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


## 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.



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

**JEL codes**: R11; R58; O31; O33.

# 1 Introduction

Set by the European Commission on the policy-agenda for "ensuring the competitiveness of European industries in the knowledge economy" (EC, 2009; 2012), the six technologies it identified as "key enabling" (i.e. KETs) – industrial biotechnology, nanotechnology, micro- and nanoelectronics, photonics, advanced materials, and advanced manufacturing technologies – have surprisingly not found much scope in the academic discourse. 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 a prominent policy role, and the proof of their relevance still seems to lay in the oven. Such a research-policy mismatch also characterises the recent prioritisation that KETs have found in the mounting debate on S3, with explicit policy recommendations for monitoring (e.g. in the S3 Platform and in the Eye@RIS3 observatory) and supporting their development (e.g. in Regional Operational Plans). In the realm of regional studies, the lack of attention for the role of KETs appears to us even more unfortunate, given a substantiating economic geography approach to S3, in which the role of KETs is for us amenable to consideration. To be sure, plugging KETs in this approach is for us more than desirable to find an actual, and possibly more specific, case for their claimed entrance in the S3 "policy-mix".

In this paper we move a first, but twofold step in this still unexplored direction. 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). These are the main bits of value added of the paper, from which original results and policy implications also emerge about the case for supporting the development of KETs in the search of S3.

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 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.

[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.

[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).

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 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. 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 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

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

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.[4]

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 product and process applications. 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 definitions actually refer to several fields of application.[5] 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.[6] Similarly to 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

[4] 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.

[5] 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).

[6] 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.

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 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 related variety and 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).[7] 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 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 economic sectors of the applicants (in which the original approach assumes the knowledge will "diffuse"), to the regions in which the applicants reside. 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,[8] in order to build up other relevant control variables (see the next sections). By merging the two, 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.

[7] 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.

[8] "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).

## 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:

$$New\_RTA_{it} = \sum_s x_{ist} \qquad (1)$$

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):

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

In our sample, *m* = 632 and *n* = 235, while a lag of *1* year is considered for the emergence of a new RTA to emerge[9].

According to the same approach, the dynamics of the RTAs of a region is first of all explained by the technological space 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

[9] Different lag specifications have been tried, and the results are fairly consistent.

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 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 be plugged in 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. $RTA_{its}$) reveals with respect to those (out of the remaining $m-1$) 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 it follows.

We first calculate a proximity measure ($\varphi$) 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:

$$\varphi_{szt} = \min\left\{P(RTA_{st} | RTA_{zt}), P(RTA_{z} | RTA_{s})\right\} \qquad (3)$$

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:

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

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:

$$Av\_dens_{it} = \sum_{z \neq s} wad_{izt-1} \times \frac{New\_RTA_{izt}}{\sum_{z \neq s} New\_RTA_{izt}} \tag{5}$$

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, as it somehow sets the "degrees of freedom" the region has available in exploring new technological advantages over time. Consistently with the patent-based nature of the model, such a size can be proxied by the number of IPC codes in which a region has registered patent applications at time *t-1*, $CountIPC_{it-1}$. 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 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:

$$\begin{aligned}&New\_RTA_{it} = f(New\_RTA_{it-1}, Av\_dens_{it},\\&KETs_{it-1}, Av\_dens_{it} * KETs_{it-1},\\&CountIPC_{it-1}, z_{it-1}, dtime, dregion, \varepsilon_{it})\end{aligned} \quad (6)$$

where, in addition to the previous positions, $z$ is the vector of our structural regional controls, *dtime* and *dregion* are year- and regional dummies, respectively, and $\varepsilon$ 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 model, and check for its robustness by implementing also a fixed effects Poisson model. Accordingly, the functional form to be estimated is the following:

$$
\begin{aligned}
&New\_RTA_{it} = \exp(\alpha + \beta_1 New\_RTA_{it-1} + \beta_2 Av\_dens_{it} + \\
&+\beta_3 KETs_{it-1} + \beta_4 Av\_dens_{it} * KETs_{it-1} + \\
&+\beta_5 CountIPC_{it-1} + \beta_5 z_{it-1} + dtime + dregion + \varepsilon_{it})
\end{aligned} \qquad (7)
$$

In augmenting this 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 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 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. 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 (Negative Binomial and Poisson 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.[10]

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 ( $Av\_dens_{it}$ ) 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).

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 $Av\_dens$.

[10] 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.

