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

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This version: September 2019

Abstract

This paper investigates the role that Key-Enabling-Technologies (KETs) play in the regional diversification of economic activities, by retaining both its place- and path-dependence. Considering their general-purpose properties, we maintain that KETs drive the different trajectories that regions could follow to move from a 'replicative' (place- and path-dependent) diversification to a diversification marked by 'saltation' (at spatial and technological level). Using an original dataset for Italian NUTS3 regions in two periods of time (2004-07 and 2008-10), we estimate a series of ordered logit models, in which the region propensity to move across industry diversification patterns depends on its endowment of KETs knowledge. A larger presence of KETs in the region corresponds to its higher capacity to move towards the more 'unrelated' patterns of diversification we observe in the sample. However, this occurs providing KETs knowledge gets combined with other non-KETs knowledge in the region, and with several nuances.

Keywords: diversification patterns, Key-Enabling-Technologies, ordered logit.

JEL: R11, R58, O31, O33

Acknowledgments: We thank the participants to: the 2018 SMARTER Conference in Seville, the 2018 ENEF meeting in Brighton, the 2019 lunch seminar series of the Department of Economics and Management, University of Florence, the 2019 seminar series of the JRC-EC of Seville, the XXII 2019 Uddevalla Symposium of L'Aquila (GSSI).

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1. Introduction

A large body of research in economic geography has shown that the *relatedness* to existing economic activities and technologies is an important driver of the regional capacity to diversify into new ones (Boschma, 2016) and to 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). The so-called "regional branching" has been claimed to be a pattern of regional diversification with lower search costs and inferior failure risks than an unrelated one (Balland et al., 2018). On the other hand, relatedness can be a double-edged sword, which limits the exploration of new growth opportunities and, at the worst, locks the region in the domain of its extant activities (Saviotti and Frenken, 2008). For these reasons, evidence of unrelated 'jumps' in industry-path creation has also attracted attention (e.g. Isaksen, 2015; Isaksen and Trippl, 2014; Hassink et al., 2019) and the need has emerged to put more focus on "the conditioning factors that facilitate more […] unrelated diversification in regions" (Boschma, 2016, p. 6).

The present paper contributes to this research by addressing two gaps in the existing literature (see Boschma, 2016). The first gap concerns the relative neglect of the socio-technical evolution that mark the industries in which regions specialize and diversify (Boschma, 2016, p. 9). Indeed, while regions enter into new industries, the knowledge-base of the latter also evolves and adds to the spatial dimension of diversification a new technological dimension, which is unfortunately neglected by diversification studies. Following Boschma et al. (2017), we try to remedy this gap by considering, for the first time in a systematic study, that the radicalness/incrementality of socio-technical development at the industry level can differently modulate the patterns through which related and unrelated diversification occur at the spatial level. In brief, we retain and empirically inspect that four, rather than two (i.e. related vs. unrelated), diversification patterns – termed 'replication', 'exaptation', 'transplantation' and 'saltation' – emerge by crossing spatial relatedness/unrelatedness with technological path-dependence/path-creation.

The second gap we address concerns the relatively scarce attention paid so far to those regional "bridging" factors, in particular of technological nature, which favor the 'complementarity' among local activities, through whose (re)combination diversification has been claimed to occur (Boschma, 2016, p. 10). Following Montresor and Quatraro (2017; 2019), we argue that Key Enabling Technologies (KETs) — such as the six recently identified by European Commission (2012)[1] — could

[1] That is, industrial biotechnology, nanotechnology, micro- and nanoelectronics, photonics, advanced materials, and advanced manufacturing technologies.

have an important role in this respect. In particular, we claim that, by allowing regions to undertake a more explorative (less relatedness dependent) kind of diversification, KETs could account for their capacity to escape the risk of lock-in by moving from ‘replication’ to ‘saltation’ in a gradual way: either by passing through the ‘transplantation’ of an existing regime in developing related activities – a “technology-upon-space” diversification trajectory – or through the ‘exaptation’ of a new niche by drawing on related capabilities – a “space-upon-technology” diversification trajectory.

We look at this 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 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[2] is regressed against its KETs endowment, the extent to which other (non-key-enabling) technologies draw on them, and on a series of additional regional characteristics. We find that a larger presence of KETs in the region corresponds to its higher capacity to move towards the more ‘unrelated’ patterns of diversification we observe in the sample. However, this occurs providing KETs knowledge gets used and combined to obtain other non-KETs one. Results hold for both types of diversification patterns, although to a larger extent with respect to a “technology-upon-space” diversification trajectory, in both periods, and are robust to several controls.

The rest of the paper is structured as follows. Section 2 illustrates the background literature of the paper. Section 3 presents the baseline empirical application and Section 4 discusses the estimation results. Section 5 includes some robustness tests. Section 6 concludes by presenting the research and policy implications.

2. Background literature

In evolutionary economic geography, the empirical analysis of unrelated regional diversification has generally treated it as a complement to the benchmark case of related diversification.[3] In turn, relatedness has been mainly accounted with the similarity between new and pre-existing regional activities in terms of their required ‘capabilities’ (for the different specifications of these capabilities, see Boschma, 2016). On this basis, the evidence of unrelated diversification has been mostly

[2] From the benchmark case of no-diversification to the radical one of saltation, either by adding technological (new niches) or spatial (unrelatedness) newness to replication.
[3] Its analysis has been more focal in the literature about new industrial path creation within regions, but with relatively less systematic empirical methodologies (e.g. case-studies and dedicated surveys) (Hassink et al., 2019).

collected in an indirect way, by looking for those factors, which could attenuate the impact of relatedness on the regional capacity to diversify. While a variety of conditions have emerged in this respect,[4] 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 spatial one, on which evolutionary economic geography has focused so far. This second dimension refers to the 'socio-technical regimes' that characterize the economic 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). At a certain moment in time, each sector reveals a consistent 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 allow the relevant actors to familiarize with its novelties (Coenen et al., 2010; Geels, 2002).

While connected to the technological system that underpins a sector, both regimes and niches 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 this social nature, both regimes and niches do have a spatial nature too, which poses regions in front of a technological 'path dependence' that interacts with the 'place dependence' of the development of local capabilities (i.e. relatedness). Their combination yields different patterns of

[4] These conditions comprehend, among the other: 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).

regional diversification, depending on the extent to which its radicalness along the spatial 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, 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.[5] 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.

Insert Table 1 about here

2.2. Relatedness in-between similarity and complementarity: KETs and regional diversification

The idea of relatedness entails an important dimension of 'complementarity' between local capabilities, 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.

Complementarity is also pivotal when, following Boschma et al.'s (2017) taxonomy, the technological dimension of regional diversification is considered (Section 2.1). According to the "bricolage" mode of creating new industry-paths (Garud and Karnøe, 2003), complementarity

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

differentiates the development of a new technological niche – passing through an experimental alignment of diverse and distributed sets of technologies and institutions (low complementarity) – from the continuation of an existing regime – based on the exploitation of the coherence among technologies and institutions that have become established and vested (high complementarity), respectively.

