Regional diversification patterns and Key Enabling Technologies (KETs) in Italian regions

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Abstract

This paper investigates the determinants of regional diversification across spatial and technology dependence. We argue that regional Key-Enabling-Technologies (KETs) could play an important and possibly differential role in making regions diversify in the two respects. We also maintain that KETs could differently drive two diverse trajectories of an ideal escaping transition from a 'replicative' kind of diversification to a diversification marked by 'saltation'. Using an original dataset for Italian NUTS3 regions in two periods (2004-07 and 2008-10), we estimate a series of ordered logit models, in which the regional propensity to diversify following the two identified patterns depends on the local endowment of KETs knowledge (patents) and by the extent to which other (than key-enabling) technologies draw on it (through citations). We find that a larger regional endowment of KETs actually corresponds to a higher probability to diversify into unrelated industries. However, this occurs only when KETs knowledge gets explicitly used by other technological domains in their inventive activity. Results hold for both types of diversification patterns, in both periods, and are robust to endogeneity. On the other hand, the diversification role of KETs appears limited to regions that contain a large urban area, and which presumably reach a critical mass of KETs for their effects.

Key-words: related diversification; unrelated diversification, key enabling technology, ordered logit

JEL-Codes: R11, R58, O31, O33

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1. Introduction

A large body of research has shown that, providing it is driven by 'relatedness' (Balland, 2016), regional economic diversification can spur growth in terms of employment and (labor and total factor) productivity (Frenken et al., 2007; Boschma and Iammarino, 2009; Boschma et al., 2011; Hartog et al., 2012). Benefiting from the cumulative and path-dependent spatial dynamics of knowledge, diversifying by branching new activities/technologies out of related ones appears a trajectory of change with lower search costs and lower failure risks than an unrelated one (Balland et al., 2018).

While relatedness has become the real "driver of regional diversification" (Boschma, 2016), unrelated diversification should not be automatically dismissed. The local capabilities of the region are actually a double-edged sword, which not only provides it with opportunities of related growth, but do also pose it a limit to their development. At the worst, related diversification could lock the region in the domain of its extant activities and prevent longer term development by opening up place-independent market opportunities (Saviotti and Frenken, 2008). For these reasons, evidence of regional industrial evolution through unrelated 'jumps' of industry-path creation deserves special attention (e.g. Isaksen, 2015; Isaksen and Trippl, 2014). More in general, systematic analysis is required about "the conditioning factors that facilitate more related or more unrelated diversification in regions" (Boschma, 2016, p. 6).

The present paper positions along this prospected research agenda and investigates the determinants of related vs. unrelated regional diversification by trying to fill two gaps. The first concerns the simplified treatment that regional diversification has received in evolutionary economic geography so far, by neglecting the socio-technical development of the sectors in which regions specialize and diversify (Boschma, 2016, p. 9). In trying to overcome this limitation, we follow Boschma et al. (2017) and maintain that the radicalness/incrementality of socio-technical development at the sector level can differently modulate the patterns through which related and unrelated diversification occur at the spatial level. In brief, we retain that four, rather than two, diversification patterns – termed 'replication', 'exaptation', 'transplantation' and 'saltation' – could emerge by crossing spatial related/unrelatedness with technological path-dependence/independence.

The second gap we address concerns the 'similarity bias' that has affected the relatedness literature so far, by neglecting the 'complementarity' among local existing activities through whose combination new techno-economic ones can emerge (Boschma, 2016, p. 10). We try to fill this gap by encapsulating among the diversification determinants the regional endowment of technologies that could favor complementarity among local activities, which would otherwise remain cognitively distant and hard to recombine. Following Montresor and Quatraro (2017), we argue that the six technologies that the European Commission has recently identified as "Key Enabling" (KETs) (EC, 2012) — industrial biotechnology, nanotechnology, micro- and nanoelectronics, photonics, advanced materials, and advanced manufacturing technologies — could have a twofold role in this respect. First of all, they can drive regional diversification, to a different extent depending on the specific pattern among the four along which it occurs. Second, KETs could also account for the regional capacity of escaping lock-in situations, still to a possibly different extent depending on the adopted trajectory between the two available in the ideal transition from replication to saltation: a "technology-upon-space" kind of diversification, in which regions pass through the "transplantation" of an existing regime in developing related activities; a "space-upon-technology" one, in which regions pass through an "exaptation" of a new niche by drawing on related capabilities.

We look at this twofold role of KETS in an empirical application to Italian NUTS3 regions in two periods of time (2004-2007 and 2008-2010), with respect to which secondary patent and employment data could be merged. We estimate a series of two ordered logit models, where the probability for a region to enter into progressively more diversified industries from the benchmark case of no-diversification, either by adding technological (new niches) or spatial (unrelatedness) newness to replication, is regressed against its KETs endowment, the extent to which other (non-key-enabling) technologies draw on them (in terms of citations), and on a series of additional regional characteristics. We find that a larger regional endowment of KETs actually corresponds to a higher probability to diversify into unrelated industries. However, this occurs only when KETs knowledge gets explicitly used by other technological domains in their inventive activity. Results hold for both types of diversification patterns, in both periods, and are robust to endogeneity. On the other hand, the diversification role of KETs appears limited to regions that contain a large urban area, and which presumably reach a critical mass of KETs for their effects.

The rest of the paper is structured as follows. Section 2 illustrates the theoretical background of the paper. Section 3 presents the empirical application and Section 4 discusses its results. Section 5 concludes by presenting the research and policy implications of these results.

2. Theoretical background

In evolutionary economic geography, unrelated regional diversification is usually defined indirectly as the simple 'complement' to related diversification, in turn revealed by the similarity of new to pre-existing activities in terms of labor and capital inputs, workers' skill requirements, user-supplier relationships, and more generic capabilities (for a recent review, see Boschma, 2016). Still by using an indirect approach, evidence of unrelated diversification has been mainly collected by looking for those factors, which could attenuate the impact of relatedness on the regional capacity to diversify, among which a variety of conditions have emerged at different levels of analysis.[1]

While quite reach, the previous analytical framework is far from capturing the full complexity of regional diversification. As Boschma (2016) has pointed out in a recent critical review, some additional aspects need to be considered, among which in this paper we focus on two.

2.1. Regional diversification in-between place and path dependence.

The first aspect to consider is that, as Boschma et al. (2017) have recently argued, regional diversification embraces (at least) an additional dimension to the socio-spatial one, on which evolutionary economic geography has focused so far. This second dimension relates to the evolution of the 'socio-technical regimes' that characterize the sectors in which regions operate and diversify, and on which the transition literature has instead focused since long (Geels, 2002; Kemp et al., 1998; Markard et al., 2012; Rip and Kemp, 1998). In brief, at a certain moment in time, each sector reveals

[1] These conditions comprehend: at the macro-level, the socio-political conditions of diversifying countries (e.g. West vs. East European countries) (Boschma and Capone, 2016), their level of economic development (Petralia et al., 2016), and the kind of their governance set-up (e.g. liberal vs. coordinated market economies) (Boschma and Capone, 2015); at the meso-level, the core vs. periphery status of the diversifying regions (e.g. in terms of dependence on migration and imports) (Isaksen, 2015), the configuration of their innovation systems (Isaksen and Trippl, 2014), their endowment of social capital (e.g. bridging vs. bonding) (Cortinovis et al., 2016; Antonietti and Boschma, 2018), and of specific kinds of technological knowledge (Montresor and Quatraro, 2017); at the micro-level, the nature (e.g. start-ups vs. subsidiaries of incumbents) of the diversifying plants and the location (e.g. regional vs. extra-regional) of their control (Neffke et al., 2016); the inflow of multinational corporations with specific entry strategies (Cantwell and Iammarino, 2003) and of specific kinds of migrants (e.g. return) (Saxenian, 2006); the presence of universities (Gilbert & Campbell, 2015; Lester, 2007; Tanner, 2016), of 'smart-thinking' government structures (Foray, 2014), and of collective actors contributing to the institutional kind of entrepreneurship that unrelated diversification requires (Marquis and Raynard, 2015; Sotarauta and Pulkkinen, 2011; Strambach, 2010)

a coherent alignment of socio-technical elements (i.e. skills, artefacts and knowledge) in a 'regime', which stimulates incremental innovations and makes the sector resist radical innovations that threaten its coherence. Still, radical novelty could occur in the sector, through the experimental creation and eventual upscale of 'niches', which protect the incubation of new radical technologies against the consolidating pressure of the regime and by allowing the relevant actors to experiment and familiarize with its novelties (Coenen et al., 2010; Geels, 2002).

While connected to the technological system that underpins a sector, both regimes and niches have a fundamental social nature, which require the active involvement of communities of practitioners (regimes) and an institutional work of entrepreneurship to get upscaled and developed (niches)(see Smith and Raven, 2012). Because of their social nature, both regimes and niches do have a spatial nature too, which the transition literature is hesitating to recognize (Truffer and Coenen, 2012): even in a global setting, socio-technical regimes do show local heterogeneity (Späth and Rohracher, 2012), while niche formation and development are typically contingent on a variety of place-specific factors (Boschma, 2016).

Given its spatial connotation, the transition of socio-technical regimes poses regions in front of a 'path dependence', which interacts with the 'place dependence' of the development of local capabilities (i.e. relatedness). Their combination yields different patterns of regional diversification, depending on the extent to which its radicalness along the regional dimension (related versus unrelated) crosses with that along the sectoral dimension (regime versus niche). Following Boschma et al. (2017), regional diversification can thus be though to take on four possible configurations (Table 1): i) 'replication', with related diversification in the presence of an established socio-technical regime; ii) 'transplantation', with unrelated industry diversification this time, but still under the dominant regime; iii) 'exaptation', with the development of a new sector niche, but in the presence of related diversification; iv) 'saltation', in which activities are developed that are new both to the region and to the world in technological terms.

As Boschma et al. (2017) illustrate, the four configurations can be argued to differ in different respects.[2] Arguably, the four diversification strategies also differ in their conditioning factors, which make regions differently prone to embrace one rather than another of them. Among these factors, one that deserves special attention is the regional capacity to exploit relatedness along a complementarity, rather than a similarity dimension.

[2] That is, their risk, their institutional work, the key-actors, and local vs. global spatial-logic they entail.