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 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. As expected, the discovery process at stake appears limited by the number of already unfolded technologies, as $Count\_IPC_{t-1}$ is significant and negative. As for the other controls, we notice that both $lnEmployment_{t-1}$ and $lnGVA_{t-1}$ show positive and significant coefficients. This is also largely expected, as it signals that richer regions are more likely to develop technological competences in new technological fields. 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

The different columns of Table (5) only report the results from the Negative Binomial estimations, as from Table (4) we can observe that the Poisson estimations yield consistent results, while from Table (3) we can infer that the observed variance of the dependent variable is far larger than the mean, suggesting that the variable is overdispersed. In column (1) we report the results of the baseline model augmented by the inclusion of the variable $KETs\_RTA_{t-1}$ and of its interaction with *Av_Dens*.

It must be noted that the coefficients are substantially stable across the different estimations, and also when comparing Tables 4 and 5. The main difference can be identified as far as the

KETs interaction variable is concerned. 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 neither *Count_IPC* nor *lnEmplt* are significant any longer.[11]

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 *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

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

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:

$$\frac{\partial y}{\partial KETs\_RTA_{it-1}} = \beta_3 + \beta_4 Av\_dens_{it} \tag{8}$$

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 of our application concerns the estimates of the same model as above (see Eq.(6)), but by "exploding" in it the knowledge availability specialization ( $KETs(j)\_RTA_{it-1}$) that regions could display in each and every of the six technologies *j* (with *j* = BIOTECH, NANOTECH, NANOELCT, PHOTO, ADVMAT, and ADVTECH) separately considered.

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_RTA*, 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 sub-set 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 fare 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.

Of course, the paper is not free from limitations, which could be addressed in its future extensions. 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 maesured, 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. Thirdly, the list of regional controls we have inserted could be also enlarged, but only at the price of loosing a lot of data and relevant information. 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.

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Figure 1 - Kernel Density Distribution of New_RTA

