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

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Smart Specialization Strategies and Key Enabling Technologies. Regional evidence from European patent data[1].

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Abstract

The paper investigates the drivers of Smart Specialisation Strategies (S3) with a focus on Key Enabling Technologies (KETs). We re-examine the interpretation of S3 as new regional technological advantages (RTAs) obtained through relatedness, by reconceptualising within it the original focus on General Purpose Technologies (GPTs) and by considering their inter-regional spillovers. Combing regional patent and economic data for a 30-year panel (1980-2010) of 26 European countries, we find that KETs positively impact on new RTAs, pointing to a novel "enabling" role for them. KETs also negatively moderate the RTAs-impact of cognitively proximate pre-existing technologies, suggesting that KETs could make relatedness less binding in pursuing S3. The net-impact of KETs is positive, pointing to a new case for plugging KETs in the S3 policy tool-box. Furthermore, KETs also display cross-regional spillovers in their RTAs-impact, leaving KETs "poor" regions with a possible back-up from closer KETs "rich" ones.

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

JEL codes: R11; R58; O31; O33.

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1 Introduction

The present paper deals with the concept of "Smart Specialization" and with the role that "Key Enabling Technologies" (KETs) can have for the implementation of "Smart Specialisation Strategies" (S3) at the regional level.

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 were originally meant as specific processes 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. In the initial formulation of the concept, the "Knowledge for Growth" Expert Group advising the Commissioner for Research on S3, identified two interrelated mechanisms for them to unfold: i) a "vertical one" (in our words), amounting to the identification of new technological opportunities, starting from and upgrading pre-existing technological advantages in the region; ii) an "horizontal one" (still in our words), represented by the differentiated (e.g. between leader and follower regions) application of General Purpose Technologies (GPTs) for exploiting these related technological opportunities into new technological advantages (Foray et al., 2009).

Since this inception, an intense debate has taken place in the attempt of translating the S3 policy concept into a sounder academic notion (Foray et al., 2011), searching for theoretical anchoring and empirical support of its two underlying mechanisms.[2] However, this has occurred asymmetrically. On the one hand, the first vertical mechanism has soon attracted the attention of economic geographers, which following an evolutionary approach have started addressing S3 with the conceptual lenses of "proximity" and "relatedness" (Boschma, 2004; Frenken et al., 2007). On the other hand, the horizontal mechanism has remained quite in the background for long and has re-emerged only recently through a policy recommended, though not (yet) theoretically founded, attention to KETs in the implementation of S3 (Sörvik et al., 2014; Pattinson et al., 2015).

Indeed, KETs are, at least in principle (see the next Section), six GPTs-like technologies that the European Commission has put forward with respect to a quite different and more general policy-agenda than S3, that is for: "ensuring the competitiveness of European industries in the

2 Quite interestingly, this kind of policy-academy translation somehow resembles the one that has accompanied the history of the notion of "industrial district" (Nuti, 2014).

knowledge economy" (EC, 2009; 2012). More precisely, what makes of the six identified technologies "*key enabling*" ones, is for the proponent European policy-makers (see, in particular, EC, 2009 and 2012) 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). 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).

Only recently, as we said, the potential role of KETs for the development of S3 has emerged in the observatory platform of S3 best-practices (Sörvik et al., 2013), referring to their contribution to the development of regional technological activities in general. More precisely, 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).

While it brings back to the front the second neglected mechanism of S3, and duly places a renewed attention on the identification and functioning of new technologies with a general (purpose) horizontal nature, this sort of revival has unfortunately occurred without a clear theoretical background. Furthermore, it has been occurring disjointedly from the economic geography approach to S3, which in the meantime has progressed in the analysis of its first mechanism of related diversification.

In the paper we aim at solving this mismatch in the analysis of S3, by putting forward a more scientifically grounded approach to KETs, which could consistently integrate the analysis of their impact on S3 in an evolutionary geography manner (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: in brief, of related diversification. On this basis, we address the following research questions: i) Do KETs increase the regional capacity of S3, meant as this particular process of new technological specialization? Ii) Are KETs able to change the impact that the techno-cognitive proximity with respect to existing technologies has for the development of new ones? Iii) More in plain, do KETs enable regions to specialize more distantly from what they know? Iv) Or do they rather make existing regional technologies more binding for acquiring new specializations?

These research questions have important policy implications. On the one hand, a positive answer to questions i) and ii) 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, iii) and iv), do also have 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 S3 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 integrating 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 identify some properties of KETs related knowledge that, consistently with their GPTs nature, can be integrated in the analysis of S3 drivers based on related diversification. On the other hand, from an empirical point of view, we augment with the moderating role of KETs and with the spatial analysis of their possible cross-regional spillovers, the patent-based econometric models through which 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 policy and 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 among the drivers of S3. Section 3 presents the empirical application for testing these hypotheses, the data and the econometric strategy through which it is pursued. Section 4 discusses the main results. Section 5 concludes.

2 Policy and theoretical background and hypotheses

Soon after the seminal policy-papers by Foray et al. (2009, 2011), the analysis of "Smart Specialisation" at the regional level attracted rapid attention in the academic debate. In particular, the idea of S3 immediately appeared susceptible to represent the natural policy leverage for a number of different approaches in regional and urban studies, which had well before addressed its basic underlying mechanism in terms of regional learning, knowledge bases, innovation patterns, and diversification, to mention a few (Wintjes, and Hollanders, 2011; Iacobucci, 2014).

In this academic translation of the S3 policy concept, particularly important have been the insights obtained by a number of studies in the realm of evolutionary economic geography, which have addressed its first "vertical" building mechanism by linking it to the Construction of Regional Advantages (CRA).[3] As discussed by Boschma (2014), the concept of smart specialisation actually shares with CRA the idea that regions need 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 (2013) argue, the geographical dimension should be rather integrated in the smart specialisation framework by looking at the effects of regional features on entrepreneurs' ability to engage in successful learning processes. Following this logic, Smart Specialisation Strategies (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.