Extending the analysis of relatedness from a similarity to a complementarity perspective, the search for the determinants of regional diversification and of its various patterns extends to the factors that such a complementarity can enable or eventually reinforce. Among the different factors that have been identified,[6] an important complementarity enabler is represented by the regional endowment of technologies that have a 'general purpose' (GP) 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. As some recent studies have shown (Montresor and Quatraro, 2017; 2019), these technologies have some special features, which can render the process of regional diversification less bounded by the relatedness between new and pre-existing activities. The same features make of KETs 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 GP development pattern (Bresnahan, 2010), following which inventions typically co-occur along with an innovative application for them. Thanks to this property, regional activities 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. The second distinguishing feature of KETs is their horizontal application pattern, which covers the entire spectrum of activities of a regional economy. By moving the entire technological frontier of the region ahead (Bresnahan, 2010), KETs can actually provide it with an extra buffer of knowledge, 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 appears more nuanced than it has been previously ascertained (Montresor and Quatraro, 2017). First, because of their nature, KETs can be expected to be more enabling of non-

[6] 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).

replicative patterns of diversification than replicative ones, which could be even disfavored by their use. Second, KETs are possibly more enabling of a transplantation kind of diversification than of an exaptation or even a saltation one. The latter are conditional on the KETs capacity to generate re-combinations, whose novelty extends beyond the regional boundaries, which appears harder given the regional specificity of their endowment. In synthesis, our first expectation is that, while being a driver of regional diversification at large, KETs should differently affect its different patterns and thus possibly explain their heterogeneous geographical distribution.

A second expectation concerns the role that KETs could have in driving an 'ideal' strategy of diversification, which escapes lock-in situations and embarks in higher opportunities of long-term development over time: that is, the shift potentially undertakable by a region from a replication to a saltation pattern (Boschma et al., 2017). Given the cumulative and path-dependent nature of regional dynamics, the same transition would be 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, learning-by-adding a novelty component at the time and passing through one of the other two diversification patterns. Regions could thus go for one of two transition trajectories (see Table 1): i) 'technology-upon-space' diversification – intermediated by 'transplantation' – in which they first exploit an existing (global) regime to diversify their economic activities into unrelated regional domains, and then "stretch" the novelty to the technology level by entering a new niche; ii) "space-upon-technology' diversification – intermediated by ' exaptation' – in which regions first enter a new technological domain (niche) to diversify "around" their extant economic activities, and then "expand" the new technology to get into unrelated regional domains too.

As both diversification trajectories entail a progressively more novel recombination of local activities, thanks to their two complementarity properties KETs could be expected to help in both respects. Furthermore, as both place- and path-dependence are contrasted along the transition, although following a different sequence, we do not have arguments to expect the KETs 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 arguments 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 argue that the diversification driving role of KETs increases with the extent to which their knowledge is directly used in and by other technological domains. Indeed, this use could favor the direct 'exposition' of these technological domains to the work of general-purpose technologies like KETs and thus increase the ensuing capacity of favoring novel knowledge re-combinations through it. In the light of that, the regional 'use' of KETs[7] can be expected to positively moderate, if not even conditioning, the impact of KETs on the regional diversification trajectories that we have identified.

3. Empirical application

3.1. Data

Our empirical application refers to 103 Italian NUTS3 regions (i.e., provinces), for which we have been able to combine two sources of data. The first is the Statistical Archive on Active Firms (*Archivio Statistico Imprese Attive – ASIA*) provided by the Italian Statistical Institute (ISTAT). From this dataset 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), in order to measure our focal diversification patterns (see Section 3.2). Although data are available from 2004 to 2010, a statistical break occurred in 2008 and forced us to split the observation period into two sub-periods: 2004-07 and 2008-10.[8] While this impedes us to carry out a dynamic analysis, on the other hand, it enables us test our arguments across the business cycle, i.e. in the pre-crisis (2004-07) and during the financial crisis period (2008-10). In the former period, we count 756 five-digit industries distributed across 103 provinces, for a total amount of 63,449 observations[9], while in the latter the number of five-digit industries is 805 and the relative observations 67,485.

To measure the regional endowment of KETs, we have used the OECD-REGPAT database. Following the use of patents as proxy of new knowledge advancements in regions (Acs et al., 2002), and aware of the relative limitations (Nagaoka et al., 2010), from this dataset we have drawn the number of

[7] In the patent-based metrics that we will follow in our empirical application, such a use could be read in terms of citations that local non-KETs make to KETs.

[8] In 2008 ISTAT followed EUROSTAT instructions and revised the industry classification system, passing from ATECO 2002 (i.e. NACE Rev. 1.1) to ATECO 2007 (i.e. NACE Rev 2). As a result, many sectors changed their industry of belonging, passing in some cases from manufacturing to services, or vice versa. Because of these changes, the available industry classifications before and after 2008 are not directly comparable and thus not mergeable at the price of a consistent drop of industry disaggregation.

[9] It should be noted that industries are not uniformly distributed across NUTS3 regions.

KETs patents that regional residents have applied at the European Patent Office (EPO) over the years 1995-2004 and 1995-2008, respectively.[10] KETs patents have been identified with those marked by at least one of the International Patent Classes (IPC) and/or Cooperative Patent Classification (CPC) that the EC feasibility study on KETs (EC, 2012b) has proposed to capture their individual and aggregate diffusion. From the same data-source we have retrieved data on the number of citations that other regional (applied) patents have made to KETs patents, to measure the extent to which the latter are used at the local level.

Finally, we have drawn on other official regional ISTAT statistics to measure additional characteristics of Italian regions to be used as controls in testing our relationship.

3.2 Variables

3.2.1. Dependent variables

Our focal dependent variables try to proxy the two trajectories of transition that the generic region *r* could experience over time – e.g. in-between *t* and *T* – from a replication to a saltation pattern of diversification, either passing through transplantation, $\textit{Tech-Space-Diver}_{rT}$ (trajectory 1 in Table 1), or by exaptation, $\textit{Space-Tech-Diver}_{rT}$ (trajectory 2). As we said, available data refer to two shorts periods of time (2004-07 and 2008-10), with respect to each of which we can just observe whether region *r* has followed, from *t* (2004 or 2008) to *T* (2007 or 2010), one of the four diversification patterns that constitute the transition, rather than the transition itself. In brief, we are uncapable to capture the dynamics of the transition. However, in a cross-sectional setting, we can at least address the region capacity of entering new industries from *t* to *T*, according to a set of diversification patterns that, while concomitant, can be assumed to be progressively more

[10] Although the regionalization of patent data with respect to inventors is usually preferred, as it would denote a closer proximity to the place of the invention, this method has possibly as many limitations as that based on applicants we use. First of all, the problem of 'daily commuting' could make the residence address of the inventor different from that of the workplace, where innovations typically occur. Second, especially in the case of large (and multinational) firms, the address of the inventors could be far from that where its core research and development took place. Third, unlike applicant organizations, whose regional location is more durable, regional inventors are more mobile and could proxy a regional capability of transitory nature. Last, but not least, a given invention is possibly more useful to a region if a local organization owns it, irrespectively from its having been obtained by an inventor in a subsidiary somewhere else.

'diversified' at the same point of time, T. Such a capacity could provide insights about the actual regional ability of moving from one to another pattern of diversification over time.