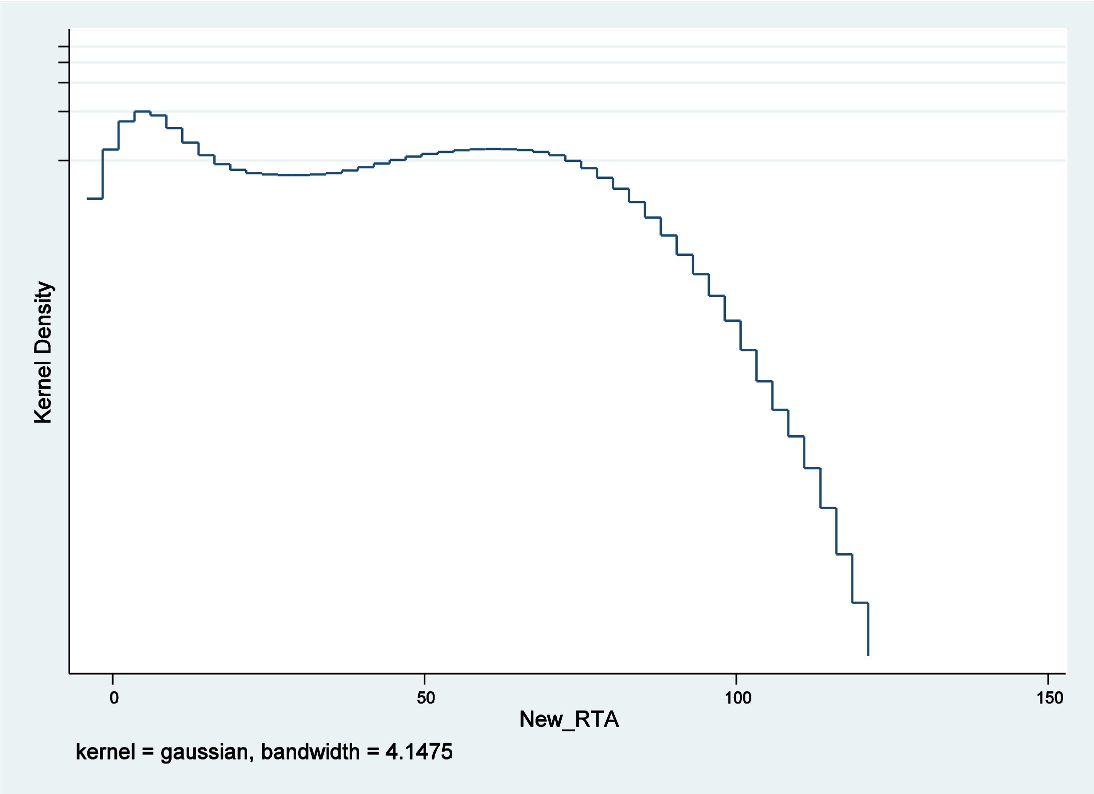

Figure 2 - Spatial Distribution of Relevant Variables

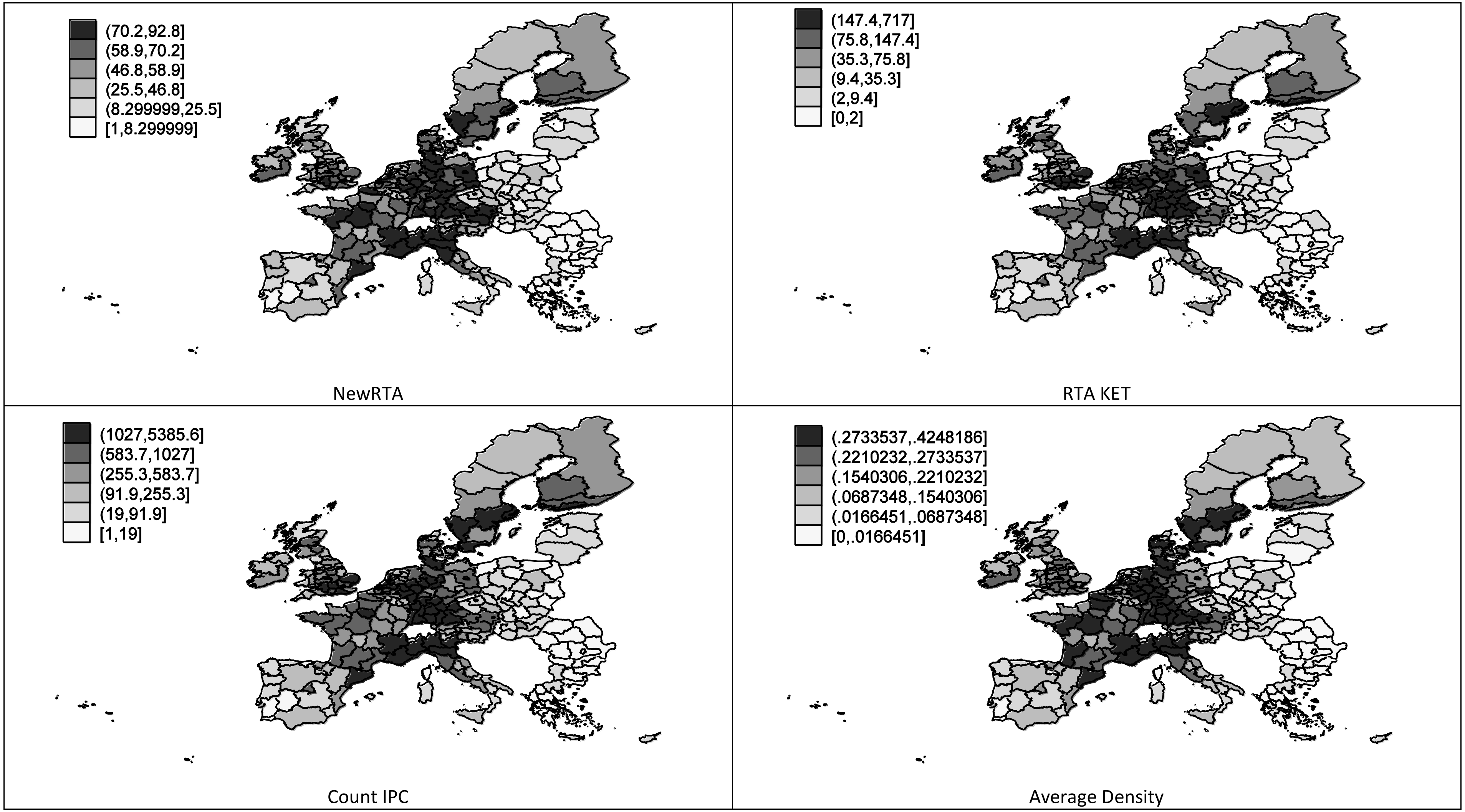

Table 1 - Variables Definition

| Variable | Definition | Source |
| --- | --- | --- |
| **$NewRTA_{i,t}$** | Number of technological specializations in region i, which were observed at time *t* but were not at time *t-1* | Elaborations on OECD RegPat Database (July 2014). |
| **$Av\_dens_{i,t}$** | Average proximity of all technologies observed at time *t* in region *i* to all other technologies observed in the same region at time *t-1* | Elaborations on OECD RegPat Database (July 2014). |
| **$KETs\_file_{i,t}$** | Number of technologies flagged as KET observed at time *t* in region *i*. | Elaborations on OECD RegPat Database (July 2014); EC (2011). |
| **$KETs\_RTA_{i,t}$** | Number of KETs for which the region *i* has developed a specialization at time *t*. | Elaborations on OECD RegPat Database (July 2014); EC (2011). |
| **$CountIPC_{i,t}$** | Number of different technologies observed in the patent portfolio of region *i* at time *t.* | Elaborations on OECD RegPat Database (July 2014). |
| **$lnGVA_{i,t}$** | Natural logarithm of Gross Value Added of region *i* at time *t*. | Cambridge Econometrics (December 2014) |
| **$lnEmployment_{it}$** | Natural logarithm of employment level in region *i* at time *t*. | 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_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 |
| **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**