2.2. Relatedness in-between similarity and complementarity

While mainly addressed in terms of 'similarity' between pre-existing and novel local capabilities, the idea of relatedness also entails an important dimension of 'complementarity' between them, which is unfortunately often neglected and needs to be recovered (Boschma, 2016). Extending the Schumpeterian theory of 'recombinant innovation' to the spatial domain (Castaldi et al., 2015; Fleming, 2001; Weitzman, 1998), it can be claimed that regions diversify in a related manner when they develop new activities by differently recombining local capabilities, which had already been combined somehow in the past. Conversely, unrelated diversification would emerge when to be combined are either non-local capabilities, for whose combination regions rely on boundary-spanners (like MNE and/or migrants), or local capabilities that had never been combined before, yielding a true case of Schumpeterian '*Neue Kombinationen*'. In other words, combining knowledge along an already established path would lead regions to 'exploit' local capabilities in order to master incrementally new activities; creating and following new paths of (re)combination, instead, enable regions to 'explore' the acquisition of radically new activities (Isaksen, 2015).

Complementarity is also pivotal when, by following Boschma et al.'s (2017) taxonomy (Section 2.1), the technological dimension of regional diversification is considered and the transition towards new socio-technical regimes is included in the analysis (Section 2.1). According to the "bricolage" mode of creating new industry-paths (Garud and Karnøe, 2003), complementarity is actually able to differentiate also the development of a new technological niche from the continuation of an existing regime. The former would actually pass through a creative, experimental alignment of diverse and distributed sets of technologies and institutions, through which networks of distributed actors would implement a "mindful deviation" from the dominant socio-technical regime (low or no complementarity). Conversely, the endurance of a socio-technical regime would be based on the exploitation of the coherence previously enriched by incumbent actors among technologies and institutions that have become established and vested, respectively (high complementarity).

Extending the analysis of relatedness from a similarity to a complementarity perspective, it becomes evident that the search for the determinants of regional diversification and of its various patterns, should pass also and above all through the search of those factors that such a complementarity can enable or eventually reinforce. As we will claim in the following, an important factor in this respect is represented by the local endowment of Key-Enabling-Technologies (KETs).

2.3. KETs and regional patterns of diversification

The set of factors that can help in connecting the activities through whose recombination regional diversification unfolds has emerged to be ample: the internal/external labor mobility of a region, the input-output linkages of its production structure, and the presence of institutional entrepreneurs and collective actors, are just some few examples (for a wider review, see Boschma, 2016).

When we look at the technological knowledge-base of the region, an important complementarity enabler is represented by its endowment of technologies that have a 'general purpose' in their application, such as those recently identified (by the EC) as key enablers (KETs) of the transition towards a knowledge-based and sustainable economy: industrial biotechnology, nanotechnology, micro- and nanoelectronics, photonics, advanced materials, and advanced manufacturing technologies. As some recent studies have shown (Montresor and Quatraro, 2017; 2019), these technologies share some special features, which can render the process of regional diversification less bounded by the relatedness between new and pre-existing activities. As we will claim in the following, these features make of them an important and possibly differential predictor of the regional patterns of diversification we are addressing as well as of the transition across them.

The first KETs characteristic refers to their typical GPT development pattern (Bresnahan, 2010), following which inventions typically co-occur along with an innovative application for them. Thanks to this property, the regional activities that are based on the applicative path of an extant technology becomes connectable, not only to the complementary activities of related technologies, but also to the non-complementary ones based on the new inventive path that KETs has created. In this way, KETs can allow the region to recombine local activities in a more novel way than their simple (related) branching and thus increase its capacity of unrelated diversification. The second distinguishing feature of KETs is their horizontal application pattern, which covers the entire spectrum of activities of a regional economy. Because of their GPT nature, the advancement of KETs knowledge actually moves ahead the entire technological frontier of the region (Bresnahan, 2010). In so doing, KETs can provide regions with an extra buffer of knowledge and ideas, which can be combined in such an afresh way to reach an extra-regional kind of novelty and eventually favor the development of new socio-technical niches.

By crossing these characteristics with the regional patterns of diversification that we have identified, the role of KETs in driving regional diversification appears more nuanced than it has been previously ascertained (Montresor and Quatraro, 2017). First of all, KETs can be expected to be more enabling of non-replicative patterns of diversification than replicative ones, which could be even disfavored by the recombinant properties of KETs. Second, KETs are possibly more enabling of a transplantation kind of diversification than of an exaptation or even a saltation one, as the latter are conditional on the KETs capacity to generate recombinations whose novelty extends beyond the regional boundaries. In synthesis, our first expectation is that KETs are actually a differential driver of regional diversification, possibly capable to explain their heterogeneous geographical distribution.

A second argument that the properties of KETs lead us to formulate concerns a normative, rather than a positive evaluation of their role in driving regional diversification. Looking at the four patterns of diversification of Boschma et al. (2017)'s taxonomy in a dynamic way, we could argue that the shift undertakable by a region from a replication to a saltation pattern represents an 'ideal' strategy for it to escape lock-in situations and embark in higher opportunities of long-term development. Given their recombinant features, KETs could be argued to have a role in driving such a transition, which is worthwhile investigating. To be sure, because of the cumulative and path-dependent nature of regional dynamics, we could also think that the same transition reveals hard and risky to be made directly, by adding 'radicalness' to both the spatial and technological dimension simultaneously. Regions could/should rather move from replication to saltation progressively, by adding a novelty component one by one, that is, by passing through one of the other two diversification patterns. In this terms, it would become interesting to investigate whether KETs can have a role, and possibly a differential one, in driving two possible trajectories of the "escape" transition. A first trajectory can be termed 'technology-upon-space diversification' and is one in which the diversification transition passes through an intermediate transplantation pattern (Table 1). In brief, regions first exploit an existing (global) regime to diversify their economic activities into unrelated regional domains, and then "stretch" the novelty to the technology level and enter a new niche. A second trajectory, which is instead intermediated by an exaptation pattern, can be termed "space-upon-technology diversification". In this case, regions first enter a new technological domain (niche) to diversify "around" their extant economic activities, and then "stretch" the new technology to get into unrelated regional domains too.

Table 1 about here

As both of the trajectories entail a progressively more novel recombination, KETs could be expected to help in both. Still, we do not have theoretical and empirical arguments to expect their eventual impact could be larger for one rather than for the other trajectory. Accordingly, we leave this aspect to be ascertained by the empirical application, to which we turn in the next Section.

Before moving to that, an important point in the development of our research hypothesis should be raised about the availability of KETs in the regional knowledge base. In principle, KETs knowledge could be expected to exert the previous recombinant effects on regional diversification for the "simple" fact of being locally produced and somehow available "in the air": for example, as we will say later, through local inventive efforts and their possible knowledge spillovers. On the other hand, we can expect that the diversification driving role of KETs increases with the extent to which their knowledge is directly used in other technological domains, by favoring their direct contamination with general purpose technologies and their ensuing capacity of creating novel knowledge recombinations. In the light of this comment, the regional 'use' of KETs, which in the patent metrics (that we will also follow) could be read in terms of citations that local non-KETs make to KETs, can be expected to positively moderate, if not even conditioning, the impact of KETs on regional diversification.

3. Empirical application

3.1. Data

Our empirical application refers to more than 100 Italian NUTS3 regions (i.e., provinces), for which we have been able to combine two sources of data for the investigation of our focal relationship. The first one is the Statistical Archive on Active Firms (*Archivio Statistico Imprese Attive – ASIA*) provided by the Italian Statistical Institute (ISTAT), from which we have drawn data on the number of plants and employees, disaggregated by industry (up to the five-digit level) and region (at NUTS3 level which corresponds to Italian administrative provinces), in order to measure our diversification patterns. Although data are available from 2004 to 2010, a change occurred in 2008 in the used industry classification forced us to split the sample in two.[3] While this impedes us to carry out a

[3] In 2008 ISTAT followed EUROSTAT instructions and revised the classification system of industries, from ATECO 2002 (i.e. NACE Rev. 1.1) to ATECO 2007 (i.e. NACE Rev 2). As a result of this change, some sectors changed their industry

dynamic analysis, on the other hand, it enables us to investigate whether the testing of our arguments could differ between 2004-07, as the period before the arrival of the economic crisis, and 2008-10, as the crisis period. In the former period, we count 756 five-digit industries distributed across 103 provinces, for a total amount of 63,449 observations.[4] In the latter period, instead, the number of five-digit industries is 805 and observations are 67,485.

The second source of information is OECD-REGPAT database, from which we have drawn information on the regional endowment of KETs, using the IPC classificatory scheme of the EC feasibility study on KETs (EC, 2012b). Specifically, by using the applicant address to assign patents to NUTS3 regions, we have considered patent applications to the European Patent Office (EPO) in the IPC classes of the six KETs and we have then pooled them together. From the same data-source we have retrieved data on the citations that other regional (applied) patents have made to KETs patents (cited), as a way to measure the extent to which they are applied and used at the local level.

Finally, we have drawn on other official regional ISTAT statistics information on other characteristics of Italian provinces to be used as control in testing our relationship.

3.2 Variables

3.2.1. Dependent variables

Our focal dependent variables are two variables through which we proxy the two transitional trajectories across the identified diversification patterns experienced by region *r*, that is: *Tech-Space-Diver*$_r$ (trajectory 1 in Table 1) and *Space-Tech-Diver*$_r$ (trajectory 2). As available data only allow us to observe these patterns for two short periods (2004-2007 and 2008-2010), we are unfortunately incapable to investigate these two escaping strategies over time. However, in a cross-sectional setting, we can at least address the region capacity of creating new industries according to a set of diversification patterns that, while concomitant, can be assumed to be progressively more 'diversified' at the same point of time. Such a capacity could actually provide insights about the real region ability of moving from one to another pattern of diversification over time, should data permit to observe it.

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belonging, for example passing from manufacturing to services and vice versa, making the available industry classification in the two periods not easily comparable.

[4] Note that industries are not uniformly distributed across NUTS3 regions.

In order to accomplish such an analysis, we define our dependent variables as two ordered, three-item variables, in which the first and the third items are replication and saltation, respectively, and in which the second item is, alternatively, transplantation (for *Tech-Space-Diver*$_r$) and exaptation (for *Space-Tech-Diver*$_r$). As we will show in the following, this methodological choice enables us to also look at our first research question, that is, at the determinants of the individual diversification patterns that constitute the ordered variables and to compare the role of KETs across them.

