1051)	1.4673*** (0.1035)	1.2604*** (0.1124)	1.2301*** (0.1055)	1.4714*** (0.1036)	1.2887*** (0.1156)	1.1896*** (0.1091)	1.4663*** (0.1041)	1.2900*** (0.1157)	1.1897*** (0.1091)
ADVMAT _{t-1}	0.0048*** (0.0004)	0.0044*** (0.0004)	0.0034*** (0.0004)	0.0053*** (0.0004)	0.0045*** (0.0004)	0.0035*** (0.0004)						
Av_Dens _t * ADVMAT _{t-1}	-0.0177*** (0.0016)	-0.0151*** (0.0015)	-0.0118*** (0.0014)	-0.0158*** (0.0016)	-0.0126*** (0.0016)	-0.0097*** (0.0014)						
ADVTECH _{t-1}							0.0025*** (0.0005)	0.0021*** (0.0005)	0.0008* (0.0005)	0.0024*** (0.0005)	0.0020*** (0.0005)	0.0009* (0.0005)
Av_dens _t * ADVTECH _{t-1}							-0.0165*** (0.0016)	-0.0137*** (0.0016)	-0.0088*** (0.0014)	-0.0165*** (0.0016)	-0.0137*** (0.0016)	-0.0087*** (0.0014)
lnEmpl _t	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO
lnGVA _t	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES
Count_IPC _{t-1}	NO	NO	NO	YES	YES	YES	NO	NO	NO	YES	YES	YES
_cons	2.8014*** (0.0496)	2.1818*** (0.2429)	-2.4599*** (0.3243)	2.9089*** (0.0524)	2.0214*** (0.2510)	-2.5237*** (0.3247)	2.9450*** (0.0525)	2.2039*** (0.2499)	-2.3973*** (0.3315)	2.9425*** (0.0527)	2.2152*** (0.2511)	-2.4082*** (0.3321)
N	6472	5103	5103	6472	5103	5103	6472	5103	5103	6472	5103	5103
AIC	43488.4650	34645.4081	34386.5237	43436.0461	34609.8509	34344.3374	43421.7780	34587.3307	34337.0332	43423.5618	34589.1577	34338.7842
BIC	43684.9470	34841.5356	34582.6512	43639.3033	34812.5160	34547.0025	43618.2600	34783.4582	34533.1607	43626.8191	34791.8228	34541.4493
chi2	2261.3300	1515.6182	1944.7106	2317.8626	1553.4874	1976.1143	2322.8849	1567.4565	1978.3561	2323.1754	1567.4894	1978.1043
ll	-21715.2325	-17292.7040	-17163.2618	-21688.0230	-17273.9255	-17141.1687	-21681.8890	-17263.6653	-17138.5166	-21681.7809	-17263.5788	-17138.3921

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9 - GMM Dynamic Count Model (KET breakdown)

	(1) New_RTAt	(2) New_RTAt	(3) New_RTAt	(4) New_RTAt	(5) New_RTAt	(6) New_RTAt
New_RTAt _{t-1}	0.0155*** (0.0007)	0.0177*** (0.0007)	0.0169*** (0.0007)	0.0163*** (0.0007)	0.0158*** (0.0007)	0.0152*** (0.0007)
Av_dens _t	2.5698*** (0.1777)	1.8489*** (0.1280)	2.1162*** (0.1473)	2.3057*** (0.1489)	2.4789*** (0.1551)	2.6191*** (0.1610)
BIOTECH _{t-1}	0.0194*** (0.0015)					
Av_dens _t * BIOTECH _{t-1}	-0.0697*** (0.0059)					
NANOTECH _{t-1}		0.1451*** (0.0222)				
Av_dens _t * NANOTECH _{t-1}		-0.5494*** (0.0897)				
NANOELCT _{t-1}			0.0105*** (0.0015)			
Av_dens _t * NANOELC _{t-1}			-0.0387*** (0.0055)			
PHOTO _{t-1}				0.0199*** (0.0025)		
Av_dens _t * PHOTO _{t-1}				-0.0741*** (0.0090)		
ADVMAT _{t-1}					0.0078*** (0.0012)	
Av_dens _t * ADVMAT _{t-1}					-0.0279*** (0.0041)	
ADVTECH _{t-1}						0.0081*** (0.0010)
Av_dens _t * ADVTECH _{t-1}						-0.0296*** (0.0043)
Count_IPC _{t-1}	-0.0000** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000* (0.0000)	-0.0000 (0.0000)
Const	2.4946*** (0.0361)	2.5643*** (0.0361)	2.5401*** (0.0354)	2.5338*** (0.0353)	2.5175*** (0.0355)	2.5205*** (0.0359)
<i>N</i>	6475	6475	6475	6475	6475	6475

Region clustered Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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European Commission

Joint Research Centre – Institute for Prospective Technological Studies

Title: Key Enabling Technologies and Smart Specialization Strategies. European Regional Evidence from patent data

Authors: Sandro Montresor and Francesco Quatraro

Spain: European Commission, Joint Research Centre

2015 – 37 pp. – 21.0 x 29.7 cm

EUR – Scientific and Technical Research series – ISSN 1831-9408 (online)



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