| | New_RTA | Av_dens | KETs_RTA | Av_dens* KETs_RTA | Count_IPC | LnEmplt | lnGVA |
|---|---|---|---|---|---|---|---|
| **New_RTA** | 1 | | | | | | |
| **Av_dens** | 0.8978* | 1 | | | | | |
| **KETS_RTA** | 0.8890* | 0.8822* | 1 | | | | |
| **Av_dens* KETs_RTA** | 0.8993* | 0.9424* | 0.9574* | 1 | | | |
| **Count_IPC** | 0.9225* | 0.9185* | 0.9686* | 0.9702* | 1 | | |
| **LnEmplt** | 0.4613* | 0.4424* | 0.4678* | 0.4711* | 0.4880* | 1 | |
| **lnGVA** | 0.7462* | 0.7431* | 0.7548* | 0.7699* | 0.7832* | 0.7986* | 1 |

**Table 4 - Baseline estimation**

| | (1) New_RTA | (2) New_RTA | (3) New_RTA | (4) New_RTA | (5) New_RTA | (6) New_RTA | (7) New_RTA | (8) New_RTA | (9) New_RTA | (10) New_RTA |
|---|---|---|---|---|---|---|---|---|---|---|
| $New\_RTA_{t-1}$ | $0.0084^{***}$ | $0.0053^{***}$ | $0.0067^{***}$ | $0.0043^{***}$ | $0.0067^{***}$ | $0.0043^{***}$ | $0.0054^{***}$ | $0.0031^{***}$ | $0.0046^{***}$ | $0.0031^{***}$ |
| | (0.0003) | (0.0002) | (0.0003) | (0.0002) | (0.0003) | (0.0002) | (0.0004) | (0.0002) | (0.0004) | (0.0002) |
| $Av\_dens_{t}$ | $0.8822^{***}$ | $0.4530^{***}$ | $1.6128^{***}$ | $1.0704^{***}$ | $1.6142^{***}$ | $1.0612^{***}$ | $1.4744^{***}$ | $0.7948^{***}$ | $1.3592^{***}$ | $0.8514^{***}$ |
| | (0.0931) | (0.0547) | (0.1056) | (0.0644) | (0.1056) | (0.0644) | (0.1181) | (0.0759) | (0.1106) | (0.0749) |
| $KETs\_File_{t-1}$ | | | $0.0012^{***}$ | $0.0006^{***}$ | $0.0015^{***}$ | $0.0012^{***}$ | $0.0015^{***}$ | $0.0009^{***}$ | $0.0011^{***}$ | $0.0008^{***}$ |
| | | | (0.0001) | (0.0001) | (0.0002) | (0.0001) | (0.0002) | (0.0001) | (0.0002) | (0.0001) |
| $Av\_dens_{t}$* $KETS\_File_{t-1}$ | | | $-0.0061^{***}$ | $-0.0044^{***}$ | $-0.0060^{***}$ | $-0.0040^{***}$ | $-0.0052^{***}$ | $-0.0029^{***}$ | $-0.0037^{***}$ | $-0.0028^{***}$ |
| | | | (0.0005) | (0.0003) | (0.0005) | (0.0003) | (0.0005) | (0.0003) | (0.0005) | (0.0003) |
| $Count\_IPC_{t-1}$ | | | | | $-0.0001^{**}$ | $-0.0001^{***}$ | $-0.0001^{**}$ | $-0.0001^{***}$ | $-0.0001^{***}$ | $-0.0001^{***}$ |
| | | | | | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| $lnGVA_{t}$ | | | | | | | $0.1537^{***}$ | $0.2395^{***}$ | | |
| | | | | | | | (0.0384) | (0.0361) | | |
| $lnEmplt_{t}$ | | | | | | | | | $0.5428^{***}$ | $0.2565^{***}$ |
| | | | | | | | | | (0.0319) | (0.0290) |
| _cons | $2.7184^{***}$ | | $2.8629^{***}$ | | $2.8808^{***}$ | | $2.1498^{***}$ | | $-2.4522^{***}$ | |
| | (0.0475) | | (0.0516) | | (0.0524) | | (0.2485) | | (0.3277) | |
| *N* | 6794 | 6794 | 6472 | 6472 | 6472 | 6472 | 5103 | 5103 | 5103 | 5103 |
| *AIC* | 45199.7970 | 47876.1442 | 43448.4925 | 45591.2715 | 43445.2385 | 45527.5286 | 34610.6650 | 35836.8602 | 34355.9796 | 35794.4411 |
| *BIC* | 45384.0395 | 48053.5629 | 43644.9745 | 45780.9783 | 43648.4957 | 45724.0106 | 34813.3301 | 36032.9877 | 34558.6447 | 35990.5686 |
| chi2 | 2380.4923 | 3189.0984 | 2292.6299 | 3258.6331 | 2298.1182 | 3321.8458 | 1546.5749 | 2058.3079 | 1969.3246 | 2087.5970 |
| ll | - 22572.8985 | -23912.0721 | -21695.2462 | -22767.6358 | -21692.6192 | -22734.7643 | -17274.3325 | -17888.4301 | -17146.9898 | -17867.2205 |