While getting rich of these economic geography insights, "the career of the [S3] concept", as Foray et al. (2011) put it, has instead obscured the role of its other, "horizontal" driving mechanism, represented by the action of General Purpose Technologies (GPTs). In its original

[3] Of course, this is not the unique theoretical approach to the notion of S3, as it is rather complemented by other approaches with which it however shares some of the main principles (see, for example, Capello et al, 2014; Camagni and Capello, 2013).

formulation, these technologies were depicted as the "framework that helps to clarify the logic of Smart Specialisation" (Foray et al., 2009, p. 3). In a nutshell, GPTs were initially taken to favor S3 because of their horizontal propagation throughout the economy of a region and thanks to the complementarity they allow for between an invention and an application development. In other words, being susceptible of application to several important domains of the regional economy, GPTs were considered capable of advancing the frontier of attainable technological improvements by spurring dynamic feedback loops between the existing and the prospective technologies of a region (Foray et al., 2009, p.4).

In spite of this important starting role, GPTs have progressively lost importance in the S3-related discourse. The causes of their oblivion could of course be multiple and their systematic detection is a hard task going beyond the aim of this manuscript. Among the tentative explanations, which includes their shadowing by the increasing focus on relatedness, the "stagnation" in which theoretical and empirical analyses of GPTs have ended up after their first seminal analysis – mainly in long-run growth economics (e.g. Jovanovic and Rousseau, 2005) – could have mattered. Indeed, this is confirmed by the awakening of attention for the second, horizontal S3 mechanism stimulated by the recent upsurge of policy interest for some newly identified GPTs-like technologies, that is the so-called Key Enabling Technologies (KETs).

Put forward as a policy concept by the former DG Enterprise and Industry at the European Commission,[4] for the first time nearly simultaneously with the S3 one (EC, 2009; 2012), KETs are six technologies – namely, i) *industrial biotechnology*; ii) *nanotechnology*, iii) *micro- and nanoelectronics*, iv) *photonics*, v) *advanced materials*, and vi) *advanced manufacturing technologies* – that currently represent the 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 definitions actually refer to several fields of application.[5] Furthermore, their individual analysis (based on

[4] 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).

[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).

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] In brief, all of the six technologies replicate in the current scenario the features of "horizontal propagation" originally identified for the first generation of GPTs, like electricity, electronics, informatics, control theory (automation), and the Internet, to mention a few. To be sure, this is not the main distinguishing feature of KETs to be claimed, which the proponents rather characterise as "knowledge intensive and associated with high R&D intensity, rapid innovation cycles, high capital expenditure and highly skilled employment" (EC, 2012). Furthermore, unlike the first generation of GPTs, KETs are marked by 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). Still, similarly to GPTs, KETs represent technological inputs for obtaining new "KETs-based products and applications", that are "key" as they are expected to enable economic systems to face new societal challenges.

Quite interestingly, and for sure not casually, the new list of KETs includes some technologies, which were already in the GPTs framework of the first presentation of the smart specialisation concept, like: "*biotechnology* applied to the exploitation of maritime resources; *nanotechnology* applied to the wine quality control, fishing, cheese and olive oil industries; *information technology* applied to the management of knowledge about and the maintenance of archaeological and historical patrimonies" (Foray et al., 2009, p. 3, our emphasis). Not surprisingly, therefore, European policy makers have recently ridden the new wave and started recommend regions to insert the diffusion and/or application of KETs among the priority areas on which to build their S3: 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.[7]

[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.

[7] 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).

Quite unfortunately, this is occurring mainly pragmatically and somehow disconnectedly from the policy recommendations deriving from the sounder theoretical implications economic geography is providing in terms of relatedness. Re-connecting (again) the two driving mechanisms of S3 in a modern coherent framework is however possible, if we just think that KETs have some characteristics that can be assumed to affect the S3 of the regions according to the RCA-based economic geography rationale.[8]

The first characteristic is, as we said, the *general purpose* of KETs, in terms of number and variety of their possible applications. As we also said, this appears clearly from the technical work that has accompanied their identification (EC, 2011), from which they have emerged as the basic "ingredients" of a large number of both already existing and future available products and applications. Similarly GPTs, 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 endowed with KETs knowledge (see footnote 7) 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.*

[8] 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. Thirdly, we will refrain from addressing whether these characteristics actually define the functional boundaries of the "KETs-club" with respect to non-/less key enabling ones, 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.

A second KETs characteristic with important implications for the development of S3 is their *systemic* 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 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 S3 and KETs is represented by European regions. As usual, the empirical coverage of the application 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).[9] 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.

[9] As clarified in the Feasibility Study (EC, 2011), 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.

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 to the best of our knowledge is still under revision. In the current application, we have referred to the latest available version of it (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.

In order to build up the proxies for the other S3 drivers and for the relevant controls (see the next sections), regional patent data at the NUTS2 level have been crossed with those of the European Regional Database, maintained by Cambridge Econometrics,[10] 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. Moreover, 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.

[10] "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 $x_{ist} = 1,\ \text{if } RTA_{ist} \geq 1 \text{ and } 0 < RTA_{ist-1} < 1$.

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.[11]

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

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

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 and 2014). 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) 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_De_i) 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:

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

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

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:

$$wad_{i\,z\,t-1} = \frac{\sum_{s \neq z} \varphi_{s\,z\,t-1} New\_RTA_{i\,s}}{\sum_{s \neq z} \varphi_{s\,z\,t-1}} \qquad (4)$$

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:

$$A\_vDe_{i} = \sum_{z \neq s} sw \; a_{i,t-1,z} \times \frac{New\_RTA_{i,t}}{\sum_{z \neq s} New\_RTA_{i,t}} \qquad (5)$$

All in all, A_vDe_{i} 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. As we said, a smart specialisation strategy would suggest this variable to be positively correlated with our dependent one, 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 accounts for the "degrees of freedom" the region has available in exploring new technological advantages over time.[12]

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.