The constitutive items of the two ordered variables are measured by following the extant literature (see, for example, Neffke et al., 2016) and looking at the spatial and technological specificities of the entry of regions into new economic activities through job creation in our two periods of time (2004-07 and 2008-10). In other words, we consider as one region *r'*s entry in industry *i*, a five-digit industry that has at least one employee[5] in the region at time *T* (2007 or 2010), having had zero employees in the region at time *T* – *t* (2004 or 2008, respectively).

In order to see whether these new regional entries are related or unrelated to existing regional capabilities – the two columns of Table 1, along the space dimension – we play with their industry classification at progressively less aggregated digits. That is, we see whether a new five-digit regional industry at *T* (2007 or 2010) belongs to a three-digit one, which already existed – '*related'* – or did not already exist – '*unrelated*' – in the region at time *T* - *t* (2004 or 2008, respectively).[6]

In order to measure the technological novelty of the observed entries – the two rows of Table 1, along the technology dimension – we try to relate them to the technological "World" in which our focal regions operate. Although the extant socio-technical regime (i.e., the World) with which regions deal is obviously defined on a global scale, because of data constraints, we are unfortunately forced to refer to the (much) smaller word represented by the country in which the regions are

[5] We have also fixed a threshold to five employees, but, in doing so, we halve the amount of entry events and we are not able to observe any diversification pattern than replication.

[6] As a robustness check, we also use the location quotient, at three-digit level, to discriminate between a related and an unrelated entry. In this case, we consider as related, a new five-digit industry that belongs to a three-digit industry of specialization for the region, i.e. a three-digit industry with a location quotient that is higher or equal than 1. An unrelated entry is, instead, a new five-digit industry that belongs to a three-digit industry of de-specialization for the region, i.e. a three-digit industry with a location quotient lower than 1. The results of the estimates do not change, but, adopting this approach, we observe more cases of transplantation than replication, which seems to contradict the stylized fact according to which regions are more likely to diversify in related rather than in unrelated activities. Moreover, we observe only 21 cases of exaptation in 2004-07.

located, that is, Italy. Accordingly, we classify as '*new to the World*' ('*known to the World*') those new five-digit industries *i* of region *r* at time *T* (2007 or 2010), which did not (did already) exist(ed) in the country, i.e. with zero (positive) employment in $T - t$ (2004 or 2008, respectively). Of course, this is a substantial simplification of the degree of technological novelty that regions can experience in their diversification strategy. Still, being a forerunner in a new industry within the country can be assumed to expose the region to at least some of those processes of experimentation and radical innovation that a new "real" niche would entail.

Combining the previous two sets of specifications, we define the constitutive items of our dependent variables, *Tech-Space-Diver* and *Space-Tech-Diver*, as follows:

- *Replication*: a new 5-digit industry at *T*, whose 3-digit industry already existed at *T-t*, both in the region and in Italy (neither new to the region, nor to the World);
- *Transplantation*: a new 5-digit industry at *T*, whose 3-digit industry did not exist in the region, but already existed in Italy at *T-t* (new to the region, but not to the World);
- *Exaptation*: a new 5-digit industry at *T*, whose 3-digit industry already existed in the region, but did not in Italy at *T-t* (new to the World, but not to the region);
- *Saltation*: a new 5-digit industry at *T*, whose 3-digit industry did not exist in *T-t*, neither in the region nor in Italy (new to the region and new to the World).

Table 2 shows the distribution of all these variables in the sample and across the two periods. Before the arrival of the economic recession, i.e. in 2004-07, we observe all the four cases of regional diversification. In particular, we note that replication is the most frequent option (explaining three quarters of entries), whereas, as expected, saltation represents the rarest, with only 16 cases (0.6% of entries). Looking at the industry distribution of *saltation*, we also note that it is rare and actually concentrated in one single three-digit industry, i.e. ATECO code 652 "other financial intermediation". As this makes of saltation a very limited and industry-specific kind of diversification strategy in the first period, we chose not to include it in the regression analysis, and build our dependent variables using only the other three diversification modes. During the economic crisis, i.e. in 2008-10, we observe a smaller number of entries with respect to 2004-07 and we do not register any case of exaptation and saltation. Therefore, we cannot identify the corresponding *Space-Tech-Diver* variable, and we thus use only *Tech-Space-Diver*.

To recap, the dependent variables that we actually use in the empirical application are the following two: for both periods of time, $\textit{Tech-Space-Diver}_{r,T}$, assuming value 0 in the benchmark case of no diversification, 1 in the replication case, and 2 in the case of transplantation; in the first period only, *Space-Tech-Diver*$_{r,T}$, taking value 0 in the case of no-diversification, 1 in the case of replication and 2 in the case of exaptation.

Table 2 about here

3.2.2. Focal regressors

Our focal explanatory variable is region *r*'s endowment of KETs knowledge, $KETs_{rt}$. Following innovation studies, we consider local patent applications as a proxy (although not free from limitations) of the inputs of the regional knowledge stock. Accordingly, we compute the regional stock of KETs patents in the two periods by applying the perpetual inventory method to the flows of KETs patents (*PATKETs*) over the periods 1995-2004 and 1995-2008, respectively, that is, by using the following formula:

$$[1]\ KETs_{rt} = KETs_{rt-1}(1-\delta) + PATKETs_{rt} \text{ for t} > 1995$$

where, following the extant literature, the depreciation rate δ is set equal to 0.15.

In order to disentangle the role of the six individual KETs, we repeat the same procedure and build up the patent stocks of: advanced manufacturing technologies (*AMT*), advanced materials (*ADV*), biotechnology (*BIOTECH*), nanoelectronics (*NANOEL*), nanotechnologies (*NANOTECH*) and photonics (*PHOTO*).

Figures 1 and 2 show the geographical distribution of the total stock of KETs and of each single KET stock, respectively.

Insert Figure 1 about here

Insert Figure 2 about here

Figure 1 shows that KETs endowment is higher in Northern regions, even though we find evidence of a very high stock of KETs in some regions in the Centre and the South of Italy[7]. When we look at the spatial distribution of each single KETs (Figure 2), we find that advanced manufacturing technologies and advanced materials are the most pervasive, whereas nano-technologies are concentrated in few regions in Italy.

As we said in Section 2.3, an important variable to integrate the analysis of the role of KETS in driving regional diversification is represented by the 'use' that other local technologies make of them. Following the extant literature (Trajtenberg, 1990), a way to proxy the extent to which the local KETs knowledge is actually accessed by (and not simply exposed to) the rest of the regional knowledge base is to look at the citations that the patents in the latter domain make to those in the former. Following this logic, we build the variable $CITKETS_{rt}$ by summing the number of these citations and by dividing it by the total amount of citations in the region in our two focal periods (1995 – 2004 and 1995 - 2008). It should be noticed that, as this latter variable is dependent on the local production and availability of the non-KETS knowledge base that cites KETs, its inclusion prevents us to consider the stock of non-KETs patents among the regressors as it would be collinear. Although an indirect one, $CITKETS_{rt}$ is thus the way through which the local availability of non-KETs knowledge is somehow controlled for.

3.2.3. Other regional characteristics

Following the extant literature we expect that our trajectories of progressively more 'radical' diversification depend on other regional characteristics than KETs. In particular, we maintain that four regional characteristics should be salient. The first one is the level of 'economic complexity' of a region (Pinheiro et al. 2018), *ECI*, as it connects to its level of economic development: the higher this level, the higher the degree of local product complexity, the higher the potential of unrelated recombinations. Following Hidalgo and Hausmann (2009), we measure such a complexity a $T - t$ (2004 and 2008) by using export data for Italian NUTS3 regions and three-digit industries provided by Coeweb (ISTAT), and by working out the following indicator:

[7] We also run a Moran-I test to detect potential spatial autocorrelation in KETs endowment. In both periods, the test never rejects the null hypothesis of absence of spatial autocorrelation (I=-0.010, p-value=0.491 in 2004-07 and I=-0.006, p-value=0.355 in 2008-10).

$$[2]\ ECI_r = \sum_j \frac{M_{ij}}{k_i k_j} \sum_r M_{rj} ECI_r.$$

where the ubiquity of regional industries *j* – in terms of number of regions that have a revealed comparative advantage, M_{rj} , in them – is combined with the average knowledge intensity of all the exporting industries (see Hidalgo and Hausmann (2009) for details).

A second variable that we consider is the human capital stock of the region, HK. Being a potential source of innovation, as well as a source of entrepreneurship, we could expect a higher capability to discover new, unrelated, pathways in regions that are more endowed of highly educated individuals. However, a higher amount of human capital can also represent a potential obstacle to regional diversification, to the extent to which discovering radically new activities makes existing knowledge and capabilities rapidly obsolete, thus requiring the existing workforce to be (re-)trained. With this ambiguous expectation, we measure the human capital of the region through the number of graduated students (bachelor and master degrees) on resident population, using ISTAT data from ASTI (A*tlante Statistico Territoriale delle Infrastrutture*).

The third regional characteristic that we include to capture the presence of urbanization economies, which could favor inventive activities and diversifying recombinations, is the population density of the region, *POPDEN*, measured by its resident population per km^2.

Fourth, we also control for two economic variables of the region: the growth rate of regional value added (*GROWTH*) over the three years before *T* (i.e., 2001-2004 and 2005-2008), to capture the role of the business cycle in affecting the creation of new activities in a region; the regional trade openness (*TRADE*), given by the sum of imports and exports on regional value added, to check for the potential influence of international competition.

Finally, we add a series of NUTS2 region dummies and 2-digit industry dummies to account for fixed effects at regional and industry level. Table 3 shows the main summary statistics.