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

## Table 5 - RTA in KETs

| | (1) New_RTA | (2) New_RTA | (3) New_RTA | (4) New_RTA |
|---|---|---|---|---|
| $New\_RTA_{t-1}$ | $0.0066^{***}$ | $0.0066^{***}$ | $0.0053^{***}$ | $0.0046^{***}$ |
| | (0.0003) | (0.0003) | (0.0004) | (0.0004) |
| $Av\_dens_{t}$ | $1.7178^{***}$ | $1.7092^{***}$ | $1.5598^{***}$ | $1.4332^{***}$ |
| | (0.1076) | (0.1077) | (0.1204) | (0.1127) |
| $KETs\_RTA_{t-1}$ | $0.0015^{***}$ | $0.0018^{***}$ | $0.0018^{***}$ | $0.0013^{***}$ |
| | (0.0002) | (0.0002) | (0.0002) | (0.0002) |
| $Av\_dens_{t}$* $KETs\_RTA_{t-1}$ | $-0.0074^{***}$ | $-0.0072^{***}$ | $-0.0062^{***}$ | $-0.0045^{***}$ |
| | (0.0006) | (0.0006) | (0.0006) | (0.0005) |
| $lnEmplt_{t}$ | | | $0.1516^{***}$ | |
| | | | (0.0383) | |
| $lnGVA_{t}$ | | | | $0.5385^{***}$ |
| | | | | (0.0319) |
| $Count\_IPC_{t-1}$ | | $-0.0001^{***}$ | $-0.0001^{***}$ | $-0.0001^{***}$ |
| | | (0.0000) | (0.0000) | (0.0000) |
| _cons | $2.8511^{***}$ | $2.8753^{***}$ | $2.1515^{***}$ | $-2.4174^{***}$ |
| | (0.0516) | (0.0525) | (0.2482) | (0.3276) |
| *N* | 6472 | 6472 | 5103 | 5103 |
| *AIC* | 43429.3233 | 43422.8695 | 34595.8547 | 34344.5047 |
| *BIC* | 43625.8053 | 43626.1267 | 34798.5198 | 34547.1698 |
| chi2 | 2310.0281 | 2319.0571 | 1559.3238 | 1980.2319 |
| ll | -21685.6617 | -21681.4347 | -17266.9273 | -17141.2523 |

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

##### Table 6 - GMM Dynamic Count Data Model

| | (1) New_RTA | (2) New_RTA | (3) New_RTA |
|---|---|---|---|
| $New\_RTA_{t-1}$ | $0.0149^{***}$ | $0.0130^{***}$ | $0.0120^{***}$ |
| | (0.0007) | (0.0007) | (0.0006) |
| $Av\_dens_t$ | $2.7556^{***}$ | $2.8996^{***}$ | $2.6368^{***}$ |
| | (0.1636) | (0.1484) | (0.1435) |
| $KETs\_RTA_{t-1}$ | $0.0030^{***}$ | $0.0032^{***}$ | $0.0030^{***}$ |
| | (0.0004) | (0.0004) | (0.0004) |
| $Av\_dens_t$* $KETs\_RTA_{t-1}$ | $-0.0114^{***}$ | $-0.0115^{***}$ | $-0.0105^{***}$ |
| | (0.0015) | (0.0014) | (0.0013) |
| $lnEmplt_t$ | | 0.0145 | |
| | | (0.0175) | |
| $lnGVA_t$ | | | $0.1172^{***}$ |
| | | | (0.0163) |
| $Count\_IPC_{t-1}$ | 0.0000 | -0.0000 | -0.0000 |
| | (0.0000) | (0.0000) | (0.0000) |
| Const | $2.4993^{***}$ | $2.4833^{***}$ | $1.4973^{***}$ |
| | (0.0351) | (0.1123) | (0.1665) |
| *N* | 6475 | 5103 | 5103 |