In order to accomplish such an analysis, we define *Tech-Space-Diver*$_{rT}$ (TSD) and *Space-Tech-Diver*$_{rT}$ (STD) as two ordered variables of four values. Taking value 0 as the benchmark case of no diversification for the region over the period [t - T], values 1 and 3 of these variables are assigned to cases of 'replication' and 'saltation', respectively, while value 2 is assigned, alternatively, to 'transplantation' (for TSD) or 'exaptation' (for STD). As we will illustrate in the following, this methodological choice enables us to look also 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 values of the two ordered variables are determined by following the literature on regional diversification (see, for example, Neffke et al., 2016). In brief, we look at the spatial and technological specificities of the entries into new economic activities that regions show over our two periods of time (2004-07 and 2008-10) through their job creation. To start with, we consider as an entry of region r into a new economic activity, any five-digit industry, j, which is present at the end of the period (in 2007 or 2010), having been absent at its beginning (in 2004 or 2008, respectively). In order to avoid the effect of spurious entries (e.g., spot-like hires), an employment threshold is set at the median level of employment for the whole sample of newly created five-digit industries, which correspond to 3.5 in 2004-07 and 2.13 in 2008-10. Accordingly, we consider as a "true" entry for the sake of diversification, a new five-digit industry with a number of employees equal to or higher than the corresponding median.[11]

The identified regional entries are then classified along our two dimensions. Looking at the spatial dimension – the two columns of Table 1 – we consider as '*related'* ('*unrelated*'), any 5-digit entry at T (2007 or 2010) occurred within a three-digit industry that already existed (did not exist yet) in the region at time t (2004 or 2008, respectively).[12] Focusing on the technological dimension – the two

[11] As a robustness check, we have also computed the employment medians for each and every new five-digit industry and consider as true entry any one of them with a number of employees larger than the correspondent median. Tables A1 and A2 in Appendix show that the results are mainly robust to the use of different employment thresholds. An even higher threshold in the number of employees would have been preferable to detect regional diversification. However, making an industry-entry more stringent (e.g., five employees or more) would entail to halve the amount of entry events and hamper the observation of any other diversification pattern than replication.

[12] As a robustness check, in order to discriminate between a related and an unrelated entry, we have also used the location quotient. Accordingly, we consider as related (unrelated), a five-digit entry occurred in a three-digit industry of specialization (de-specialisation) for the region; that is, a three-digit industry with a location quotient equal or higher (lower) than 1. Although results do not change, by adopting this approach we observe more cases of transplantation

rows of Table 1 – we try to consider the technological "World" in which regions operate. Although the extant socio-technical regime (i.e., the World) with which regions deal is obviously defined on a global scale, data constraints forced us to refer to the (much) smaller world represented by the country in which the regions are located, Italy. Accordingly, we classify as '*new to the World*' ('*known to the World*'), and thus revealing a new '*niche*' (an existing '*regime*'), any new 5-digit entries of region *r* at time *T* (2007 or 2010) within a three-digit industry, which did not (did already) exist(ed) in the country at *t*. 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, $\textit{Tech-Space-Diver}_{rT}$ and $\textit{Space-Tech-Diver}_{rT}$, as follows:

- *Replication*: a 5-digit entry at *T*, occurred in a 3-digit industry that already existed at *t*, both in the region and in Italy (neither new to the region, nor to the World);
- *Transplantation*: a 5-digit entry at *T*, occurred in a 3-digit industry that did not exist in the region, but already existed in Italy at *t* (new to the region, but not to the World);
- *Exaptation*: a 5-digit entry at *T*, occurred in a 3-digit industry that already existed in the region, but did not in Italy at *t* (new to the World, but not to the region);
- *Saltation*: a 5-digit entry at *T*, occurred in a 3-digit industry that did not exist in *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 across our two periods. As expected, the picture is different between the two. Along the pre-crisis period (2004-07), Italian provinces show all the four cases of diversification. However, the occurrence of *saltation* is rare and concentrated in one single three-digit industry (the ATECO code 652, "other financial intermediation"). This suggested us not to include it in the first period, and to build up our dependent variables using only the other three diversification patterns. In the aftermath of the economic crisis (2008-10), the number of entries drops substantially, and we do not register any case of exaptation and saltation. Accordingly, we are incapable to identify the correspondent *Space-Tech-Diver* variable and we thus use only *Tech-Space-Diver*.

than replication, which seems inconsistent with the stylized fact of regions more likely to diversify in related rather than in unrelated activities. Moreover, we observe only 21 cases of exaptation in 2004-07.

To recap, the dependent variables that we use in the empirical application are the following two: for both periods of time, TSD_{rT}, 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, STD_{rT}, taking value 0 in the case of no-diversification, 1 in the case of replication and 2 in the case of exaptation.

Insert Table 2 about here

3.2.2. Focal regressors

Our focal explanatory variable is region *r*'s endowment of KETs at the beginning of each of the two sub-periods ($KETs_{rt}$). Following innovation studies, we proxy it with the regional stock of KETs patents in our two focal periods, by applying the perpetual inventory method to the flows of KETs patents (*PATKETst*) over the years 1995-2004 and 1995-2008, respectively. We thus use the following formula:

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

where the depreciation rate δ is, consistently with extant studies (e.g. Montresor and Vezzani, 2015) set equal to 0.15.

In order to disentangle the role of the six individual KETs identified by the EC, we repeat the same procedure and build up the separate patent stocks of: advanced manufacturing technologies (AMT_{rt}), advanced materials (ADV_{rt}), biotechnology ($BIOTECH_{rt}$), nanoelectronics (*NANOELrt*), nanotechnologies ($NANOTECH_{rt}$) and photonics ($PHOTO_{rt}$).

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

The total stock of KETs is larger in Northern regions, even though we find evidence of substantial values of it in some Central and Southern regions too. As far as 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 discussed in Section 2, another important variable is represented by the 'use' that other local technologies make of KETs. Following the patent literature (Trajtenberg, 1990), we proxy this use by looking at the citations that the patents in the non-KETs domains make to KETs' patents. Following this logic, we build up the variable $CITKETs_{rt}$ by summing the number of these citations per year and by dividing it by the total amount of regional citations in our two focal periods (1995 – 2004 and 1995 – 2008). It should be noticed that, as this latter variable obviously depends on the local production and availability of the non-KETS regional 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.

3.2.3. Other regional characteristics

The diversification trajectories that regions follow might also depend on other characteristics than KETs. Looking at previous studies about the determinants of related vs. unrelated diversification, we maintain that three regional factors should be salient: i) the level of economic complexity of the focal region (Pinheiro et al. 2018; Petralia et al., 2016: Balland et al., 2018); ii) its level of human capital (Gilbert & Campbell, 2015; Lester, 2007; Tanner, 2016; Consoli et al., 2019); iii) and the presence of urbanization and agglomeration economies.