Table 3 here

3.3. Econometric strategy

We estimate the following two models:

[3] $Y_r^{2004/07} = \beta_0 + \beta_1 KETS_r^{95-04} + \beta_2 CITKETS_r^{95-04} + \beta_3 KETS_r * CITKETS_r + \boldsymbol{X_r^{2004}} \boldsymbol{\beta_4} + \varphi_R + \mu_j + \varepsilon_r$

[4] $Y_r^{2008/10} = \beta_0 + \beta_1 KETS_r^{95-08} + \beta_2 CITKETS_r^{95-08} + \beta_3 KETS_r * CITKETS_r + \boldsymbol{X_r^{2008}} \boldsymbol{\beta_4} + \varphi_R + \mu_j + \varepsilon_r$

where Y_r, refers to our two ordinal diversification variables (*Tech-Space-Diver* and *Space-Tech-Diver*) for region *r,* and vector $\boldsymbol{X_r}$ includes the other regional characteristics and the selected controls. The terms φ_R and μ_j represent, respectively, the NUTS2 region and NACE two-digit industry dummies, while ε_r is the stochastic error component. Let us notice that, while somehow controlling for local non-KETS knowledge in additive terms, *CITKETS* are also interacted with KETS in order to test for their moderating role of the impact of *KETs* on *Y*.

Since *Y* is built up as an ordered variable, we estimate equations 3 and 4 by using an ordered logit model, and we cluster the standard errors at NUTS3 region-two-digit industry level. We also compute the average marginal effects for KETs variables to quantify the impact that additional amounts of KETs have on the probability for a region to transit from one state to the other. To test for the validity of the parallel lines (or proportional odds) assumption, we use both a likelihood ratio (LR) and a Brant test. In case of rejection of the null hypothesis of correct specification of the model, which can be the case in large samples, we make use of the Bayesian Information Criterion (BIC) to compare a model where the estimated coefficients are equal across outcomes and one where the coefficients can vary across outcomes (Williams, 2016).

To test whether our focal regional diversification trajectories are differently driven by some specific KETs of the six, we also re-estimate equations 3 and 4 by replacing the total KETs endowment with the regional endowment of AMT, ADV, BIOTECH, NANOEL, NANOTECH and PHOTO. Due to their high correlation, we insert them separately in the models.

We also re-estimate equations 3 and 4 by using a linear specification and OLS, so to compare the sign and statistical significance of our interaction terms with the ordered logit specification and with the subsequent IV-GMM estimates.

Finally, we conduct two additional robustness tests. First, we re-estimate equations 3 and 4 on two different datasets, which distinguish provinces including large urban zones (LUZ) from the others.[8] In this way, we test whether our results are driven by the clustering of patents in large metropolitan

[8] We define LUZ as a dummy taking the value of 1 when population in the region, at Census year 2001, is higher than the median, and 0 otherwise.

areas, like, among others, Milan, Rome or Turin. The second robustness test concerns endogeneity. The relationship between KETS endowment and regional diversification can actually be affected by unobserved heterogeneity and simultaneity. For instance, it can be that an unobserved, unpredicted, positive or negative shock can affect both variables, by altering the KETs patent intensity of a region and its capability to generate new activities. Alternatively, it can be that local, unobserved characteristics make new and unrelated industries to emerge in regions that are more endowed with KETS, but without these latter playing a clear role. We deal with these problematic issues in three ways. First, we measure the endowment of KETs in a region before the advent of new activities in it, thus avoiding any type of observable simultaneity between *Y* and *KETS*. Second, we estimate our focal relationship in two periods, 2004-07 and 2008-10, which refer to a positive and a negative phase of the business cycle, respectively. Third, we also adopt an instrumental variable approach recently suggested by Lewbel (2012), which exploits the heteroskedasticity of the errors to identify a set of internal instruments that are particularly useful when reliable external instruments are not available. In this setting, we also test for the exogeneity of KETs using a difference in Sargan test, which relies on a test statistic distributed as a chi-squared with degrees of freedom equal to the number of endogenous regressors.

4. Results

The first set of results refer to the period 2004-2007, with respect to which Table 4 shows the ordered logit and OLS estimates for *Tech-Space-Div* (Columns 1-4) and *Space-Tech-Div* (Columns 5-8). In both cases, the first columns (1 and 5, respectively) refer to the specifications that only include the stock of KETs as focal regressor, while in the remaining columns (2-4 and 6-7, respectively) the interaction between *KETS* and *CITKETS* is inserted. Such an insertion actually makes the difference. The stock of regional KETs alone does not significantly affect the probability of a region to diversify into progressively more 'diversified' industries. Such an effect does instead emerge when the interaction between KETs and their use by other technologies available in the region, *CITKETS*, is added.[9] Columns 2 and 3, for *Tech-Space-Div*, and 6 and 7, for *Space-Tech-Div*, show that the estimated coefficient of KETS is negative and statistically significant, but that the interaction term is always positive and highly significant. Columns 4 and 8 confirm these results for the two diversification trajectories, respectively, when equation 3 is estimated through OLS.

[9] As a further check, we also replace the share of citations (*CIT*) with the cumulative amount of citations of KETs patents by the other patents between 1995 and 2004 (2008). We do not find any change in the results.

Overall, a first interesting result emerges with respect to the Italian regions before the burst of the financial crisis. The sole creation of KETs knowledge, and its presumed diffusion over the local knowledge base in terms of pure knowledge spillovers, is not enough to make them exert the recombinant power that could lead to progressively more diversifying patterns. On the contrary, for that to happen KETs need to be actually combined with local non-KETs knowledge, through its drawing on KETs in its inventing activities. In brief, consistently with the original message that the EC put forward about them (EC, 2009), it is not so much the local production of KETs that help regions change and escape possible lock-in traps in moving towards the new knowledge-based economy; but rather an effective use of them by the players involved in the production of the "normal" knowledge base of the region.

Still with respect to the first period, Table 4 shows that, as expected, the probability of progressively more unrelated diversification increases with trade openness and, although in a non-linear way, also with population density and human capital: in the squared specification that we used, their effect actually increases after a minimum threshold for them is achieved in the region. No significant effect is instead found for the growth rate of value added per capita, whereas regional knowledge complexity has only a weakly significant effect on the space-upon-technology pattern.

In concluding the results of Table 4, some comments are due about the LR and Brant tests for the validity of the parallel lines assumption that we run in Columns 3 and 7.[10] Results in Column 3 show that the parallel lines assumption cannot be rejected for *Tech-Space-Div*, at least for our focal regressor (*KETS**CITKETS*). Results in Column 7, instead, show that both the tests reject the null hypothesis for *Space-Tech-Div*. On the other hand, the BIC statistics show that a model where the coefficients of our variables are imposed to be equal across the ordered classes is preferable to a model where coefficients can vary.

Table 4 about here

[10] As we could not run the Brant test on the full specifications of Columns 2 and 6, for the two trajectories, respectively, we chose to test the parallel lines assumption on a specification of equation 3 without the regional and industry dummies.

Looking at the marginal effects of KETs over the first period, Table 5 provides some interesting results too. To start with, our conjecture about a positive effect of KETs, even in presence of a significant negative coefficient for the relative regressor, is confirmed. As the interaction term *KETS*CITKETS* is positive and always of a larger size, the net marginal effect of KETs on regional diversification is positive. Apart from that, we find that doubling the citation-weighted KETs endowment in a region corresponds to an average 20% increase in the probability to transit from replication to transplantation and to a lower 12% increase in the probability to transit from replication to exaptation. As also expected, the role of KETs in regional diversification does actually appear heterogeneous with respect to its diverse patterns, being more effective when further radicalness is obtained within an existing technological regime than with the creation of a new niche. This appears confirmed by the fact that one standard deviation increase in citation-weighted KETs endowment corresponds to a 0.12% increase in the probability of a technology-upon-space diversification, and to a sole increase of 0.05% in that of a space-upon technology one.

Table 5 here

Moving to the second period of the analysis, 2008-2010, with respect to which only the trajectory *Tech-Space-Diver* is detectable, Table 6 mainly confirms the results obtained for the previous period. The propensity of a region to diversify progressively more increases significantly with KETs, providing their local availability is interacted with the share of citations from other patents (*CITKETS*). Quite interestingly, this thus appears a robust result of our analysis that, net of the disappearance of the *Space-Tech-Diver* trajectory, is revealed by regions even in the aftermath of an economic crisis. In brief, the business cycle does not appear to alter the recombinant role of KETs in driving regional diversification. For what concerns the other variables, we only observe a more significant coefficient of *ECI*, while the results for all the others are in line with those reported in Table 4. Moreover, both the LR and the Brant tests lead not to reject the null hypothesis of validity of the parallel lines assumption this time.

Table 6 here

Still with respect to the second period, Table 7 reports the marginal effects of KETs related to the estimates in Table 6, which are closed to those reported in Table 5.

Table 7 here

Quite interestingly, the results that we have obtained with respect to the role of KETs in general terms appear confirmed when their six constituent technologies are separately considered. Both for the first period (Table 8) and the second one – not reported for reasons of space, but available from the authors upon request – each and every citation-weighted KETs positively correlates with *Y* but biotechnology, for which the effect is not significant. While for sure unexpected, this result suggests that, in some specific technological domains, the recombinant properties that we have recognized to KETs could be less intense and prevent them to exert an effect on diversification. Still, with this unique exception, the relationship that we have ascertained appears to hold irrespectively of the specific KETs.

Table 8 here

Coming to our robustness checks, Tables 9 shows that the results presented in Tables 4 and 6 hold true only in regions that include a large urban zone (LUZ). Conversely, in regions that do not comprehend LUZ, we do not find any significant effect of KETs on regional diversification: neither with, nor without the interaction term *KETS*CITKETS*. This is an extremely important element of non-robustness of our results, which make them contingent on the urban size of the regions in which KETs are available. As large urban zones are systematically marked by a higher intensity of patenting activities and outputs, such a result seems to suggest that a critical mass of KETs is needed for their relationship with regional diversification to emerge. In other words, the relationship that we have detected appears a urban phenomenon, whose specification appears prodromal to the other ones we have obtained.

Table 9 here

As for our second robustness check, Table 10 reports the results of the estimates when equations 3 and 4 are run using a linear IV approach, following Lewbel (2012). As we said, in absence of suitable external instruments, the Lewbel's (2012) approach builds internal instruments from the residuals of the first-stage regression where the endogenous variables (i.e. *KETS, CITKETS* and *KETS*CITKETS*) are regressed on all exogenous regressors. Instruments are then computed by multiplying the first-stage heteroskedastic residuals by mean-centered exogenous variables included in the first-stage regression[11]. The Hansen J statistics is used to test for overidentification, while a difference in Sargan statistic is used to test for the exogeneity of our KETs-related variables.