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 | 0.000772 | 0.00016 | 4.82 | 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_RTA | (2) New_RTA | (3) New_RTA | (4) New_RTA | (5) New_RTA | (6) New_RTA | (7) New_RTA | (8) New_RTA | (9) New_RTA | (10) New_RTA | (11) New_RTA | (12) New_RTA |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $New\_RTA_{t-1}$ | $0.0068^{***}$ | $0.0054^{***}$ | $0.0046^{***}$ | $0.0068^{***}$ | $0.0053^{***}$ | $0.0045^{***}$ | $0.0072^{***}$ | $0.0056^{***}$ | $0.0048^{***}$ | $0.0072^{***}$ | $0.0055^{***}$ | $0.0048^{***}$ |
| | (0.0003) | (0.0004) | (0.0003) | (0.0003) | (0.0004) | (0.0004) | (0.0003) | (0.0004) | (0.0003) | (0.0003) | (0.0004) | (0.0003) |
| $Av\_dens_t$ | $1.5460^{***}$ | $1.4846^{***}$ | $1.4551^{***}$ | $1.5504^{***}$ | $1.3976^{***}$ | $1.3928^{***}$ | $0.9135^{***}$ | $0.8094^{***}$ | $0.8370^{***}$ | $0.9719^{***}$ | $0.8050^{***}$ | $0.8503^{***}$ |
| | (0.1049) | (0.1150) | (0.1081) | (0.1047) | (0.1155) | (0.1087) | (0.0907) | (0.0987) | (0.0925) | (0.0916) | (0.0983) | (0.0925) |
| $BIOTECH_{t-1}$ | $0.0103^{***}$ | $0.0102^{***}$ | $0.0089^{***}$ | $0.0108^{***}$ | $0.0101^{***}$ | $0.0089^{***}$ | | | | | | |
| | (0.0009) | (0.0009) | (0.0009) | (0.0009) | (0.0009) | (0.0009) | | | | | | |
| $Av\_dens_t$* $BIOTECH_{t-1}$ | $-0.0393^{***}$ | $-0.0367^{***}$ | $-0.0319^{***}$ | $-0.0374^{***}$ | $-0.0334^{***}$ | $-0.0289^{***}$ | | | | | | |
| | (0.0032) | (0.0033) | (0.0031) | (0.0033) | (0.0034) | (0.0031) | | | | | | |
| $NANOTECH_{t-1}$ | | | | | | | $0.0431^{***}$ | $0.0645^{***}$ | $0.0471^{***}$ | $0.0508^{***}$ | $0.0589^{***}$ | $0.0414^{**}$ |
| | | | | | | | (0.0130) | (0.0170) | (0.0161) | (0.0132) | (0.0170) | (0.0161) |
| $Av\_dens_t$ * $NANOTECH_{t-1}$ | | | | | | | $-0.2944^{***}$ | $-0.3529^{***}$ | $-0.2713^{***}$ | $-0.2998^{***}$ | $-0.3195^{***}$ | $-0.2370^{***}$ |
| | | | | | | | (0.0472) | (0.0576) | (0.0531) | (0.0479) | (0.0580) | (0.0538) |
| $lnEmplt_t$ | 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 | $2.7882^{***}$ | $2.0435^{***}$ | $-2.6178^{***}$ | $2.8793^{***}$ | $1.9485^{***}$ | $-2.6740^{***}$ | $2.9427^{***}$ | $2.1576^{***}$ | $-2.5615^{***}$ | $2.9922^{***}$ | $2.0541^{***}$ | $-2.6302^{***}$ |
| | (0.0497) | (0.2467) | (0.3212) | (0.0524) | (0.2524) | (0.3223) | (0.0499) | (0.2502) | (0.3271) | (0.0517) | (0.2554) | (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 Break down (2/3)**