[12] 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.

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, , 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 on the extent to 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 separately considered.

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:

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

where, in addition to the previous positions, z is the vector of our structural regional controls (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, which also shows the pairwise correlations among all the regressors. As it can be observed, while some correlations are actually significant, a VIF test (available on request) excludes problems of collinearity in all the cases but those involving variable $CountIPC_{it-1}$ and those including the interaction terms of our model, as it usually happens for the sake of construction.[13]

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:

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

[13] It should be noted that, once the components of the interaction variable are normalized around their mean, problems of collinearity disappear also with respect to them (results are available from the authors on request). Still, being more easily interpretable and guaranteeing a more pervasive convergence among the different models we used, we decided to base our analysis on the actual values of the relevant variables. Moreover, the results of the estimations are robust to the exclusion of the variable $CountIPC_{it-1}$ from the list of regressors.

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, such as a Generalized Method of Moments (GMM) model. As its direct application to our original dependent variable, which is a count (i.e. discrete and non-negative) one, raises some problematic issues[14], we follow Bonaccorsi et al. (2013) and use as a dependent variable for the GMM estimations the inverse hyperbolic sine transformation of the number of new revealed technological specializations, defined as $\log\left[NewRTA_{i,t} + \left(NewRTA_{i,t} + 1\right)^{\frac{1}{2}}\right]$. In a nutshell, this transformation can be interpreted as a logarithmic transformation, but it is more appropriate when the dependent variable assumes value zero for some observations (Burbidge et al. 1988).

The final step of our econometric strategy goes one step further the models used up to now to address the construction of regional advantages, and takes into account that our dependent variable, *New_RTA*, is actually the outcome of a process of innovation dynamics at the local level, which might be affected by the KETs-related technological efforts of geographically closer regions. In particular, the kind of technological relationships that KETs can set at work within the regional knowledge base, and which we have illustrated in Section 2 by referring to technology or cognitive proximity, could extend over its geographical boundaries, and make the KETs knowledge/specialization of a given region significant for the development of new technological specializations in neighbour ones.[15] With the regional units of analysis of our application, this amounts to considering geographical proximity along with cognitive one in building up S3.

Let us notice that Figure 2 actually suggests that the phenomenon at stake could have an important spatial specification across the regions of our sample.

[14] GMM estimators for dynamic count data models are still in their inception phase and there is no convergence yet towards a standard approach. Cameron and Triverdi (2005; 2010), for example, propose a set of possible alternatives to estimate Poisson-like just identified and over-identified models by using the Stata software. However, the relative routine does not allow to implement the test on the moment conditions that are necessary to validate the model. Windmeijer (2002) has developed a routine working with the Gauss software, to run estimates drawing upon Chamberlain and Wooldridge moment conditions, which instead reports the full set of validation tests. However, one main issue is that these estimators are appropriate for dependent variables that are Poisson distributed, which is not our case. For this reason, although we have run also these alternative estimations by using both Stata and Gauss routines, obtaining consistent results for our focal regressor and satisfactory validation tests (available on request), we have opted to implement a different modeling strategy, as explained in the main text.

[15] This is consistent with a large body of literature, which has shown that knowledge externalities play indeed a key role in shaping the spatial distribution of innovation activities and are likely to engender significant differences in the performances of different territories (Antonelli et al, 2011).

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.

If, as the previous descriptive evidence actually seems to suggest, spatial dependence is at stake, traditional econometric models may yield biased results. Accordingly, a different model has to be drawn on spatial econometrics. Among the different alternatives[16] , we found that a Spatial Durbin Model (SDM) is the most consistent with our research question., Moreover, Elhorst (2014) shows that it is the one out of many possible alternatives, that performs relatively better. Indeed, the SDM model allows us to appreciate the effects of the spatially lagged dependent variable, along with that of a spatially lagged regressor, and thus enable us to focus on the effect that the specialization of neighbour regions in KETs-related technologies has on the new technological specialisation of a focal one.

Due to the panel structure of the dataset, the implementation of this spatial econometric model calls once again for the transformation of our dependent variable so as to solve the problems

[16] Former treatment of spatial econometric issues can be found in Anselin (1988), subsequently extended by Le Sage (1999). In brief, there are two basic ways to cope with this spatial issue. First, one may apply spatial filters to the sample data, so as to remove the spatial structure of the data and then apply traditional estimation techniques. Second, the relationship can be reframed by using different kinds of models for panel data, like: i) the spatial autoregressive model (SAR), which consists of including the spatially lagged dependent variable in the structural equation; ii) the spatial autocorrelation model (SAC), in which not only the spatially lagged dependent variables is included in the right hand side of the equation, but also the error term is further decomposed so as to include a spatial autocorrelation coefficient; iii) the spatial Durbin model (SDM), which includes the spatial lag of one or more exogenous variables in the matrix Z of the covariates (Varga, 1998; Elhorst, 2003 and 2010).

due to its nonnegative and discrete nature[17]. For this reason we use the same transformation implemented to run the GMM estimations. .

4 Results

Let us now consider the results of the estimates, starting with those on the role of KETs in aggregate terms. Looking at the baseline (static) model, quite interestingly, the results we get by using $KETs\_File_{i,t-1}$ and $KETs\_RTA_{i,t-1}$ as proxy of KETs-related regional knowledge are overall consistent, suggesting that the KETs driving role of S3 does not require a regional specialization to show up, as it is already enabled by the learning processes of the "simple" activities of KETs-patenting of the region. Although by keeping this result in mind, in the following we will just present the results with respect to $KETs\_RTA_{i,t-1}$, as a more standard and (at least theoretically) stringent indicator of the regional mastering of a certain technology. Results based on $KETs\_File_{i,t-1}$ (available from the authors on request) will be occasionally referred to only if markedly different from those based on $KETs\_RTA_{i,t-1}$.