As for the level of 'economic complexity', following the seminal idea by Hidalgo and Hausmann (2009), for each region *r* we calculate, at the beginning of each of the two periods, an indicator, ECI_{rt}, which combines the diversity of the industries in which the region has a revealed comparative advantage, and the ubiquity of these industries. Using regional export data from the Coeweb archive provided by ISTAT, the ECI is based on three-digit industries in which each province has a revealed comparative advantage. We compute the revealed comparative advantage (RCA) as follows:

[2] $RCA_{pi} = \frac{X_{pi}}{\sum_p X_{pi}} / \frac{\sum_i X_{pi}}{\sum_{pi} X_{pi}}$

where X_{pi} represents the value of exports of province *p* in (three-digit) industry *i*; and where the province has a revealed comparative advantage in that industry, if the index is higher than 1 (RCA>1). From the RCA index we derive the ubiquity and diversity measures: the former corresponds

to the number of provinces with comparative advantage in an industry, while the latter to the number of industries in which a province has a comparative advantage. Putting these two measures together in a proximity matrix between industries and provinces, we obtain the ECI as follows:

[3] $ECI_p = \frac{K_p - \langle K \rangle}{std(K)}$,

where K_p represents the eigenvector associated with the second largest eigenvalue of the proximity matrix, obtained using the method of reflections, while $\langle K \rangle$ is its average.

Coming to the other variables, the human capital stock of the region at the beginning of each period, HK_{rt}, is measured with the number of graduated students (bachelor and master's degrees) in the resident population, using ISTAT data from ASTI (A*tlante Statistico Territoriale delle Infrastrutture*). Urbanisation economies are instead proxied with the population density of the region, $POPDEN_{rt}$, measured by its resident population per km^2.

Two further sets of regressors are inserted to control for some additional issues. On the one hand, a potential problem of reverse causality could emerge, if the mostly KETs-endowed regions are also those where the rate of firm creation is traditionally the highest: indeed, regional diversification could be the source of this industrial demography. To control for this issue, we include a variable measuring the relative firms' birth rate in the regions. Using data from the Register of companies provided by the Italian Chambers of Commerce through Infocamere, we build up and use the number of newly active companies over the total amount of registered companies in 1995 in each NUTS 3 region (*BIRTH RATE*). On the other hand, as results could be affected by the business cycle and the international climate regions operate within, we control for the growth rate of regional value added per capita ($GROWTH_{rt}$) over the three years before *T* (i.e., 2001-2004 and 2005-2008), and for the regional trade openness ($TRADE_{rt}$), given by the sum of imports and exports on regional value added, respectively.

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

Insert Table 3 about here

3.3. Econometric strategy

We start by estimating the following two models:

[4] $Y_r^{2004/07} = \beta_0 + \beta_1 KETS_r^{95-0} \;\; + \beta_2 CITKETS_r^{95-04} + \beta_3 KETS_r * CITKETs_r + \boldsymbol{X_r'^{2004}\beta_4} + \varphi_R + \mu_j + \varepsilon_r$

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

In equations [4] and [5], Y_{rT}, refers to our two ordinal diversification variables (*TSD* and *STD*) for region *r*, $KETs_{rt}$ and $CITKETs_{rt}$ are our two focal regressors, and vector $\boldsymbol{X_{rt}}$ 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. The term $CITKETs_{rt}$ is also interacted with $KETS_{rt}$ in order to test for the moderating role of the use of KETs on their impact on *Y*.

In order to see whether our regional diversification trajectories are differently driven by some specific KETs of the six, equations [4] and [5] are first estimated by using the generic stock of KETs and then by replacing it with the single regional endowment of AMT_{rt}, ADV_{rt}, $BIOTECH_{rt}$, $NANOEL_{rt}$, $NANOTECH_{rt}$ and $PHOTO_{rt}$. Due to their high correlation, we insert them separately in the models.

Since Y_{rT} is built up as an ordered variable, we estimate equations [4] and [5] by using an ordered logit model, and we cluster the standard errors at NUTS3 region-two-digit industry level. We test for the validity of the parallel lines (or proportional odds) assumption by using both a likelihood ratio (LR) and a Brant test. In case of rejection of the null hypothesis of correct specification of the model, 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).

4. Results

The first set of results refer to the first period, 2004-2007, with respect to which Table 4 shows the ordered logit and OLS estimates for *Tech-Space-Div* (TSD, Columns 1-3) and *Space-Tech-Div* (STD, Columns 4-6). With respect to each trajectory, the first column (1 and 4, respectively) refers to the specification that includes only the stock of KETs as main regressor, while in the remaining columns (2-3 and 5-6, respectively) the results include the interaction between *KETs* and *CITKETs*. In Column

2, both the LR and the Brant tests do not reject the null hypothesis of correct specification of the model: therefore, the parallel lines assumption is valid in the TSD case. Results in Column 5, instead, show that both the tests reject the same null hypothesis for STD. However, 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 are not (Williams, 2016).

At the outset, the stock of regional KETs alone never affects the probability of a region to diversify into progressively unrelated industries. A significant effect emerges only when the stock of KETs is interacted with citations from other technologies available in the region.[13] To be sure, columns 2-3 and 5-6 show that, in absence of any citation (i.e. when *CITKETS*=0), the KETs' stock even reduces the regional propensity to diversify through new entries, being apparently more functional to the conservation of the existing economic structure of the region. In the presence of citations, instead, the diversification propensity at stake increases, more significantly in the case of TSD than for STD diversification, thus counteracting the negative effect of the sole KETs regressor: its total net marginal affect thus requires to be considered, as we will do in the following.

This is a first interesting result. The sole creation of KETs knowledge is not enough to make regions follow the trajectories of diversification we are investigating. For that to happen KETs need to be combined with local non-KETs knowledge, through its drawing on KETs in its inventing activities. Consistently with the original message of the European Commission (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.[14]

Insert Table 4 about here

Table 5 shows the marginal effects related to the estimates of Table 4. We report both the reaction of our dependent variable to a marginal change (i.e. 1%) in the regressors and the reaction to a one

[13] As a further check about the role of this use, we also replace the share of KETs citations with the cumulative amount of citations of KETs patents by the other patents between 1995 and 2004, in the first period, and 2008, in the second one. Results remain robust to such a change.

[14] Among the other regressors, Table 4 shows that the probability of (progressively more) unrelated diversification increases with trade openness and, although in a non-linear way, with population density. No significant effect is found for the other control variables.

standard deviation change. As for the TSD trajectory (as from Columns 2 of Table 4), we note that the positive marginal effect of *KETS*CITKETS* is always larger than the negative effect of *KETS*, so that the final net effect is positive. More precisely, a 1% (1 standard deviation) increase in KETs endowment corresponds to an average 0.007% (0.05%) increase in the probability for a region to diversify, transiting from replication to transplantation. This means that increasing the stock of KETs from a value of 0 to a value of 38 (i.e. the 90^{th} percentile, corresponding to the province of Brindisi in Apulia) would increase the probability of unrelated diversification by an average 26%, while increasing the stock of KETs from 0.622 (the 25^{th} percentile of the province of Foggia in Apulia) to 10.81 (the 75^{th} percentile of the province of Treviso in Veneto) would increase that probability by an average 12%. Instead, raising the stock of KETs from 0 to 991 (the highest value, corresponding to the province of Milan) would increase the probability by almost 700%.