Results in Table 10 confirm those presented in Tables 4 and 6: the interaction term between *KETS* and *CITKETS* is always positive and statistically significant, even when we drop regional and industry dummies from the estimates of equations 3 and 4 (Columns 2 and 6), or when we use only one additional regressor (i.e. *POPDEN*) in order to have a perfectly identified equation (Columns 3 and 7). Moreover, the difference in Sargan test does never reject the null hypothesis of exogeneity of our KETs variables.

Overall, the results we have obtained can be deemed to be robust with respect to the possible problems of reverse causality and simultaneity that the (non-confirmed) endogenous nature of the main regressors could entail.

Table 10 here

5. Conclusions

In this paper we have analyzed the extent to which KETs could fit among the drivers of regional diversification when its place dependence is enriched with the consideration of its path-dependence. By combining a similarity and a complementarity dimension of relatedness, we have focused on the recombinant properties of KETs, based on which we expect they could affect regional diversification at large. More precisely, we have maintained that, on the one hand, KETs could have a differential effect on the different diversification patterns that can emerge along the spatial and the technological dimension; on the other hand, that KETs could help regions to escape the eventual risk of lock-in that no-diversification and a pure replication strategy would entail. By extending the taxonomy put forward by Boschma et al. (2017), we have focused on two possible trajectories of an

[11] The Breusch-Pagan test in each first-stage regression always rejects at 1% level the null hypothesis that the residuals are homoskedastic.

‘ideal’ escaping transition from a ‘replicative kind of diversification, subject to both path and spatial dependence. A first trajectory is represented by a ‘technology-upon-space’ kind of diversification, in which regions pass through the ‘transplantation’ of an existing regime in developing related activities. The second one is a ‘space-upon-technology’ diversification, in which regions pass through the ‘exaptation’ of a new niche but by drawing on related capabilities. Still by referring to the recombinant properties of KETs, we have argued they could help regions in creating progressively more diversified industries along both of these two trajectories; furthermore, we have retained that the extent to which KETs are actually used by, rather than simply exposed to, the rest of the regional knowledge base could positively moderate their effect on regional diversification.

Merging employment data from ISTAT and patent information from OECD-Regpat, we have estimated a series of ordered logit and linear models, where the propensity of regions to generate new activities that are progressively less related to those already existing, is regressed against the regional citation-weighted KETs endowment and on other regional characteristics.

The results of the estimates show that a higher endowment of KETS, *per se*, does not have any direct effect on regional diversification. Conversely, it corresponds to a higher probability of transition from replication to unrelated diversification (replication or exaptation) when the regional stock of KETs is interacted with the share of KETs citations coming from other patents. This result is neither affected by economic crisis in 2008-10 nor by reverse causality. However, it holds true only in regions that contain a large urban area, and which thus presumably have a critical mass of KETs.

This evidence can have important implications in both academic and policy terms. With respect to the former, we contribute to enlarge the still scanty evidence and theory about unrelated diversification by pointing to the role of general-purpose kind of technologies like KETs. In policy terms, instead, we provide evidence on how KETs could be used by the policy-makers to allow regions to escape from lock-iness situations in which they might have followed by replicating their local capabilities. In particular, our results support the original message that the EC put forward about KETS (EC, 2009), according to which it is not so much the local production of KETs that help regions change and escape possible lock-in traps in moving towards the new knowledge-based economy; but rather an effective use of them by the players involved in the production of the “normal” knowledge base of the region.

References

Antonietti, R., and Boschma, R. (2018), Social capital, resilience and regional diversification in Italian regions. Papers in Evolutionary Economic Geography, Working Paper n. 2018

Arts, S., & Veugelers, R. (2015). Technology familiarity, recombinant novelty, and breakthrough invention. Industrial and Corporate Change, 24(6), 1215–1246. doi:10.1093/icc/dtu029.

Balland, P.A. (2016), "Chapter 6: Relatedness and the geography of innovation", in Shearmu, R., Carrincazeaux, C. and Doloreux. D. (eds), Handbook on the Geographies of Innovation. London, Edward Elgar.

Balland, P.A., Boschma, R., Crespo, J. and Rigby, D.L. (2018): Smart specialization policy in the European Union: relatedness, knowledge complexity andregional diversification, Regional Studies, DOI: 10.1080/00343404.2018.1437900

Boschma, R. (2016). Relatedness as driver of regional diversification: a research agenda, Regional Studies (forthcoming), DOI: 10.1080/00343404.2016.1254767.

Boschma, R., & Capone, G. (2015). Institutions and diversification: Related versus unrelated diversification in a varieties of capitalism framework. Research Policy, 44, 1902–1914.

Boschma, R., and Giannelle, C. 2014. Regional branching and smart specialisation policy. S3 Policy Brief Series 06/2014. Seville: European Commission.

Boschma, R., and Iammarino, S. (2009). Related Variety, Trade Linkages, and Regional Growth in Italy, Economic Geography, 85:3, 289-311, DOI: 10.1111/j.1944-8287.2009.01034.x

Boschma, R., Asier Minondo, Mikel Navarro (2011). Related variety and regional growth in Spain. Papers in Regional Science, 91: 2, 241-256, DOI: 10.1111/j.1435-5957.2011.00387.x

Boschma, R., Lars Coenen, Koen Frenken and Bernhard Truffer (2017). Towards a theory of regional diversification: combining insights from Evolutionary Economic Geography and Transition Studies, Regional Studies, 51:1, 31-45, DOI: 10.1080/00343404.2016.1258460.

Boschma, R., Rikard Eriksson, Urban Lindgren (2009). How does labour mobility affect the performance of plants? The importance of relatedness and geographical proximity, Journal of Economic Geography, Volume 9, Issue 2, 1 March 2009, Pages 169–190, doi.org/10.1093/jeg/lbn041.

Bresnahan, T. 2010. General purpose technologies. In Handbook of the economics of innovation, Vol. 2, ed. B. H. Hall, and N. Rosenberg, 761–91. Amsterdam, the Netherlands: Elsevier.

Broekel, T., & Brachert, M. (2015). The structure and evolution of inter-sectoral technological complementarity in R&D in Germany from 1990 to 2011. Journal of Evolutionary Economics, 25, 755–785. doi:10.1007/s00191-015-0415-7.

Bresnahan, T. 2010. General purpose technologies. In Handbook of the economics of innovation, Vol. 2, ed. B. H. Hall, and N. Rosenberg, 761–91. Amsterdam, the Netherlands: Elsevier.

Cantwell, J. A., & Iammarino, S. (2003). Multinational corporations and European regional systems of innovation. London: Routledge.

Castaldi, C., Frenken, K., and Los, B. 2015. Related variety, unrelated variety and technological breakthroughs: An analysis of US state-level patenting. Regional Studies 49 (5): 767–81. doi:10.1080/00343404.2014.940305 Coenen et al., 2010;

Cortinovis, N., Xiao, J., Boschma, R., &Van Oort, F. (2016). Quality of government and social capital as drivers of regional diversification in Europe (Papers in Evolutionary Economic Geography No.16.10). Utrecht: Utrecht University.

Crescenzi, R., Gagliardi, L., and Percoco, M. (2013a). Social Capital and the Innovative Performance of Italian Provinces, Environment and Planning A, 45, 908-929.

Dewald, U., & Truffer, B. (2012). The local sources of market formation: Explaining regional growth differentials in German photovoltaic markets. European Planning Studies, 20, 397–420. doi:10.1080/09654313.2012.651803

EC 2012a. A European strategy for key enabling technologies—A bridge to growth and jobs. Final communication from the commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions. COM (2012)-341. Brussels, Belgium: European Commission.

EC 2012b. Feasibility study for an EU monitoring mechanism on key enabling technologies. Brussels, Belgium: European Commission.

Essletzbichler, J. (2015). Relatedness, Industrial Branching and Technological Cohesion in US Metropolitan Areas, Regional Studies, 49:5, 752-766, DOI: 10.1080/00343404.2013.806793.

Fleming, L. (2001). Recombinant uncertainty in technological space. Management Science, 47, 117–132. doi:10.1287/mnsc.47.1.117.10671

Foray, D. (2014). From smart specialisation to smart specialization policy. European Journal of Innovation Management, 17(4), 492–507. doi:10.1108/EJIM-09-2014-0096.

Frenken, K., Frank Van Oort & Thijs Verburg (2007) Related Variety, Unrelated Variety and Regional Economic Growth, Regional Studies, 41:5, 685-697, DOI: 10.1080/00343400601120296.

Fuenfschilling, L., & Binz, C. (2016). Global socio-technical regimes. Paper presented at the 50th SPRU Anniversary Conference, Brighton, UK, 7–9 September 2016.

Garud, R., Hardy, C., & Maguire, S. (2007). Institutional entrepreneurship as embedded agency: An introduction to the special issue. Organization Studies, 28, 957–969. doi:10.1177/0170840607078958.

Garud, R., & Karnøe, P. (2003). Bricolage versus breakthrough: Distributed and embedded agency in technology entrepreneurship. Research Policy, 32, 277–300. doi:10.1016/S0048-7333(02)00100-2

Geels, F. W. (2002). Technological transitions as evolutionary reconfiguration processes: A multi-level perspective and a case-study. Research Policy, 31, 1257–1274. doi:10.1016/S0048-7333(02)00062-8

Gilbert, B. A., & Campbell, J. T. (2015). The geographic origins of radical technological paradigms: A configurational study. Research Policy, 44, 311–327. doi:10.1016/j.respol.2014.08.006.

Hartog, M., R. Boschma and M. Sotarauta (2012) The Impact of Related Variety on Regional Employment Growth in Finland 1993–2006: High-Tech versus Medium/Low-Tech, Industry and Innovation, 19:6, 459-476, DOI: 10.1080/13662716.2012.718874.

Hidalgo, C., and Hausmann, R. (2009). The building blocks of economic complexity, Proceedings of the National Academy of Science, 106(26), 10570-10575.

Kemp, R., Schot, J., & Hoogma, R. (1998). Regime shifts to sustainability through processes of niche formation: The approach of strategic niche management. Technology Analysis and Strategic Management, 10, 175–198. doi:10.1080/09537329808524310.