As Table 4 shows, at first sight, our model reports an expected story of S3 for the regions at stake, with some new interesting insights when the role of KETs is considered.

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 ($New\_RTA_{i,t-1}$) contributes positively to a further gain of them in the following period. Regions having entered new technological fields in the past develop the capacity of doing it persistently, showing evidence of a certain hysteresis in the process already found in other studies (e.g. 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.[18]

[17] The standard estimator proposed by Lambert et al. (2010) for dealing with this issue is not appropriate in this context for two main reasons. First, it has proved to work well with cross sectional data only. Second, it is conditional on spatial count models based on a Poisson distribution, while our dependent variable is clearly overdispersed.

[18] 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

The construction of new RTAs also builds on the knowledge locally accumulated over time, insofar as the former is related to the latter. 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 S3 (Frenken, 2014).

We can focus now on the two variables for capturing the impact of KETs on the entry of regions in new technological domains, i.e. $KETs\_RTA_{i,t-1}$ and its interaction with $Av\_d\epsilon$.

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 acquiring new technological specializations: $KETs\_RTA_{i,t-1}$ is indeed 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, $KETs\_RTA_{i,t-1}$ exerts a significant moderating role of the impact of $Av\_d\epsilon$ 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 (3) to (8) 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 specifications (3), 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 (5) and (6). When, at the price of an important loss of observations, a more standard proxy of innovation efforts at the regional level is included, $R\&D_{i,t-1}$ turns out significant and positive in specifications (7) and (8), signaling that higher spenders in R&D are more likely to develop technological competencies in new fields than those in the regional knowledge base.

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.

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 results obtained from the estimates of the baseline (static) model are also confirmed when a more suitable dynamic estimation strategy is followed, like the GMM one. In particular, we have implemented the GMM estimator originally proposed by Arellano and Bond (1991), which obtains asymptotically efficient estimators in the presence of arbitrary heteroscedasticity, taking into account the structure of residuals to generate consistent estimates. More precisely, we use the GMM-System (GMM-SYS) estimator in order to increase the efficiency of the estimates (Arellano and Bover, 1995; Blundell and Bond, 1998). Indeed, this estimator instruments the variables in levels with lagged first-differenced terms, to obtain a dramatic improvement in the relative performance of the system estimator as compared to the usual first-difference GMM estimator. Through the analysis of the information criterion, we ended up with a dynamic model in which the dependent variable is lagged three times.

Although those based on $KET\underline{s}Fil$ are consistent, in Table 5 we show only the results concerning $KET\underline{s}RT$ (results on the former are available from the authors on request), which confirm our previous arguments.

Insert Table 5 about here

We can notice that all of the coefficients are consistent with the previous estimations. The only exception concerns the control variables. Actually *Count_IPC* is no longer significant when it is included in the estimations along with *R&D* (columns 4 and 5), 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.[19]

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 consistent results of 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

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

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 4, 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:

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

The first row of Table 6[20] provides the results of the calculation, along with a z-test indicating if the overall effect is statistically different from zero.

Insert Table 6 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. $KETs(j)\_RTA_{it-1}$).[21] 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 last part of the analysis to the benchmark specifications of Table 4, that is by excluding the

[20] It should be noticed that the table shows margins at means drawing upon static negative binomial estimation.

[21] Those in terms of patent applications (i.e. $KETs(j)\_Fil$) are available from the authors on request.

regional R&D intensity among the regressors. Finally, still as they are consistent, we just report the results for the dynamic specification of the model, that is the GMM .

As Table 7 shows, the basic mechanisms underlying the construction of new RTAs are confirmed when individual KETs specialisations are considered.

Insert Table 7 about here

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 is 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.

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 6 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*. The coefficient of the latter is also consistently non significant in Table 7. 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.

The third and last set of results refers to the spatial econometric analysis of the relationship between KETs and S3.

Insert Table 8 about here

The first part of Table 8 shows the point estimates of the SDM, obtained by using a row-normalized inverse distance-weighting matrix, with respect to the latitude and longitude coordinates of the relevant regions.[22] In particular, the odd columns report the estimations including only time fixed effects, while even ones include both time and region fixed effects.

Focusing on our focal regressors, let us observe that $Av\_dens_{i,t}$ appears still characterized by a persistent positive and significant coefficient, while the interaction term $Av\_dens_{i,t}*KETs\_RTA_{i,t-1}$ *still* shows a negative and significant coefficient. So far the results are thus consistent with our benchmark estimations.

As for the spatially lagged regressors, it should be noticed that they all show positive and significant coefficients in all of the models. This is in line with expectations. Indeed, as we used an inverse distance weighting matrix, a positive coefficient means that a region's capacity to enter in new technological specializations is favoured by the introduction of new technological specializations in neighbor ones. Second, the spatially lagged $KETs\_RTA_{i,t-1}$ variable exhibits a positive and significant coefficient in most of the models (the result is persistent across even columns), by suggesting that the technological relationships that KETs have the potential to set in place are actually transmitted through inter-regional spillovers effects of the same nature to some extent. However, as noted in Le Sage and Pace (2009), focusing on these coefficients to conclude that spatial spillovers actually exist could lead to erroneous interpretations. Quoting Elhorst (2014: p. 20), "[I]n order to gain a better understanding of spatial dynamics, "a partial derivative interpretation of the impact from changes to the variables of different model specifications represents a more valid basis for testing this hypothesis". Indeed, still in his own words, the main point is that "if a particular explanatory variable in a particular unit changes, not only will the dependent variable in that unit itself change but also the dependent variables in other units. The first is called a *direct* effect and the second an *indirect* effect" (Elhorst, 2014: p. 21).