On the other hand, with respect to the other diversification trajectory, that is STD (as from column 5 of Table 4), the marginal effect is consistently lower and amounts to 0.003% (0.011%). As expected, the role of KETs in regional diversification is heterogeneous, being more effective when further radicalness is obtained within an existing technological regime (TSD) than with the creation of a new niche (STD).

Insert Table 5 about here

Moving to the second period of the analysis, 2008-2010, Table 6 confirms the results obtained for the previous period with respect to TSD only, that is, the only trajectory we are capable to observe. Quite interestingly, the citation-weighted role of KETs for regional diversification is confirmed also in a negative phase of the business cycle, thus appearing as a sort of 'structural' driver of it.

Insert Table 6 about here

This result finds confirmation in Table 7, which reports the corresponding marginal effects (referred to Column 2), as these are in line with those reported in Table 5.

Insert Table 7 about here

Finally, Table 8 reports the ordered logit estimates when the endowment of each single typology of KET is included separately. From Columns 1, 3, 5, 7, 9 and 11 we find that only two of them, when combined to the other non-KETs technologies, significantly affect the TSD trajectory, that is, advanced manufacturing technologies and advanced materials.[15] Similarly, Columns 2, 4, 6, 8, 10 and 12, show that the only relevant KET in affecting STD is advanced manufacturing technology. This is a last, but not least, important result, which shows how it is only the two more GPT-line KETs of the group that are capable to exert an effect on the regional propensity to transit across diversification, even in absence of (that is, without considering) the other ones. Quite interestingly, while all the six KETs affect regional technological branching, in general and in the green domain (Montresor and Quatraro, 2017, 2019), their role appears more selective when diversification trajectories are considered in the economic domain.

Insert Table 8 about here

5. Robustness tests and result specifications

In this section, we present a series of robustness tests for the baseline estimations of equations [4] and [5].

5.1. Non-linearities and the role of large urban areas

First, we control for the possible presence of non-linearities in the relationship between KETs endowment and regional diversification patterns. Table 9 shows the ordered logit and OLS estimates where we include, among the main regressors, *KETS* and $KETS^2$. For reasons of space, we omit to show the estimated coefficients of the other covariates, which remain the same with respect to those presented in Table 4. Columns 1 and 2 confirm that the relationship between KETs and TSD is non-linear: specifically, we find it to be negative up to a minimum threshold of 547 (522) KET-patents, beyond which it turns positive. The same result holds in 2008-10 (Columns 5 and 6) and for STD (Columns 3 and 4). Interestingly, we find that only one province, i.e. Milan, corresponds to such a high KETs endowment: this means that only in Milan such a high amount of KETs is capable to

[15] The coefficient of nanotechnologies is only marginally significant.

stimulate regional diversification without being interacted with non-KETs through citations. To do it in all the other regions, KETs need to combine with non-KETs.

Insert Table 9 about here

This result leads us to investigate the role of large urban areas in favoring the role of KETs in regional diversification. To do so, we re-estimate equations [4] and [5] on two different subsamples of regions, including and excluding large urban zones (LUZ), respectively.[16] In this way, we test whether our results are driven by the clustering of patents in the largest metropolitan areas of Italy. Table 10 shows that, for both periods and for both types of regional diversification, the baseline results on KETs hold only in largely urbanized regions, implying that KETS accumulation and effective use are a pretty urban phenomenon.

5.2. Self-selection into KETS

The second robustness test concerns the possible self-selection of Italian NUTS 3 regions into KETs accumulation. It is possible that regions cannot be completely comparable, due to some intrinsic characteristics that are not observable. In this respect, for instance, 19 regions out of 103 do not register any KETs-patent application, and only 25 of them count more than 10 KETs-related patents. To increase the comparability across regions, we proceed as follows. First, we estimate a logit model on our sample of NUTS 3 regions using as dependent variable a dummy that takes the value of 1 if the region is endowed with a positive amount of KETs between 1995 and 2004. Since the process of KETs production, and accumulation, is mainly a science-push phenomenon, as an explanatory variables we use the share of academic professors per million of population ($PROF/POP_{1996}$) in year 1996 and the number of universities per million of population in 1996 ($UNIV/POP_{1996}$), which is the first available year in the ASTI database (data provided by the Italian Ministry of Education and Research).

[16] We define LUZ through a dummy taking the value of 1 when population in the region, in 1996, is higher than the median (i.e. 383,075), and 0 otherwise. We achieve the same results if we define as a LUZ a NUTS 3 region the population of which is higher than 500,000.

We do expect regions more endowed with university personnel and facilities to be more able to accumulate KETS across time.

Once run this first probit estimation, we then drop 23 regions of our sample with a propensity score falling outside the common support (CS). These regions are actually not comparable to the rest in terms of the selected regressor, i.e. share of university professors on total population: looking at the propensity score distribution in Figure 3, these correspond to regions characterized by the presence of the oldest universities in Europe (like Bologna, Padua and Siena) and where this share is particularly high. These are also among the regions with the highest KETs endowment in Italy. Appendix, Table A3, shows the results of the first stage logit estimates.

Insert Figure 3 about here

We also follow an alternative strategy, and we drop from the sample those regions where *KETS*=0, and we re-estimate equations [4] and [5] using only regions with a non-zero KETS endowment in 1995-2004. Table 11 shows the results of the ordered logit estimates for 2004-07.

Columns 1 and 2 show that the baseline results on TSD hold both in regions with KETS>0 and in regions on the common support (i.e. where CS=1). For what concerns STD, instead, we find the same results of Table 4 in regions with KETS>0, whereas the estimated coefficients of *KETS* and *KETS**CITKETS*, despite having the same sign, become not statistically significant in regions on the common support. This implies that, unlike for the TSD regime, the role of KETS in promoting regional unrelated diversification through a STD pattern relies on the presence of regions largely endowed with these technologies.

Insert Table 11 about here

5.3. Reverse causality

As a third robustness test, we address the possible endogeneity of our focal regressor, *KETS*. The relationship between KETS endowment and regional diversification can be affected by unobserved heterogeneity and simultaneity. For instance, it can be that an unobserved shock can affect both

variables, altering the KETs patent intensity of a region and its capability to generate new industries. It could also be the case 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. While the structure of our econometric strategy is already capable to deal with these problematic issues to a certain extent,[17] we address it by adopting an instrumental variable approach, proposed by Lewbel (2012).

This method uses the conditional second moments of our potentially endogenous variables (*KETS, CITKETS* and *KETS*CITKETS*) to address potential endogeneity. Identification occurs when the residuals of the first-stage regression are heteroskedastic and at least a subset of the regressors used for estimating equations [4] or [5] is correlated with the variance of these residuals but is independent from the covariance between these first-stage residuals and the residuals from the second-stage regression. If this condition is satisfied, instruments are computed multiplying the first-stage residuals by the mean-centred regressors. To test for the heteroskedasticity of the first-stage residuals we use a Breusch-Pagan test, where the null hypothesis is that errors are homoskedastic. In addition, we test for overidentification using the Hansen J test, and we use a difference in Sargan statistic to test for the exogeneity of our KETs-related variables.