Isaksen, A. (2015). Industrial development in thin regions: Trapped in path extension? Journal of Economic Geography, 15, 585–600. doi:10.1093/jeg/lbu026.

Isaksen, A.,&Trippl, M. (2014). Regional industrial path development in different regional innovation systems: A conceptual analysis (Papers in Innovation Studies No. 2014/17). Lund: Lund University, Centre for Innovation, Research and Competence in the Learning Economy (CIRCLE).

Lester, R. K. (2007). Universities, innovation, and the competitiveness of local economies: An overview. Technology Review, 214, 9–30.

Lewbel, A. (2012). Using heteroskedasticity to identify and estimate mismeasured and endogenous regressor models. Journal of Business & Economic Statistics, 30(1): 67-80. doi: 10.1080/07350015.2012.643126.

March, J. G. (1991). Exploration and exploitation in organizational learning. Organization Science, 2(1), 71–87. doi:10.1287/orsc.2.1.71

Markard, J., Raven, R., & Truffer, B. (2012). Sustainability transitions: An emerging field of research and its prospects. Research Policy, 41, 955–967. doi:10.1016/j.respol.2012.02.013

Marquis, C., & Raynard, M. (2015). Institutional strategies in emerging markets. Academy of Management Annals, 9(1), 291–335. doi:10.1080/19416520.2015.1014661

Maskell, P., & Malmberg, A. (1999). Localised learning and industria competitiveness. Cambridge Journal of Economics, 23(2), 167–185. doi:10.1093/cje/23.2.167

Montresor, S. & Quatraro, F. (2017) Regional Branching and Key Enabling Technologies: Evidence from European Patent Data, Economic Geography, 93:4, 367-396, DOI: 10.1080/00130095.2017.1326810.

Montresor, S. and Quatraro, F. (2019) Green technologies and smart specialisation: a European patent-based analysis of the intertwining of technological relatedness and Key Enabling Technologies. Paper prepared for the S3 JRC Conference.

Neffke, F., Hartog, M, Boschma, R., and Henning, M. (2018). Agents of structural change: the role of firms and entrepreneurs in regional diversification, Economic Geography, 94(1), 23-48, DOI: 10.1080/00130095.2017.1391691.

Neffke, F., Otto, A. and Hidalgo, C. (2016) The mobility of displaced workers: how the local industry mix affects job search strategies, Papers in Evolutionary Economic Geography, Working Paper n. 2016-03, Utrecht University.

Neffke, F., & Henning, M. (2013). Skill relatedness and firm diversification. Strategic Management Journal, 34(3), 297–316. doi:10.1002/smj.2014

Olsson, O., and Frey, B. S. 2002. Entrepreneurship as recombinant growth. Small Business Economics 19 (2): 69–80. doi:10.1023/A:1016261420372.

Petralia, S., Balland, A., & Morrison, A. (2016). Climbing the ladder of technological development (Papers in Evolutionary Economic Geography No. 16.29). Utrecht: Utrecht University, Utrecht.

Pinheiro, F.L., Alshamsi, A., Hartmann, D., Boschma, R., and Hidalgo, C. (2018). Shooting low or high: do countries benefit from entering unrelated activities? Papers in Evolutionary Economic Geography, Working Paper n. 2018-07, Utrecht University.

Rigby, D. (2015). Technological relatedness and knowledge space: Entry and exit of US cities from patent classes. Regional Studies, 49(11), 1922–1937. doi:10.1080/00343404.2013.854878.

Rip, A., & Kemp, R. (1998). Technological change. In S. Rayner & E. L. Malone (Eds.), Human choice and climate change. Resources and technology (pp. 327–399). Columbus: Battelle.

Saxenian, A. L. (2006). The new Argonauts. Regional advantage in a global economy. Cambridge, MA: Harvard University Press.

Saviotti, P. P., & Frenken, K. (2008). Export variety and the economic performance of countries. Journal of Evolutionary Economics, 18(2), 201–218. doi:10.1007/s00191-007-0081-5.

Sengers, F.,&Raven, R. P. J. M. (2015). Toward a spatial perspective on niche development: The case of bus rapid transit. Environmental Innovation and Societal Transitions, 17, 166–182.

Simmie, J. (2012). Path dependence and new path creation in renewable energy technologies. European Planning Studies, 20, 729–731. doi:10.1080/09654313.2012.667922

Sotarauta, M., & R. Pulkkinen (2011). Institutional entrepreneurship for knowledge regions: In search of a fresh set of questions for regional innovation studies. Environment and Planning C, 29, 96–112. doi:10.1068/c1066r.

Späth, P., & Rohracher, H. (2012). Local demonstrations for global transitions. Dynamics across governance levels fostering sociotechnical regime change towards sustainability. European Planning Studies, 20, 461–479

Strambach, S. (2010). Path dependency and path plasticity. The coevolution of institutions and innovation – the German customized business software industry. In R. A. Boschma, & R. Martin (Eds.), Handbook of evolutionary economic geography (pp. 406–431). Cheltenham: Edward Elgar.
Tanner, A. N. (2016). The emergence of new technology-based industries: The case of fuel cells and its technological relatedness to regional knowledge bases. Journal of Economic Geography, 16 (3), 611–635. doi:10.1093/jeg/lbv011.
Trajtenberg M. (1990) A penny for your quotes: patent citations and the value of innovations, RAND Journal of Economics 21, 172–187. doi:10.2307/2555502.
Truffer, B., & Coenen, L. (2012). Environmental innovation and sustainability transitions in regional studies. Regional Studies, 46, 1–21. doi:10.1080/00343404.2012.646164.
Weitzman, M. L. (1998). Recombinant growth. Quarterly Journal of Economics, 113(2), 331–360. doi:10.1162/003355398555595.
Williams, R. (2016). Understanding and interpreting generalized ordered logit models. The Journal of Mathematical Sociology, 40(1): 7-20. doi: 10.1080/0022250X.2015.1112384.
Zhu, S., He, C., & Zhou, Y. (2015). How to jump further? Path dependent and path breaking in an uneven industry space (Papers in Evolutionary Economic Geography No. 15.24). Utrecht: Utrecht University.

TABLES AND FIGURES

Table 1. Regional diversification patterns

Trajectory 1: "Technology-upon-space diversification"		**Space**	
Technology		**Related** Place-dependent: know to the region	**Unrelated** "New to the region"
	Regime Path-dependent: known to the World	*Replication*	*Transplantation*
	Niche "New to the World"	*Exaptation*	*Saltation*

Trajectory 2: "Space-upon-technology diversification"		**Space**	
Technology		**Related** Place-dependent: know to the region	**Unrelated** "New to the region"
	Regime Path-dependent: known to the World	*Replication*	*Transplantation*
	Niche "New to the World"	*Exaptation*	*Saltation*

Table 2. Distribution of entries and regional diversification patterns

	2004-07		2008-10	
	N. of 5-dgt industries	%	N. of 5-dgt industries	%
Entry	2,782	4.38	2,248	3.33
- *Replication*	*2,109*	*75.81*	*1,760*	*78.29*
- *Transplantation*	*522*	*18.76*	*488*	*21.71*
- *Exaptation*	*135*	*4.85*	*0*	*0.00*
- *Saltation*	*16*	*0.58*	*0*	*0.00*
Total obs.	63,449	100.0	67,485	100.0

Table 3. Summary statistics

Variable	Year	Mean	Std. dev.	Min	Max
KETS	1995-2004	18.43	98.50	0	991.42
	1995-2008	20.25	96.36	0	966.76
CITKETS	1995-2004	0.020	0.022	0	0.143
	1995-2008	0.022	0.023	0	0.133
HK	2004	0.322	0.034	0.240	0.451
	2008				
ECI	2004	-0.009	0.151	-0.374	0.337
	2008	-0.009	0.084	-0.217	0.175
GROWTH	2001-04	0.093	0.055	-0.038	0.252
	2005-08	0.077	0.104	-0.098	0.667
POPDEN	2004	244.5	329.5	37.235	2603.31
	2008	249.1	330.0	38.753	2586.5
TRADE	2004	53.17	54.26	1.542	335.11
	2008	53.730	55.512	1.562	383.27

Table 4. KETs and regional diversification: 2004-07

	Tech-Space-Diver				Space-Tech-Diver			
Method	OLOGIT	OLOGIT	OLOGIT	OLS	OLOGIT	OLOGIT	OLOGIT	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
KETS	-0.001	-0.020***	-0.015***	-0.000***	-0.000	-0.014***	-0.010**	-0.000***
	(0.000)	(0.004)	(0.004)	(0.000)	(0.000)	(0.005)	(0.005)	(0.000)
CITKETS		-2.839**	-1.050	-0.110*		-2.002	-0.759	-0.063
		(1.261)	(1.474)	(0.057)		(1.332)	(1.467)	(0.043)
KETS*CITKETS		0.538***	0.377***	0.013***		0.378***	0.281**	0.013***
		(0.111)	(0.119)	(0.003)		(0.127)	(0.137)	(0.003)
ECI	0.187	0.264	0.049	0.011	0.436*	0.496**	0.211	0.011
	(0.238)	(0.238)	(0.203)	(0.012)	(0.241)	(0.242)	(0.200)	(0.012)
POPDEN	-0.001***	-0.001***	-0.001***	-0.000***	-0.001***	-0.001***	-0.001***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$POPDEN^2$	0.000***	0.000***	0.000***	0.000**	0.000***	0.000***	0.000***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GROWTH	0.277	0.178	0.669	0.015	0.802	0.736	0.670	0.015
	(0.526)	(0.521)	(0.511)	(0.023)	(0.545)	(0.545)	(0.493)	(0.023)
HK	-30.80***	-30.64***	-19.20**	-1.321***	-26.51**	-26.11**	-22.37**	-1.321***
	(10.21)	(10.28)	(9.740)	(0.445)	(10.25)	(10.40)	(11.27)	(0.445)
HK^2	37.36**	39.80**	26.63*	1.692**	35.29**	36.84**	31.91**	1.692**
	(15.67)	(15.80)	(15.02)	(0.668)	(15.42)	(15.72)	(17.66)	(0.668)
TRADE	0.004***	0.003***	0.003***	0.000***	0.003***	0.002***	0.002***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Regional dummies	Yes	Yes	No	Yes	Yes	Yes	No	Yes
Industry dummies	Yes	Yes	No	Yes	Yes	Yes	No	Yes
N	63449	63449	63449	63449	63449	63449	63449	63449
Pseudo R^2	0.158	0.159	0.010	0.180	0.128	0.129	0.006	0.116
LR test (p-value)			0.456				0.000	
Brant test (p-value)								
All var			0.064				0.000	
KET			0.070				0.001	
CIT			0.361				0.318	
KETS*CITKETS			0.848				0.001	
BIC (pl)							20430.3	
BIC (npl)							20459.2	