In the light of this argument, the second part of Table 8 reports direct, indirect and total effects of the focal variables of our analysis. The direct effects resemble the results of the point estimates. On the other hand, closer attention is required by the indirect and the total effects, as the former only could be interpreted in terms of spatial spillovers. Since the vector of spatially lagged variables only includes $NewRTA_{i,t}$ and $KETs\_RTA_{i,t-1}$, the indirect effects

[22] Estimated have been obtained by using the software STATA 12 and running the XSMLE command, which allows for the maximum likelihood estimation of spatial panel data models (Belotti et al., 2013). In particular, distances have been obtained with the STATA command SPMAT.

show how changes in these variables in neighbor regions shape the effects of the other variables in a given region. The indirect effects are consistent with expectations and persistent across all of the models for all of our variables of interest. $Av\_dens_{i,t}$ and $KETs\_RTA_{i,t-1}$ actually show a positive and significant effect, while the interaction term is characterized by a negative and significant one. The same applies to total effects reported at the end of Table 8.

All in all, we can conclude that significant geographical spillovers can be detected in the analysis of the emergence of new technological specializations, when the role of KETs is considered. In other words, spatial proximity to KETs-specialized regions adds to the role of the cognitive proximity to previously acquired technologies in the region as a driver of S3: an extremely important results that should be considered among the implications of the paper to which we turn in the last section.

5 Conclusions

The recent identification by the European policy makers of a new generation of GPTs-like technologies, and their latest recommendations to plug them in the regional policy tool-box, represent an interesting opportunity to re-align the analysis of the two original driving mechanisms of S3, that is, in modern terms: relatedness and KETs. Furthermore, taking stock of the insights obtained in the meantime by economic geography studies, this can be done in a theoretically consistent way, by looking at the role of KETs in driving the acquisition of new revealed technological advantages in the presence of path-dependence and related variety. Last but not least, with the help of spatial econometrics, this analysis can be enriched with the inspection of possible cross-regional spillovers in the RTA impact of KETs.

By making a combined and longitudinal use of regional patent and economic data for European countries, in this paper we have moved a first step in the exploitation of this important research opportunity. In particular, by identifying some pivotal characteristics of KETs, we have investigated whether their alleged enabling role could be seen 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 KETs “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. 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. Finally, a spatial econometric analysis of the relationship at stake suggests that interregional spillovers could extend its working across the boundaries of the focal region. The acquisition of new technological specializations by a certain region could also be helped by the KETs knowledge developed by closer ones, suggesting that the technologies of the KETs club could also have an interesting cross-regional innovation enabling role.

These results convey to KETs an important and specific policy impact. 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. Finally, an important alternative to the regional development of KETs for acquiring new technologies in a S3 fashion, or possibly a complementary strategy to the latter, could be represented by the exploitation of those mechanisms through which the interregional spillovers we have detected in the S3 driving role of KETs could be better absorbed, like inter-regional technology transfer, cooperation agreements and the like. Whether KETs “poor” region could actually benefit from closer KETs “rich” ones in pursuing their S3 is by now a suggestion, which we also postpone to our future research agenda.

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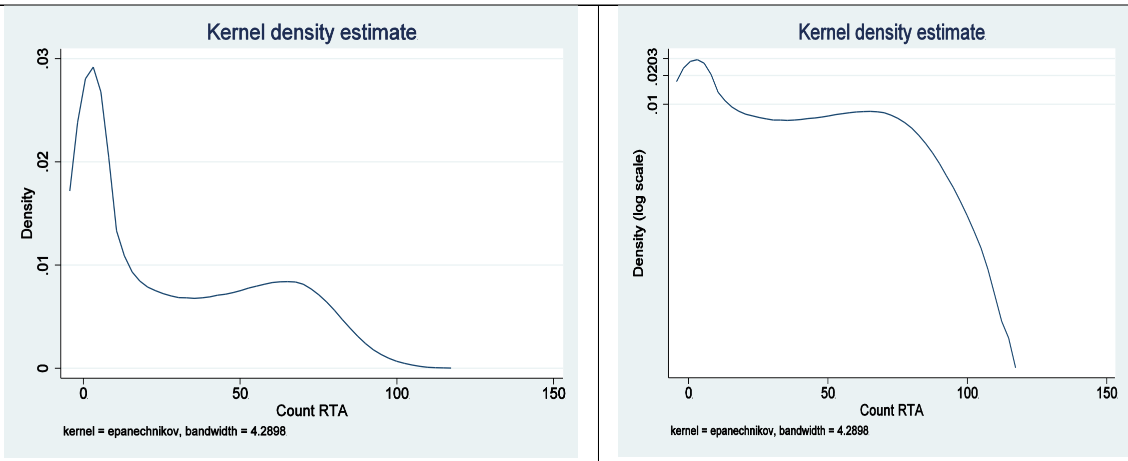
Figure 1 - Kernel Density Distribution of New_RTA