| | (1)<br>New_RTA | (2)<br>New_RTA | (3)<br>New_RTA | (4)<br>New_RTA | (5)<br>New_RTA | (6)<br>New_RTA | (7)<br>New_RTA | (8)<br>New_RTA | (9)<br>New_RTA | (10)<br>New_RTA | (11)<br>New_RTA | (12)<br>New_RTA |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $New\_RTA_{t-1}$ | $0.0073^{***}$ | $0.0059^{***}$ | $0.0050^{***}$ | $0.0073^{***}$ | $0.0058^{***}$ | $0.0050^{***}$ | $0.0071^{***}$ | $0.0057^{***}$ | $0.0049^{***}$ | $0.0071^{***}$ | $0.0057^{***}$ | $0.0048^{***}$ |
| | (0.0003) | (0.0004) | (0.0003) | (0.0003) | (0.0004) | (0.0003) | (0.0003) | (0.0004) | (0.0004) | (0.0003) | (0.0004) | (0.0004) |
| $Av\_dens_t$ | $1.1670^{***}$ | $1.0693^{***}$ | $1.0343^{***}$ | $1.2058^{***}$ | $1.0197^{***}$ | $1.0105^{***}$ | $1.2927^{***}$ | $1.1830^{***}$ | $1.1368^{***}$ | $1.3072^{***}$ | $1.1325^{***}$ | $1.1010^{***}$ |
| | (0.0974) | (0.1073) | (0.1002) | (0.0973) | (0.1069) | (0.1001) | (0.0985) | (0.1075) | (0.1013) | (0.0983) | (0.1077) | (0.1014) |
| $NANOELCT_{t-1}$ | $0.0038^{***}$ | $0.0037^{***}$ | $0.0024^{***}$ | $0.0046^{***}$ | $0.0036^{***}$ | $0.0024^{***}$ | | | | | | |
| | (0.0007) | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) | | | | | | |
| $Av\_dens_t * NANOELCT_{t-1}$ | $-0.0185^{***}$ | $-0.0160^{***}$ | $-0.0111^{***}$ | $-0.0184^{***}$ | $-0.0139^{***}$ | $-0.0094^{***}$ | | | | | | |
| | (0.0027) | (0.0028) | (0.0025) | (0.0027) | (0.0029) | (0.0026) | | | | | | |
| $PHOTO_{t-1}$ | | | | | | | $0.0083^{***}$ | $0.0080^{***}$ | $0.0057^{***}$ | $0.0095^{***}$ | $0.0083^{***}$ | $0.0062^{***}$ |
| | | | | | | | (0.0012) | (0.0013) | (0.0012) | (0.0012) | (0.0013) | (0.0012) |
| $Av\_dens_t * PHOTO_{t-1}$ | | | | | | | $-0.0389^{***}$ | $-0.0343^{***}$ | $-0.0245^{***}$ | $-0.0382^{***}$ | $-0.0315^{***}$ | $-0.0218^{***}$ |
| | | | | | | | (0.0042) | (0.0044) | (0.0039) | (0.0043) | (0.0045) | (0.0040) |
| $lnEmplt_t$ | 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 | $2.8423^{***}$ | $2.2384^{***}$ | $-2.6306^{***}$ | $2.9152^{***}$ | $2.0882^{***}$ | $-2.7054^{***}$ | $2.8506^{***}$ | $2.2097^{***}$ | $-2.4962^{***}$ | $2.9106^{***}$ | $2.1001^{***}$ | $-2.6124^{***}$ |
| | (0.0495) | (0.2445) | (0.3258) | (0.0519) | (0.2519) | (0.3259) | (0.0497) | (0.2447) | (0.3261) | (0.0520) | (0.2504) | (0.3269) |
| *N* | 6472 | 5103 | 5103 | 6472 | 5103 | 5103 | 6472 | 5103 | 5103 | 6472 | 5103 | 5103 |
| *AIC* | 43572.5866 | 34712.4949 | 34436.2800 | 43542.8540 | 34689.0037 | 34405.4753 | 43528.5196 | 34677.5198 | 34414.5901 | 43509.4760 | 34662.7453 | 34389.9812 |
| *BIC* | 43769.0686 | 34908.6224 | 34632.4075 | 43746.1112 | 34891.6688 | 34608.1404 | 43725.0016 | 34873.6473 | 34610.7176 | 43712.7332 | 34865.4104 | 34592.6463 |
| chi2 | 2182.5421 | 1453.1585 | 1895.7712 | 2214.4558 | 1481.2778 | 1921.8039 | 2222.8979 | 1484.4741 | 1911.6029 | 2245.2125 | 1503.0804 | 1932.9937 |