Clustered (at NUTS3 region and two-digit industry level) standard errors in parentheses. All the estimates include a constant term. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5. Marginal effects: 2004-07

		Marginal Change	
TSD	Replication	Transplantation	Total
KETS	-0.001***	-0.000***	-0.001
	(0.000)	(0.0000)	
KETS*CITKETS	0.015***	0.004***	0.019
	(0.000)	(0.000)	
Total	*0.014*	*0.004*	*0.018*
STD	Replication	Exaptation	Total
KETS	-0.000***	-0.000***	-0.000
	(0.001)	(0.0000)	
KETS*CITKETS	0.011***	0.001***	0.012
	(0.003)	(0.0002)	
Total	*0.011*	*0.001*	*0.012*
		+SD change	
TSD	Replication	Transplantation	Total
KETS	-0.028***	-0.007***	-0.035
	(0.000)	(0.0000)	
KETS*CITKETS	0.122***	0.036***	0.158
	(0.000)	(0.000)	
Total	*0.014*	*0.004*	*0.123*
STD	Replication	Exaptation	Total
KETS	-0.025***	-0.002***	-0.027
	(0.001)	(0.0000)	
KETS*CITKETS	0.074***	0.007***	0.081
	(0.003)	(0.0002)	
Total	*0.008*	*0.0009*	*0.054*

Table 6. The role of KETs on regional diversification: 2008-10

	Tech-Space-Diver			
Method	OLOGIT	OLOGIT	OLOGIT	OLS
	(1)	(2)	(3)	(4)
KETS	-0.003	-0.023***	-0.019***	-0.000***
	(0.002)	(0.004)	(0.004)	(0.000)
CITKETS		-0.265	-0.727	0.006
		(1.015)	(1.168)	(0.053)
KETS*CITKETS		0.605***	0.494***	0.013***
		(0.116)	(0.103)	(0.003)
ECI	0.945**	0.978**	-0.029	0.033*
	(0.452)	(0.437)	(0.316)	(0.019)
POPDEN	-0.001***	-0.001***	-0.001***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
$POPDEN^2$	0.000***	0.000***	0.000***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
GROWTH	-0.115	-0.060	0.158	-0.011
	(0.273)	(0.279)	(0.231)	(0.015)
HK	-0.748***	-0.556***	-0.374**	-0.024***
	(0.165)	(0.163)	(0.159)	(0.006)
HK^2	0.341***	0.292***	0.175*	0.012***
	(0.092)	(0.093)	(0.092)	(0.004)
TRADE	0.001***	0.001**	0.001***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Regional dummies	Yes	Yes	No	Yes
Industry dummies	Yes	Yes	No	Yes
N	67485	67485	67485	67485
Pseudo R^2	0.080	0.081	0.012	0.031
LR test (p-value)			0.560	
Brant test (p-value)				
All var			0.361	
KET			0.763	
KETS*CITKETS			0.775	
CIT			0.106	

Clustered (at NUTS3 region and two-digit industry level) standard errors in parentheses. All the estimates include a constant term. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7. Marginal effects: 2008-10

		Marginal Change	
TSD	Replication	Transplantation	Total
KETS	-0.001***	-0.000***	-0.001
	(0.000)	(0.0000)	
KETS*CITKETS	0.015***	0.004***	0.019
	(0.000)	(0.000)	
Total	*0.014*	*0.004*	*0.018*
		+SD change	
	Replication	Transplantation	Total
KETS	-0.024***	-0.007***	-0.031
	(0.000)	(0.0000)	
KETS*CITKETS	0.128***	0.054***	0.182
	(0.000)	(0.000)	
Total	*0.014*	*0.004*	*0.151*

Table 8. Ordered logit estimates, by single KET (2004-07)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	TSD	STD	TSD	STD	TSD	STD	TSD	STD	TSD	STD	TSD	STD
CITKETS	-1.449**	-1.298**	-1.224**	-1.113*	-0.742	-0.725	-0.793	-0.725	-0.729	-0.667	-0.850	-0.771
	(0.582)	(0.583)	(0.594)	(0.595)	(0.549)	(0.551)	(0.551)	(0.553)	(0.548)	(0.550)	(0.555)	(0.555)
AMT	-0.059***	-0.047***										
	(0.008)	(0.008)										
AMT*CITKETS	1.566***	1.299***										
	(0.217)	(0.220)										
ADV			-0.012***	-0.010***								
			(0.003)	(0.003)								
ADV*CITKETS			0.321***	0.262***								
			(0.090)	(0.090)								
BIOTECH					-0.003	-0.009						
					(0.010)	(0.010)						
BIOTECH*CITKETS					-0.087	0.235						
					(0.362)	(0.332)						
NANOEL							-0.027***	-0.022**				
							(0.009)	(0.010)				
NANOEL*CITKETS							0.733***	0.631**				
							(0.264)	(0.288)				
NANOTECH									-0.708***	-0.498**		
									(0.221)	(0.211)		
NANOTECH*CITKETS									19.756***	14.087**		
									(6.295)	(6.019)		
PHOTO											-0.018***	-0.012**
											(0.005)	(0.005)
PHOTONICS*CITKETS											0.412***	0.311**
											(0.159)	(0.145)
							omitted					
N	63449	63449	63449	63449	63449	63449	63449	63449	63449	63449	63449	63449
Pseudo R^2	0.164	0.148	0.163	0.147	0.163	0.146	0.163	0.147	0.164	0.147	0.164	0.147

All the estimates include also a constant term and the following variables: ECI, DEN, DEN^2, GROWTH, HK, HK^2, TRADE. Cluster (at NUTS3 region and two-digit industry level)-robust standard errors in parentheses. *** p<0.01 ** p<0.05 * p<0.1.

Table 9. Ordered logit estimates: large urban zones

	2004-07				2008-10	
	TSD (LUZ=0)	TSD (LUZ=1)	STD (LUZ=0)	STD (LUZ=1)	TSD (LUZ=0)	TSD (LUZ=1)
	(1)	(2)	(3)	(4)	(5)	(6)
KETS	-0.004	-0.014***	-0.007	-0.012**	-0.013	-0.013***
	(0.013)	(0.005)	(0.013)	(0.005)	(0.012)	(0.005)
CITKETS	0.331	-1.743	0.869	-1.502	1.678	2.236
	(2.162)	(2.044)	(2.370)	(2.223)	(1.479)	(1.633)
KETS*CITKETS	-0.152	0.395***	0.019	0.334**	0.127	0.347***
	(0.370)	(0.136)	(0.393)	(0.151)	(0.353)	(0.127)
ECI	0.590**	0.049	0.709***	0.194	0.985*	-0.011
	(0.268)	(0.203)	(0.265)	(0.817)	(0.479)	(0.987)
POPDEN	-0.001**	-0.001***	-0.002***	-0.001*	-0.003***	-0.001**
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
$POPDEN^2$	0.000	0.000***	0.000**	0.000	0.000***	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GROWTH	-0.934	0.669	0.027	0.031	0.092	-2.763**
	(0.722)	(0.511)	(0.752)	(1.333)	(0.353)	(1.083)
HK	-80.13***	-19.20**	-58.04**	2.969	-0.040**	-0.882***
	(0.445)	(9.740)	(30.43)	(18.95)	(0.266)	(0.308)
HK^2	123.3***	26.63*	89.06***	-3.462	-0.027	0.584**
	(0.668)	(15.02)	(47.26)	(27.93)	(0.136)	(0.250)
TRADE	0.001*	0.003***	0.001*	0.002	0.001*	0.002***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	31815	31634	31815	31634	33194	34291
Pseudo R^2	0.144	0.190	0.096	0.185	0.075	0.101

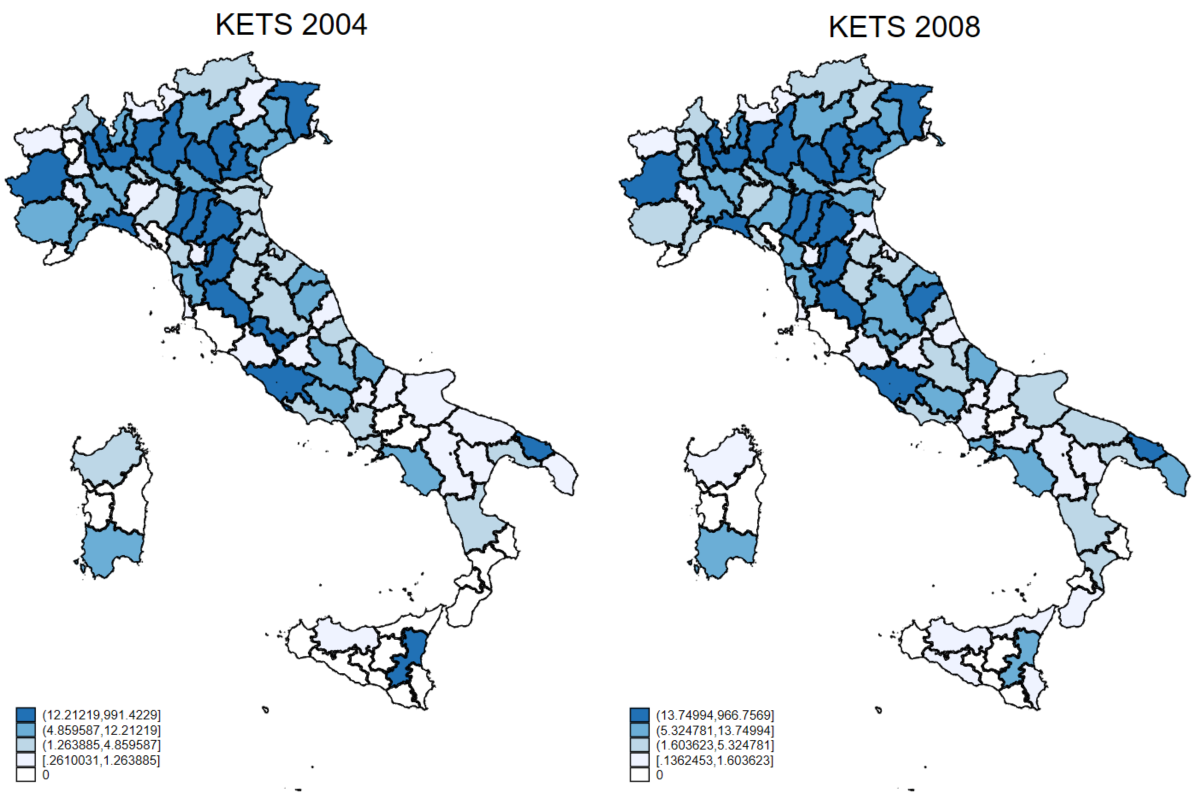
All the estimates include also a constant term. Cluster (at NUTS3 region and two-digit industry level)-robust standard errors in parentheses. *** p<0.01 ** p<0.05 * p<0.1.