Table 12 shows two interesting results. First, the sign and significance of the estimated coefficients of *KETS* and *KETS*CITKETS* remain the same as in Table 4 (2004-07) and 6 (2008-10). Second, the difference in Sargan test does not reject the null hypothesis of exogeneity of our KETS-related variables. The strength of the instruments is given by the high Kleiberger-Paap F statistic and by the absence of overidentification as given by the Hansen J test.

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

Insert Table 12 about here

[17] First, we measure the endowment of KETs in a region before the advent of new activities, thus avoiding any type of observable simultaneity between Y_{rT} and *KETS.* Second, by construction, our focal relationship is estimated in two periods, 2004-07 and 2008-10, which refer to a positive and a negative phase of the business cycle, respectively.

5.4. The role of other technologies

A fourth check is carried out to see whether KETs are the only type of technology that drives the regional unrelated diversification that we are observing. To do so, we run a sort of placebo test and we re-estimate equations [4] and [5] using an alternative explanatory variable: the stock of non-KETs technologies (*NON-KETS*), computed aggregating the stock of the IPC classes in the region concerning all the patents except the KETs. In addition, we compute the share of citations that regional non-KETs patents make to other regional non-KETs patents (*CITNONKETS*). In this way, we consider the symmetrical case were, as main regressor, we take both the stock of all the other technologies in the region, and their mutual interaction (*NONKETS*CITNONKETS*), excluding KETs. We do expect these variables not to significantly affect the probability of unrelated diversification: if they were significant, it would imply KETS not to be the only drivers of regional diversification.

Table 13 shows the ordered logit results, for both periods. From Columns 1 (2004-07) and 5 (2008-10), we find that, as for KETs, the regional stock of non-KETs *per se* does not increase the probability of regions to develop new, and progressively more unrelated, activities. As expected, Columns 2, 3, 4 and 6 show that the estimated coefficient of the interaction term is never statistically different from zero: we thus submit that regional unrelated diversification is driven only by KETs.

Insert Table 13 about here

5.5. Spatial autocorrelation

As a further robustness test, we look for the presence of knowledge spillovers across Italian NUTS3 regions, which could make unrelated diversification in region *r* affected by the KETs endowment of neighboring regions. First, we test for the presence of spatial autocorrelation in our KETS-related variables. After summing KETs at the level of each of the 103 provinces, we run a Moran-I test on *KETS, CITKETS* and *KETS*CITKETS*, using the latitude and longitude of the NUTS 3 region to compute the distance matrix and setting 3 and 5 as the upper bounds of the distance band within which regions must be taken as neighbors. The upper part of Table 14 shows that the test never rejects the null hypothesis of spatial autocorrelation.

Second, we test for the spatial autocorrelation in our dependent variables. Since *Y* is measured at (five-digit) industry-NUTS 3 regional level, we first sum the number of entries by type of

diversification pattern (i.e. replication, transplantation and exaptation) at the regional level. In so doing, we obtain the number of *Replication, Transplantation* and *Exaptation* entries in 2004-07. Then, we run the Moran I-test for the three variables: in the bottom part of Table 14 the test rejects the null hypothesis for *Replication* and *Transplantation,* but it does not reject it for *Exaptation.*

Insert Table 14 about here

Taking stock of these indications, we estimate a spatial Durbin model, to check whether the single number of entries by replication and transplantation in region *r* in 2004-07 is affected by KETs in the same region *r* (direct effect) and/or in neighboring regions (indirect effect). Table 15 shows the estimation results: for both types of diversification, we find that the only significant effect is direct and in line with the results shown in Table 4. We conclude that our results are not affected by spatial autocorrelation.

Insert Table 15 about here

5.6. Industry saturation

The final robustness test that we run concerns the role of industry saturation in eventually preventing the regional occupation of new industries. Since the entry of new activities is measured in terms of new five-digit industries based on NACE Rev. 2 classification, it can be that the possibility for a region to further create new, and unrelated, industries depends on the maximum amount of industries that can be coded by ISTAT. To ascertain this, we re-estimate equations [4] and [5] including a variable that measures the difference between the maximum number of industries and the actual number of industries in the region (*INDUSTRY SATURATION*): we do expect that the higher this number, the higher the chances for a region to further generate new industries, and vice versa. Table 16 shows the ordered logit results for 2004-07, that confirm the baseline results of Table 4: the higher the stock of citation weighted KETS the higher the propensity of a region to diversify following a *technology-upon-space* pattern, rather than a *space-upon-technology* one.

Insert Table 16 about here

6. Conclusions

Regional diversification is a complex phenomenon, which combines cumulativeness and path-dependence at both the spatial and the technological level. When these different levels of analysis are combined, heterogeneous patterns of diversification can be identified – in Boschma et al.'s (2017) framework, 'replication', 'transplantation', 'exaptation', and 'saltation' – whose unfolding has not been addressed yet, at least in systematic terms. No attention has been paid so far to the region's capacity of interchanging these diversification patterns for eventually escaping the risk of overcounting on the place- and path-dependence of its techno-economic dynamics. Indeed, while relatedness has been claimed to be a less risky diversification strategy than unrelatedness in terms of chances of success (Balland et al., 2018), the latter could be less risky than the former in terms of chances of lock-in (Saviotti and Frenken, 2008).

Leaving aside the delicate issue of the best alternative between the two, with respect to which we do not take part, in the paper we focus on the determinants of unrelated diversification. We look at the importance that the 'complementarity' between the existing activities of a region has for their recombination into progressively more unrelated ones, in both spatial and technological terms. In particular, we have addressed the role that technologies of a general-purpose nature, like the Key Enabling Technologies (KETs) recently put on the EC policy-agenda, can have in increasing such a complementarity and thus in extending the scope of the recombination into progressively more unrelated patterns of diversification.

We find that the regional capacity of creating new industries according to a set of progressively "more diversified diversification patterns" increases with its endowment of KETs knowledge. However, this does not happen because of the pure knowledge spillovers that the inventive activity in KETs create in the region, but rather because of the use the other technologies make of KETs. This is particularly through for the case of a 'technology-upon-space' type of unrelated diversification, where regions pass from replication to transplantation. Less robust is the evidence for a 'space-upon-technology' type of diversification.

These results hold in two distinct phases of the business cycle, 2004-07 and 2008-10, as well as valid in large urban areas, and are robust to regions' self-selection into KETS accumulation, endogeneity, the role of other technologies, spatial autocorrelation and industry saturation.

In terms of policy, KETs represent an important tool to be placed in the regional policy-kit for diversifying but providing the support to their creation is combined with that to their use. Such a policy implication is particularly relevant for the most urbanized regions, which our Italian empirical application has shown to drive the results. While these regions presumably reach the critical mass of KETs (inventive activities) needed for their relationship with regional diversification to emerge, in absence of an effective use the relationship does not substantiate.

An additional result that has emerged from the analysis is that, as we also expected, KETs have a differential impact on the different patterns of diversification that can be identified by crossing its place and technology path-dependence. KETs helps more in making regions span the boundaries of their local economic activities than those of the socio-technical regime that embraces them on a global (in our case, national) scale. Should regions be willing to prioritize the creation of a radically new technological niche, or to add such an exaptation strategy to a transplantation one based on unrelatedness, KETs would possibly need to be integrated with more technologically enabling tools, such as those in the standard domain of science and technology policy.