Deviance goodness-of-fit = 29388.91, Prob > chi2(5921) = 0.0000

Pearson goodness-of-fit = 27248.95, Prob > chi2(5921) = 0.0000

Figure 2 - Spatial Distribution of Relevant Variables

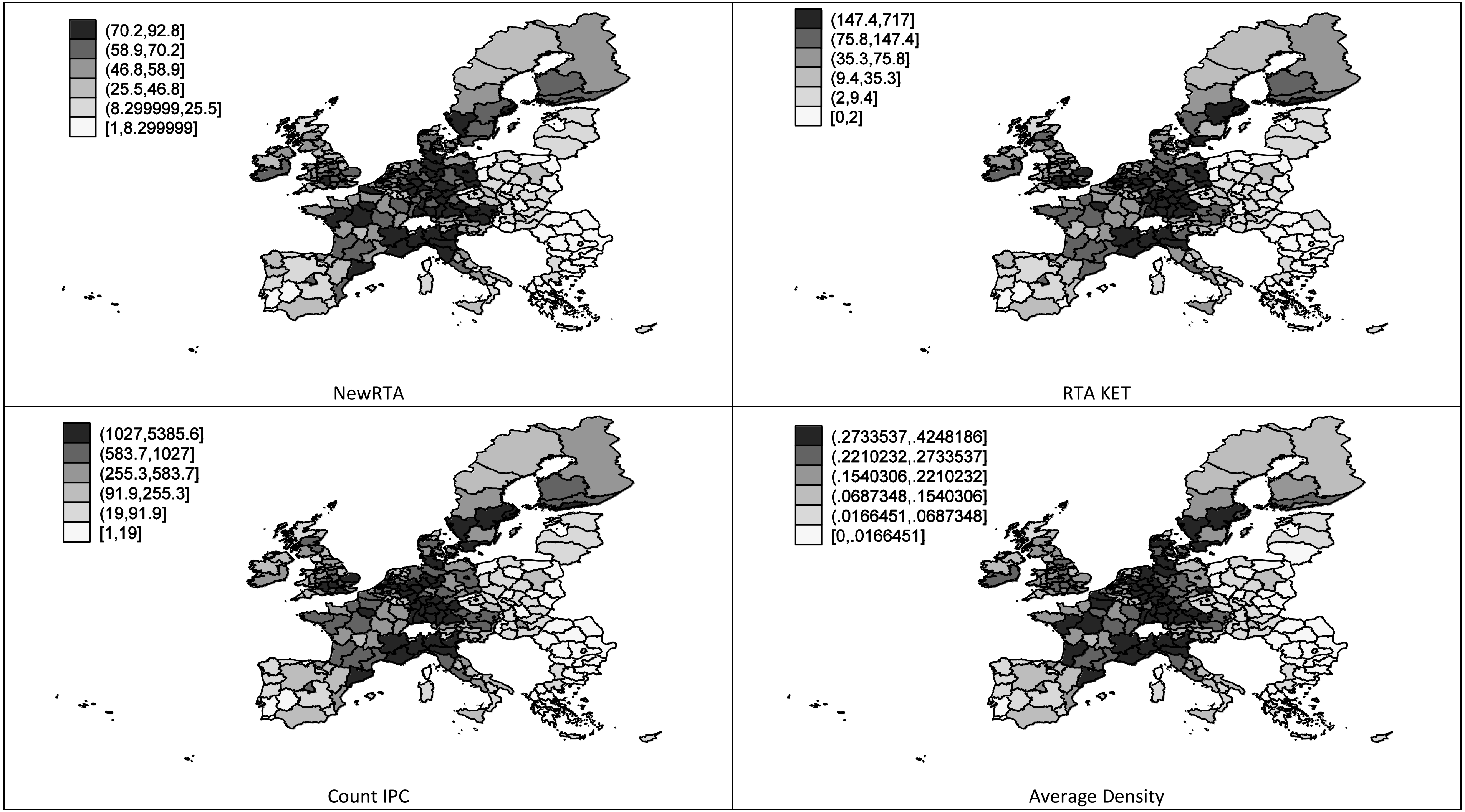


Table 1 - Variables Definition

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).
$R\&D_{i,t}$	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* 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
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 – Acquisition of New Revealed Technological Advantages (New_RTA) and Regional Specialisation in KETs (KETs_RTA) – Static baseline model.

	Dependent variable: New_RTA_t							
	(1) NegBIN	(2) MMNegBin	(3) NegBIN	(4) MMNegBin	(5) NegBIN	(6) MMNegBin	(7) NegBIN	(8) MMNegBin
New_RTA_{t-1}	0.0066^{***}	0.0194^{***}	0.0053^{***}	0.0162^{***}	0.0046^{***}	0.0143^{***}	0.0021^{***}	0.0165^{***}
	(0.0003)	(0.0005)	(0.0004)	(0.0005)	(0.0004)	(0.0005)	(0.0005)	(0.0006)
Av_dens_t	1.7178^{***}	3.0494^{***}	1.5598^{***}	3.2644^{***}	1.4332^{***}	2.9822^{***}	0.6883^{***}	2.9996^{***}
	(0.1076)	(0.1142)	(0.1204)	(0.1150)	(0.1127)	(0.1120)	(0.1626)	(0.1427)
$KETs\_RTA_{t-1}$	0.0015^{***}	0.0035^{***}	0.0018^{***}	0.0035^{***}	0.0013^{***}	0.0033^{***}	0.0012^{***}	0.0030^{***}
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$Av\_dens_t * KETs\_RTA_{t-1}$	-0.0074^{***}	-0.0140^{***}	-0.0062^{***}	-0.0141^{***}	-0.0045^{***}	-0.0128^{***}	-0.0028^{***}	-0.0120^{***}
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0006)	(0.0007)	(0.0007)
$Count\_IPC_{t-1}$			-0.0001^{***}	0.0000	-0.0001^{***}	-0.0000		
			(0.0000)	(0.0000)	(0.0000)	(0.0000)		
$lnEmplt_{t-1}$			0.1516^{***}	0.0070				
			(0.0383)	(0.0081)				
$lnGVA_{t-1}$					0.5385^{***}	0.1548^{***}		
					(0.0319)	(0.0085)		
$R\&D_{t-1}$							3.2750^{***}	3.5383^{***}
							(1.0127)	(0.6421)
_cons	2.8511^{***}	2.2301^{***}	2.1515^{***}	2.3202^{***}	-2.4174^{***}	0.9488^{***}	4.0003^{***}	2.3429^{***}
	(0.0516)	(0.0253)	(0.2482)	(0.0547)	(0.3276)	(0.0822)	(0.1181)	(0.0269)
lnalpha		-2.1171***		-2.3759***		-2.4685***		-2.4612***
		(0.0265)		(0.0310)		(0.0317)		(0.0410)
N	6472	6472	5103	5103	5103	5103	3106	3106
AIC	43429.3233	51936.7806	34595.8547	41055.9546	34344.5047	40732.2859	19547.4343	24804.7187
BIC	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 5 - Acquisition of New Revealed Technological Advantages (New_RTA) and Regional Specialisation in KETs (KETs_RTA) - GMM System estimator