| ll | -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)<br>New_RTA | (2)<br>New_RTA | (3)<br>New_RTA | (4)<br>New_RTA | (5)<br>New_RTA | (6)<br>New_RTA | (7)<br>New_RTA | (8)<br>New_RTA | (9)<br>New_RTA | (10)<br>New_RTA | (11)<br>New_RTA | (12)<br>New_RTA |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| New_RTA$_{t-1}$ | 0.0068$^{***}$ | 0.0056$^{***}$ | 0.0048$^{***}$ | 0.0067$^{***}$ | 0.0054$^{***}$ | 0.0047$^{***}$ | 0.0066$^{***}$ | 0.0052$^{***}$ | 0.0046$^{***}$ | 0.0066$^{***}$ | 0.0052$^{***}$ | 0.0046$^{***}$ |
| | (0.0003) | (0.0004) | (0.0003) | (0.0003) | (0.0004) | (0.0003) | (0.0003) | (0.0004) | (0.0004) | (0.0003) | (0.0004) | (0.0004) |
| Av_dens$_t$ | 1.4885$^{***}$ | 1.3687$^{***}$ | 1.3049$^{***}$ | 1.4673$^{***}$ | 1.2604$^{***}$ | 1.2301$^{***}$ | 1.4714$^{***}$ | 1.2887$^{***}$ | 1.1896$^{***}$ | 1.4663$^{***}$ | 1.2900$^{***}$ | 1.1897$^{***}$ |
| | (0.1040) | (0.1119) | (0.1051) | (0.1035) | (0.1124) | (0.1055) | (0.1036) | (0.1156) | (0.1091) | (0.1041) | (0.1157) | (0.1091) |
| ADVMAT$_{t-1}$ | 0.0048$^{***}$ | 0.0044$^{***}$ | 0.0034$^{***}$ | 0.0053$^{***}$ | 0.0045$^{***}$ | 0.0035$^{***}$ | | | | | | |
| | (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.0004) | | | | | | |
| Av_Dens$_t$ * ADVMAT$_{t-1}$ | -0.0177$^{***}$ | -0.0151$^{***}$ | -0.0118$^{***}$ | -0.0158$^{***}$ | -0.0126$^{***}$ | -0.0097$^{***}$ | | | | | | |
| | (0.0016) | (0.0015) | (0.0014) | (0.0016) | (0.0016) | (0.0014) | | | | | | |
| ADVTECH$_{t-1}$ | | | | | | | 0.0025$^{***}$ | 0.0021$^{***}$ | 0.0008$^{*}$ | 0.0024$^{***}$ | 0.0020$^{***}$ | 0.0009$^{*}$ |
| | | | | | | | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| Av_dens$_t$ * ADVTECH$_{t-1}$ | | | | | | | -0.0165$^{***}$ | -0.0137$^{***}$ | -0.0088$^{***}$ | -0.0165$^{***}$ | -0.0137$^{***}$ | -0.0087$^{***}$ |
| | | | | | | | (0.0016) | (0.0016) | (0.0014) | (0.0016) | (0.0016) | (0.0014) |
| lnEmplt$_t$ | 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$^{***}$ | 2.1818$^{***}$ | -2.4599$^{***}$ | 2.9089$^{***}$ | 2.0214$^{***}$ | -2.5237$^{***}$ | 2.9450$^{***}$ | 2.2039$^{***}$ | -2.3973$^{***}$ | 2.9425$^{***}$ | 2.2152$^{***}$ | -2.4082$^{***}$ |
| | (0.0496) | (0.2429) | (0.3243) | (0.0524) | (0.2510) | (0.3247) | (0.0525) | (0.2499) | (0.3315) | (0.0527) | (0.2511) | (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_RTA | (2) New_RTA | (3) New_RTA | (4) New_RTA | (5) New_RTA | (6) New_RTA |
|---|---|---|---|---|---|---|
| New_RTA$_{t-1}$ | 0.0155$^{***}$ | 0.0177$^{***}$ | 0.0169$^{***}$ | 0.0163$^{***}$ | 0.0158$^{***}$ | 0.0152$^{***}$ |
| | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) |
| Av_dens$_t$ | 2.5698$^{***}$ | 1.8489$^{***}$ | 2.1162$^{***}$ | 2.3057$^{***}$ | 2.4789$^{***}$ | 2.6191$^{***}$ |
| | (0.1777) | (0.1280) | (0.1473) | (0.1489) | (0.1551) | (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$^{***}$ | 2.5643$^{***}$ | 2.5401$^{***}$ | 2.5338$^{***}$ | 2.5175$^{***}$ | 2.5205$^{***}$ |
| | (0.0361) | (0.0361) | (0.0354) | (0.0353) | (0.0355) | (0.0359) |
| *N* | 6475 | 6475 | 6475 | 6475 | 6475 | 6475 |

Region clustered Standard errors in parentheses
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$