While adding to the still relatively 'thin' stream of literature on unrelated diversification, and providing a set of interesting regional policy implications, the results of the paper are not free from limitations. As we said, the most relevant ones are due to the methodological choices that the available dataset imposed us to make: first of all, in capturing the technological World with which regional economies deal with, in our case reduced to their reference country; secondly, in addressing the dynamics of the regional patterns of diversification over time, in our case reduced to two bits of cross-sectional analysis. As is usually the case, the search for additional datasets, possibly with respect to other countries, will be the first step of our future research agenda to address these limitations.

References

Acs, Z. J., Anselin, L., and Varga, A. (2002). Patents and innovation counts as measures of regional production of new knowledge. Research Policy 31 (7): 1069–85. doi:10.1016/S0048-7333(01)00184-6.

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 26pecialization 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. (2013°). 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 27pecialization 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.
Hassink, R., Isaksen, A. and Trippl, M. (2019). Towards a comprehensive understanding of new regional industrial path development. Regional Studies (in press), doi: 10.1080/00343404.2019.1566704.
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 secialization: a European patent-based analysis of the intertwining of technological relatedness and Key Enabling Technologies. Regional Studies (on-line first).

Nagaoka, S., Motohashi, K., Goto, A. (2010). "Chapter 25 – Patent Statistics as an Innovation Indicator", in B.H. Hall and N. Rosenberg (eds.) Handbook of the Economics of Innovation, ISSN: 2210-8807, Vol: 2, Issue: 1, Page: 1083-1127

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 (employment≥median)	1,399	2.20	1,124	1.67
- *Replication*	*942*	*67.34*	*857*	*76.25*
- *Transplantation*	*332*	*23.73*	*267*	*23.75*
- *Exaptation*	*114*	*8.15*	*0*	*0.00*
- *Saltation*	*11*	*0.79*	*0*	*0.00*

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	0.021	0	0.143
	1995-2008	0.022	0.022	0	0.133
HK	2004	0.322	0.034	0.240	0.451
	2008	0.323	0.034	0.240	0.451
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
BIRTH RATE	1995	0.114	0.200	0.053	1.293
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

	TSD			STD		
Method	OLOGIT	OLOGIT	OLS	OLOGIT	OLOGIT	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
KETS	-0.001	-0.019***	-0.0002***	-0.001	-0.010*	-0.000*
	(0.001)	(0.006)	(0.0001)	(0.001)	(0.005)	(0.000)
CITKETS		-1.060	-0.005		-0.313	-0.002
		(1.808)	(0.039)		(1.899)	(0.030)
KETS*CITKETS		0.506***	0.006***		0.261*	0.003*
		(0.155)	(0.002)		(0.154)	(0.002)
ECI	-0.468	-0.334	-0.009	0.022	0.112	0.002
	(0.356)	(0.356)	(0.008)	(0.367)	(0.371)	(0.006)
POPDEN	-0.001**	-0.001**	-0.000***	-0.001*	-0.001*	-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)
GROWTH	0.617	0.627	0.017	0.678	0.717	0.009
	(0.749)	(0.739)	(0.015)	(0.785)	(0.780)	(0.012)
HK	-21.48	-22.57	-0.452	-17.88	-18-14	-0.341
	(15.97)	(16.18)	(0.342)	(14.66)	(14.87)	(0.268)
HK^2	24.60	28.95	0.573	25.72	27.78	0.529
	(24.76)	(25.14)	(0.523)	(21.91)	(22.29)	(0.407)
BIRTH RATE	0.048	0.013	0.001	0.065	0.030	0.000
	(0.228)	(0.231)	(0.005)	(0.240)	(0.243)	(0.003)
TRADE	0.003***	0.002***	0.000***	0.002**	0.001	0.000
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	63449	63449	63449	63449	63449	63449
Pseudo R^2	0.255	0.256	0.158	0.199	0.200	0.154
LR test (p-value)		0.595			0.000	
Brant test (p-value)						
All var		0.443			0.000	
KET					0.019	
CIT					0.722	
KETS*CITKETS					0.019	
BIC (pl)					11588.5	
BIC (npl)					11648.5	

Clustered (at NUTS3 region and two-digit industry level) standard errors in parentheses. All the estimates include a constant term. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The likelihood-ratio (LR) and the Brant test of the parallel lines assumption are based on a model without regional and industry dummies.

Table 5. Marginal effects: 2004-07

		Marginal Change	
TSD	Replication	Transplantation	Total
KETS	-0.000	-0.000	-0.000
KETS*CITKETS	0.005	0.002	0.007
Total	*0.005*	*0.002*	*0.007*
STD	Replication	Exaptation	Total
KETS	-0.000	-0.000	-0.000
KETS*CITKETS	0.003	0.000	0.003
Total	*0.003*	*0.000*	*0.003*
		+SD change	
TSD	Replication	Transplantation	Total
KETS	-0.012	-0.005	-0.017
KETS*CITKETS	0.050	0.017	0.067
Total	*0.038*	*0.012*	*0.050*
STD	Replication	Exaptation	Total
KETS	-0.009	-0.001	-0.010
KETS*CITKETS	0.018	0.003	0.021
Total	*0.009*	*0.002*	*0.011*

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

	TSD		
Method	OLOGIT	OLOGIT	OLS
	(1)	(2)	(4)
KETS	-0.001	-0.017***	-0.000***
	(0.001)	(0.005)	(0.000)
CITKETS		1.193	0.047
		(1.426)	(0.039)
KETS*CITKETS		0.459***	0.005***
		(0.141)	(0.002)
ECI	0.055	0.107	-0.002
	(0.601)	(0.594)	(0.014)
POPDEN	-0.001***	-0.001***	-0.000***
	(0.000)	(0.000)	(0.000)
$POPDEN^2$	0.000***	0.000***	0.000**
	(0.000)	(0.000)	(0.000)
GROWTH	-0.229	-0.221	-0.005
	(0.378)	(0.388)	(0.011)
HK	-0.768***	-0.558**	-0.014***
	(0.208)	(0.216)	(0.005)
HK^2	0.372***	0.308***	0.008***
	(0.114)	(0.117)	(0.003)
BIRTH RATE	0.126	0.105	0.005
	(0.154)	(0.156)	(0.005)
TRADE	0.001**	0.001*	0.000*
	(0.000)	(0.000)	(0.000)
Regional dummies	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes
N	67485	67485	67485
Pseudo R^2	0.080	0.083	0.166
LR test (p-value)		0.066	
Brant test (p-value)		0.115	

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	-0.000	-0.000	-0.000
KETS*CITKETS	0.006	0.002	0.008
Total	*0.006*	*0.002*	*0.008*
		+SD change	
TSD	Replication	Transplantation	Total
KETS	-0.011	-0.003	-0.014
KETS*CITKETS	0.046	0.017	0.063
Total	*0.035*	*0.014*	*0.049*