	Dependent variable: $y_{i,t} = \log\left[NewRTA_{i,t} + (NewRTA_{i,t}+1)^{\frac{1}{2}}\right]$					
	(1) GMM-SYS	(2) GMM-SYS	(3) GMM-SYS	(4) GMM-SYS	(5) GMM-SYS	(6) GMM-SYS
y_{t-1}	0.1545^{***}	0.1556^{***}	0.1447^{***}	0.1348^{***}	0.1352^{***}	0.1110^{***}
	(0.0024)	(0.0030)	(0.0030)	(0.0022)	(0.0024)	(0.0026)
y_{t-2}	0.2537^{***}	0.2608^{***}	0.2491^{***}	0.2754^{***}	0.2733^{***}	0.2275^{***}
	(0.0015)	(0.0021)	(0.0018)	(0.0015)	(0.0017)	(0.0016)
y_{t-3}	0.1567^{***}	0.1707^{***}	0.1671^{***}	0.1338^{***}	0.1328^{***}	0.1110^{***}
	(0.0017)	(0.0025)	(0.0024)	(0.0017)	(0.0015)	(0.0017)
Av_dens_t	1.5236^{***}	1.4736^{***}	1.3212^{***}	1.3097^{***}	1.3041^{***}	0.8472^{***}
	(0.0454)	(0.0560)	(0.0675)	(0.0363)	(0.0403)	(0.0297)
$KETs\_RTA_{t-1}$	0.0007^{***}	0.0006^{***}	0.0006^{***}	0.0005^{***}	0.0005^{***}	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Av_dens_t* $KETs\_RTA_{t-1}$	-0.0035^{***}	-0.0033^{***}	-0.0028^{***}	-0.0021^{***}	-0.0021^{***}	-0.0008^{***}
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)
$Count\_IPC_{t-1}$	-0.0001^{***}	-0.0001^{***}	-0.0001^{***}	-0.0000	-0.0000	-0.0000^{***}
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$lnEmplt_{t-1}$		0.1217^{***}			0.0062	
		(0.0099)			(0.0065)	
$lnGVA_{t-1}$			0.1502^{***}			0.4365^{***}
			(0.0081)			(0.0101)
$R\&D_{t-1}$				1.6812^{**}	2.3683^{***}	-0.5760
				(0.6629)	(0.6069)	(0.6397)
Cons	1.6706^{***}	0.8488^{***}	0.2670^{***}	1.7565^{***}	1.7215^{***}	-2.1154^{***}
	(0.0129)	(0.0624)	(0.0671)	(0.0112)	(0.0391)	(0.0856)
N	6109	5348	5348	3232	3232	3232
AR(1)	-9.1953***	-8.7732***	-8.7329***	-7.5246***	-7.5307***	-7.4944***
AR(2)	0.0981	-0.3872	-0.2700	-0.6901	-0.6497	-0.1623
Sargan test	268.7980	237.3912	237.9463	237.5853	243.0572	237.9379

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

Table 6 - Net impact of KETs_RTA on New_RTA : overall and by KETs typology

	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 7 - Acquisition of New Revealed Technological Advantages (New_RTA) and Regional Specialisation in different KETs (KETs_RTA) - GMM System estimator

	Dependent variable: $y_{i,t} = \log\left[NewRTA_{i,t} + \left(NewRTA_{i,t}+1\right)^{\frac{1}{2}}\right]$					
	(1) GMM-SYS	(2) GMM-SYS	(3) GMM-SYS	(4) GMM-SYS	(5) GMM-SYS	(6) GMM-SYS
y_{t-1}	0.1603***	0.1614***	0.1592***	0.1620***	0.1588***	0.1605***
	(0.0023)	(0.0019)	(0.0025)	(0.0020)	(0.0024)	(0.0029)
y_{-2}	0.2596***	0.2599***	0.2566***	0.2587***	0.2551***	0.2569***
	(0.0020)	(0.0020)	(0.0018)	(0.0018)	(0.0018)	(0.0019)
y_{t-3}	0.1606***	0.1607***	0.1611***	0.1613***	0.1632***	0.1583***
	(0.0013)	(0.0014)	(0.0017)	(0.0014)	(0.0020)	(0.0017)
Av_dens$_t$	1.1667***	1.1467***	1.2506***	1.2212***	1.3191***	1.3194***
	(0.0366)	(0.0335)	(0.0285)	(0.0265)	(0.0348)	(0.0357)
BIOTECH $_{t-1}$	0.0008**					
	(0.0004)					
Av_dens$_t$* BIOTECH $_{t-1}$	-0.0029**					
	(0.0014)					
NANOTECH$_{t-1}$		0.0103***				
		(0.0037)				
Av_dens$_t$ * NANOTECH$_{t-1}$		-0.1123***				
		(0.0142)				
NANOELCT$_{t-1}$			0.0015***			
			(0.0003)			
Av_dens$_t$* NANOELC$_{t-1}$			-0.0060***			
			(0.0011)			
PHOTO$_{t-1}$				0.0008*		
				(0.0004)		
Av_dens$_t$ * PHOTO$_{t-1}$				-0.0054***		
				(0.0015)		
ADVMAT$_{t-1}$					0.0028***	
					(0.0002)	
Av_dens$_t$ * ADVMAT$_{t-1}$					-0.0076***	
					(0.0005)	
ADVTECH$_{t-1}$						-0.0001
						(0.0002)
Av_dens$_t$ * ADVTECH$_{t-1}$						-0.0060***
						(0.0007)
Count_IPC$_{t-1}$	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Cons	1.6789***	1.6875***	1.6419***	1.6708***	1.6322***	1.6391***
	(0.0108)	(0.0096)	(0.0145)	(0.0122)	(0.0134)	(0.0158)
N	6109	6109	6109	6109	6109	6109
AR(1)	-9.2043***	-9.2081***	-9.2164***	-9.2232***	-9.2271***	-9.2608***
AR(2)	0.0424	0.0419	0.1238	0.1081	0.2136	0.0960
Sargan test	281.2058	275.9186	286.8335	284.7966	274.4653	281.3094

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

Table 8 – Acquisition of New Revealed Technological Advantages (New_RTA) and Regional Specialisation in KETs (KETs_RTA) - Spatial Durbin Model.