Table 10. IV-GMM estimates: Lewbel (2012) approach

	2004 - 2007				2008 - 2010		
	TSD	TSD	TSD	STD	TSD	TSD	TSD
	(1)	(2)	(3)	(4)	(7)	(8)	(9)
KETS	-0.000***	-0.000***	-0.002***	-0.000***	-0.000***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CITKETS	-0.064**	-0.072	-0.009	-0.044***	-0.025	0.069	0.148
	(0.032)	(0.082)	(0.125)	(0.017)	(0.023)	(0.053)	(0.116)
KETS*CITKETS	0.006**	0.013***	0.053***	0.005***	0.007***	0.009***	0.027***
	(0.002)	(0.003)	(0.009)	(0.001)	(0.002)	(0.002)	(0.005)
POPDEN			-0.000***				-0.000***
			(0.000)				(0.000)
			omitted			*omitted*	
Regional dummies	Yes	No	No	Yes	Yes	No	No
Industry dummies	Yes	No	No	Yes	Yes	No	No
N	63449	63449	63449	63449	67485	67485	67485
Centered R^2	0.169	0.004	0.001	0.116	0.029	0.003	0.101
KP F statistics	5.3e+04	2.1e+04	22.79	5.3e+04	5.0e+04	3279.4	44.86
Hansen J	0.016	0.082		0.589	0.118	0.000	
Endogeneity test (p-value)	0.230			0.314	0.118		

All the estimates include also a constant term and the following variables: ECI, DEN, DEN^2, GROWTH, HK, HK^2, TRADE. Cluster (at NUTS3 region and two-digit industry level)-robust standard errors in parentheses. *** p<0.01 ** p<0.05 * p<0.1

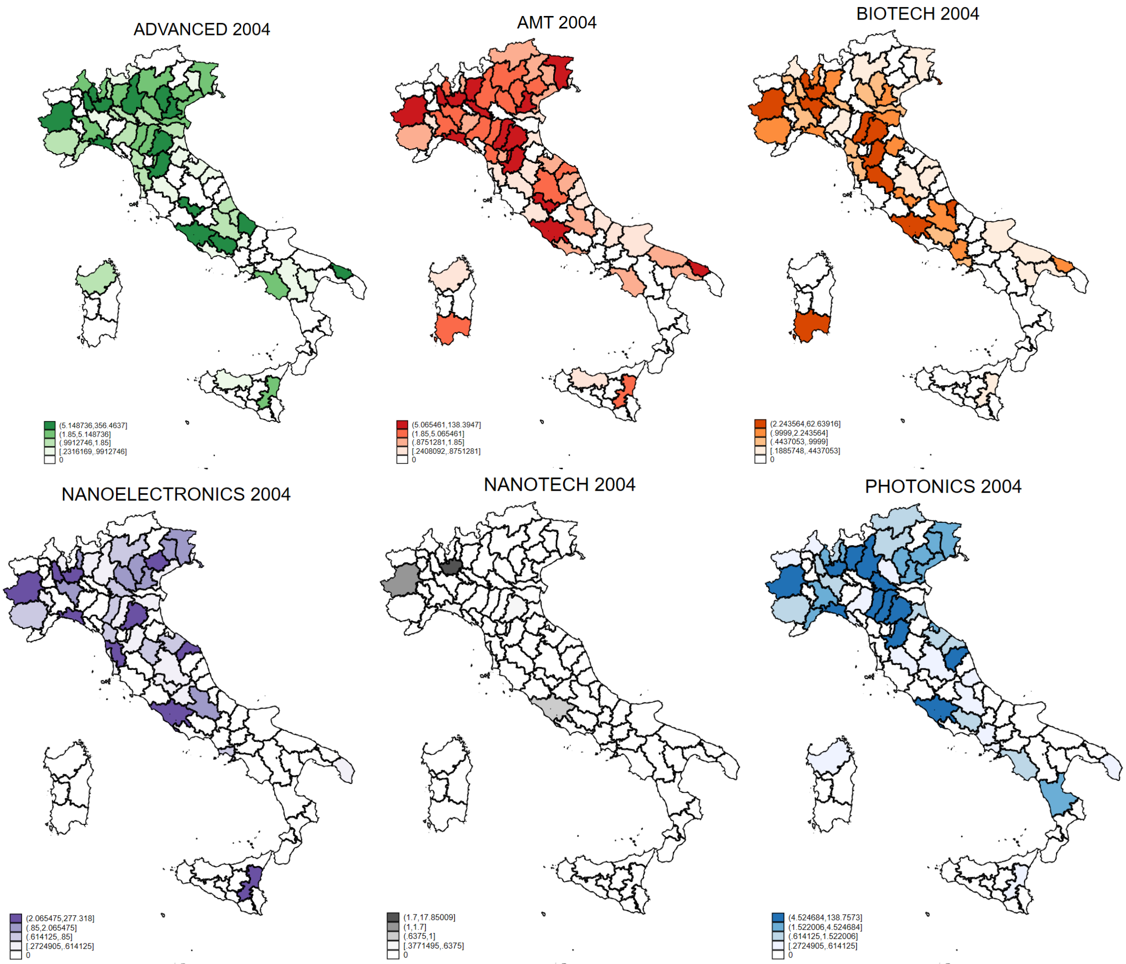
Figure 1 – The geography of KETs



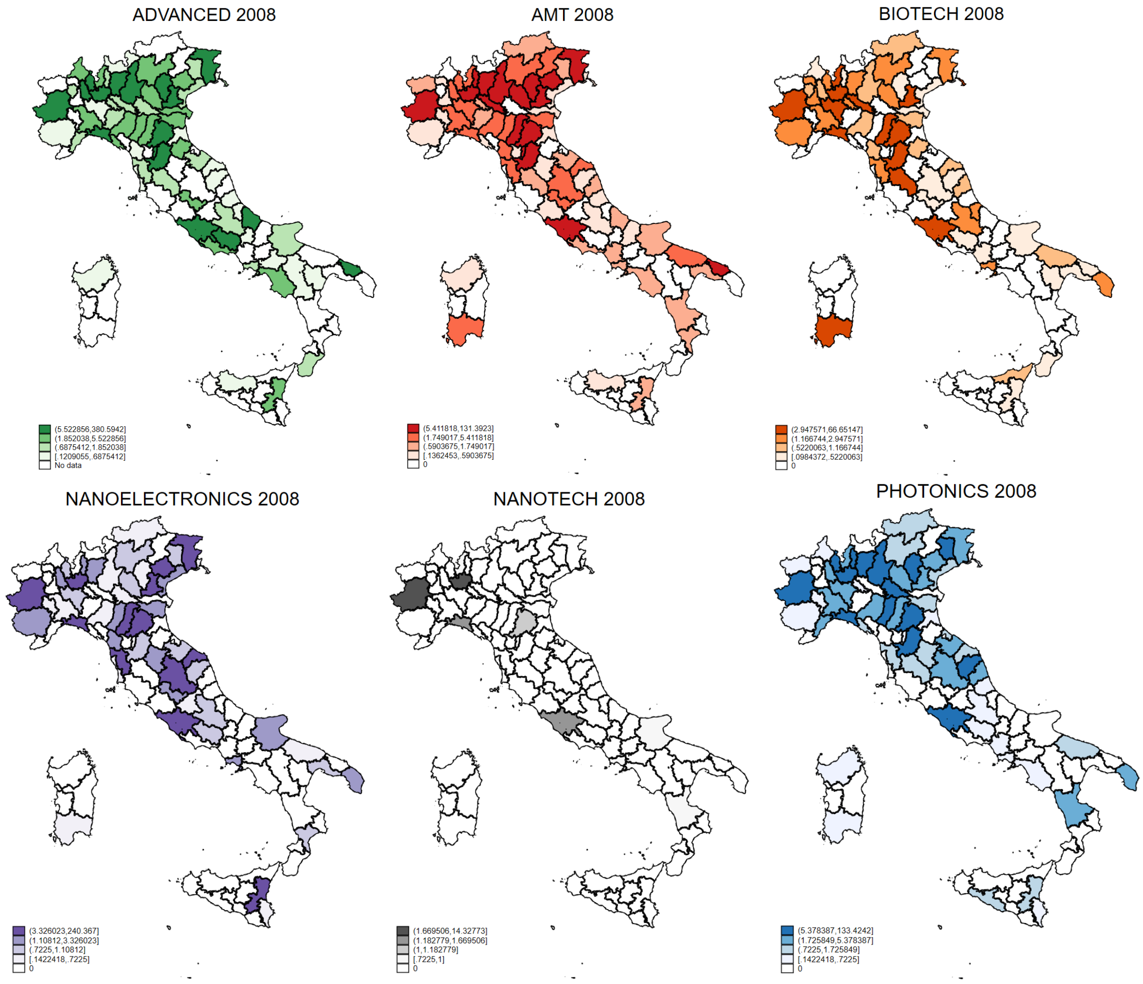
Source: author's elaborations from OECD-Regpat data.

Figure 2 – The geography of the six KETs

1995-2004



1995-2008



Source: author’s elaborations from OECD-Regpat data.