	Dependent variable: $y_{i,t} = \log\left[NewRTA_{i,t} + \left(NewRTA_{i,t} + 1\right)^{\frac{1}{2}}\right]$							
	(1) SDM	(1) SDM	(2) SDM	(2) SDM	(3) SDM	(3) SDM	(4) SDM	(4) SDM
$KETs\_RTA_{t-1}$	0.0053*** (0.0002)	-0.0001 (0.0003)	0.0041*** (0.0002)	-0.0003 (0.0003)	0.0051*** (0.0002)	-0.0001 (0.0003)	0.0051*** (0.0003)	0.0005 (0.0003)
Av_dens_t	5.7775*** (0.0911)	0.7842*** (0.1681)	4.6045*** (0.1062)	0.7083*** (0.1669)	5.5275*** (0.0971)	0.7590*** (0.1691)	5.7615*** (0.0915)	0.7530*** (0.1680)
Av_dens_t* $KETs\_RTA_{t-1}$	-0.0187*** (0.0007)	-0.0053*** (0.0009)	-0.0165*** (0.0007)	-0.0045*** (0.0009)	-0.0186*** (0.0007)	-0.0052*** (0.0009)	-0.0193*** (0.0008)	-0.0048*** (0.0009)
$lnGVA_{t-1}$			0.2194*** (0.0122)	0.5439*** (0.0652)				
$lnEmplt_{t-1}$					0.0736*** (0.0120)	0.1138 (0.0835)		
$Count\_IPC_{t-1}$							0.0001* (0.0000)	-0.0001*** (0.0000)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional dummies	No	Yes	No	Yes	No	Yes	No	Yes
W× $KETs\_RTA_{t-1}$	-0.0003 (0.0005)	0.0050*** (0.0012)	0.0029*** (0.0005)	0.0061*** (0.0012)	0.0006 (0.0005)	0.0052*** (0.0012)	-0.0003 (0.0005)	0.0058*** (0.0012)
W × $y_{i,t}$	0.6336*** (0.0581)	0.8889*** (0.0247)	0.8049*** (0.0389)	0.8840*** (0.0257)	0.7403*** (0.0488)	0.8883*** (0.0248)	0.6314*** (0.0583)	0.8892*** (0.0246)
Variance sigma2_e	0.1606*** (0.0037)	0.0729*** (0.0017)	0.1466*** (0.0033)	0.0716*** (0.0016)	0.1582*** (0.0036)	0.0729*** (0.0017)	0.1604*** (0.0037)	0.0726*** (0.0017)

Table 8 – Spatial Durbin Model (continued)

Direct effects								
$KETs\_RTA_{t-1}$	0.0054***	0.0002	0.0043***	-0.0001	0.0052***	0.0001	0.0051***	0.0008**
	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0004)
Av_dens_t	5.8251***	0.8154***	4.7031***	0.7343***	5.6074***	0.7885***	5.8076***	0.7828***
	(0.0873)	(0.1698)	(0.1022)	(0.1682)	(0.0917)	(0.1707)	(0.0871)	(0.1703)
Av_dens_t*	-0.0188***	-0.0055***	-0.0169***	-0.0046***	-0.0189***	-0.0054***	-0.0194***	-0.0049***
$KETs\_RTA_{t-1}$	(0.0007)	(0.0009)	(0.0007)	(0.0009)	(0.0007)	(0.0009)	(0.0007)	(0.0009)
Indirect Effects								
$KETs\_RTA_{t-1}$	0.0086***	0.0474***	0.0332***	0.0529***	0.0177***	0.0487***	0.0082***	0.0599***
	(0.0023)	(0.0173)	(0.0087)	(0.0184)	(0.0050)	(0.0179)	(0.0022)	(0.0204)
Av_dens_t	10.4827***	6.6636***	19.8585***	5.6504**	16.4165***	6.3315**	10.1952***	6.3348**
	(2.7156)	(2.2987)	(5.5740)	(2.2556)	(4.6599)	(2.5001)	(2.7051)	(2.5118)
Av_dens_t*	-0.0338***	-0.0448***	-0.0713***	-0.0357**	-0.0553***	-0.0438**	-0.0340***	-0.0403**
$KETs\_RTA_{t-1}$	(0.0087)	(0.0146)	(0.0208)	(0.0158)	(0.0162)	(0.0185)	(0.0092)	(0.0175)
Total Effects								
$KETs\_RTA_{t-1}$	0.0140***	0.0476***	0.0375***	0.0528***	0.0229***	0.0489***	0.0133***	0.0607***
	(0.0023)	(0.0174)	(0.0087)	(0.0185)	(0.0051)	(0.0180)	(0.0023)	(0.0205)
Av_dens_t	16.3078***	7.4790***	24.5616***	6.3848***	22.0238***	7.1200***	16.0028***	7.1176***
	(2.7099)	(2.4010)	(5.5834)	(2.3529)	(4.6590)	(2.5954)	(2.6964)	(2.6059)
Av_dens_t*	-0.0526***	-0.0502***	-0.0881***	-0.0403**	-0.0742***	-0.0492***	-0.0534***	-0.0453**
$KETs\_RTA_{t-1}$	(0.0087)	(0.0150)	(0.0210)	(0.0163)	(0.0164)	(0.0190)	(0.0092)	(0.0180)
N	3819	3819	3819	3819	3819	3819	3819	3819
AIC	3914.2821	955.6468	3647.5673	894.8841	3900.7136	961.7818	3918.6360	950.8764
BIC	4007.9983	1049.3629	3766.2744	1013.5912	4019.4207	1080.4890	4037.3431	1069.5835