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	-0.899	-0.289	-0.863	-0.027	0.077	0.141	0.001	0.195	0.082	0.279	-0.052	0.156
	(1.778)	(1.888)	(1.820)	(1.905)	(1.680)	(1.827)	(1.694)	(1.837)	(1.689)	(1.830)	(1.706)	(1.842)
AMT	-0.089***	-0.045*										
	(0.023)	(0.024)										
AMT*CITKETS	2.295***	1.256*										
	(0.651)	(0.678)										
ADV			-0.026***	-0.006								
			(0.010)	(0.012)								
ADV*CITKETS			0.670***	0.177								
			(0.250)	(0.329)								
BIOTECH					-0.043	-0.049						
					(0.037)	(0.032)						
BIOTECH*CITKETS					0.564	1.300						
					(1.270)	(1.063)						
NANOEL							-0.039	-0.034				
							(0.029)	(0.028)				
NANOEL*CITKETS							1.035	0.960				
							(0.820)	(0.811)				
NANOTECH									-1.049	-0.600		
									(0.635)	(0.552)		
NANOTECH*CITKETS									28.62	17.12		
									(18.11)	(15.78)		
PHOTO											-0.031*	-0.017
											(0.016)	(0.013)
PHOTONICS*CITKETS											0.655	0.461
											(0.494)	(0.429)
							omitted					
N	63449	63449	63449	63449	63449	63449	63449	63449	63449	63449	63449	63449
Pseudo R^2	0.256	0.200	0.256	0.199	0.256	0.200	0.255	0.200	0.256	0.200	0.256	0.200

All the estimates include also a constant term and the following variables: ECI, DEN, DEN^2, GROWTH, HK, HK^2, BIRTH RATE, 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: non-linearities

	2004-07				2008-10	
	TSD		*STD*		*TSD*	
	(1) OLOGIT	(2) OLS	(3) OLOGIT	(4) OLS	(5) OLOGIT	(6) OLS
KETS	-0.014***	-0.00016***	-0.007*	-0.00008**	-0.007**	-0.00008**
	(0.004)	(0.0001)	(0.004)	(0.00004)	(0.003)	(0.00004)
$KETS^2$	0.000013***	1.57e-07***	7.56e-06*	7.82e-08**	6.45e-06**	8.08e-08**
	(0.0000)	(6.81e-06)	(3.92e-06)	(3.94e-08)	(2.77e-06)	(3.68e-08)
				omitted		
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	63449	63449	63449	63449		
Pseudo R^2	0.256	0.287	0.200	0.154	0.082	0.021
Min. (KETS)	547.2	522.3	518.2	515.3	536.96	491.3

All the estimates include also a constant term and the following variables: ECI, DEN, DEN^2, GROWTH, HK, HK^2, BIRTH RATE, 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 10. 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	-0.012	-0.019***	-0.017	-0.013*	-0.006	-0.015**
	(0.017)	(0.007)	(0.018)	(0.007)	(0.017)	(0.006)
CITKETS	2.045	-2.023	2.600	-2.101	2.054	4.060*
	(3.206)	(2.982)	(3.461)	(3.447)	(2.326)	(2.305)
KETS*CITKETS	-0.069	0.514***	0.281	0.364*	0.166	0.408**
	(0.531)	(0.197)	(0.561)	(0.190)	(0.493)	(0.178)
				omitted		
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	31815	31634	31815	31634	33876	33609
Pseudo R^2	0.243	0.291	0.155	0.269	0.084	0.103

All the estimates include also a constant term and the following variables: ECI, DEN, DEN^2, GROWTH, HK, HK^2, BIRTH RATE, 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 11. KETs and regional diversification, 2004-07: common support

	TSD		STD	
	KETS>0	CS=1	KETS>0	CS=1
	(1)	(2)	(3)	(4)
KETS	-0.020***	-0.015**	-0.011*	-0.006
	(0.006)	(0.006)	(0.006)	(0.006)
CITKETS	-1.745	-0.747	-0.701	-0.229
	(2.693)	(1.843)	(2.954)	(1.940)
KETS*CITKETS	0.551***	0.389**	0.310*	0.181
	(0.167)	(0.169)	(0.161)	(0.160)
ECI	-0.458	-0.348	0.042	0.126
	(0.430)	(0.367)	(0.460)	(0.380)
POPDEN	0.000	-0.001**	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.001)
$POPDEN^2$	-0.000	0.000*	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
GROWTH	-0.024	0.650	-0.104	0.720
	(0.962)	(0.771)	(0.997)	(0.823)
HK	24.57	-20.03	8.820	-16.32
	(0.404)	(16.88)	(20.00)	(15.26)
HK^2	-38.76	23.49	-9.827	24.11
	(0.605)	(26.49)	(29.23)	(23.10)
BIRTH RATE	0.201	0.007	-0.037	0.034
	(0.268)	(0.230)	(0.312)	(0.241)
TRADE	0.002***	0.003***	0.001	0.001
	(0.000)	(0.001)	(0.001)	(0.001)
Regional dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
N	53002	47996	53002	47996
Pseudo R^2	0.270	0.255	0.227	0.194
LR test (p-value)	0.745	0.400	0.000	
Brant test (p-value)				
All var	0.780	0.529	0.000	0.000
KET			0.019	0.198
CIT			0.960	0.888
KETS*CITKETS			0.019	0.187
BIC (pl)			9627.7	10527.2
BIC (npl)			9691.6	10591.6

Clustered (at NUTS3 region and two-digit industry level) standard errors in parentheses. All the estimates include a constant term. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The likelihood-ratio (LR) and the Brant test of the parallel lines assumption are based on a model without regional and industry dummies.

Table 12. IV-GMM regressions: Lewbel's (2012) approach

	2004-07		2008-10
	TSD	STD	TSD
	(1)	(2)	(3)
KETS	-0.0001***	-0.00004**	-0.0001**
	(0.0000)	(0.001)	(0.000)
CITKETS	-0.018	-0.009	-0.008
	(0.017)	(0.008)	(0.011)
KETS*CITKETS	0.003**	0.001**	0.002**
	(0.001)	(0.000)	(0.001)
ECI	0.000	0.004	0.001
	(0.005)	(0.004)	(0.010)
POPDEN	-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)
GROWTH	0.027**	0.001	0.004
	(0.011)	(0.009)	(0.009)
HK	-0.280	-0.179	-0.012***
	(0.226)	(0.173)	(0.003)
HK^2	0.374	0.289	0.008***
	(0.340)	(0.285)	(0.002)
BIRTH RATE	-0.000	-0.002	0.002
	(0.003)	(0.003)	(0.004)
TRADE	0.001***	0.000*	0.000***
	(0.000)	(0.000)	(0.000)
Regional dummies	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes
N	63449	63449	67485
Centered R^2	0.285	0.153	0.019
Kleiberger-Paap rk F statistic	51427.2		
Nr. Of excluded instrumemts	222		
Hansen J (pval)	0.514	0.905	0.965
Endogeneity test	0.703	0.636	0.486
Breusch-Pagan test (p-value)			
- KETS	0.000		0.000
- CITKETS	0.000		0.000
- - KETS*CITKETS	0.000		0.000

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 13. The role of non-KETs

	2004-07				2008-10	
	TSD		STD		TSD	
	(1)	(2)	(3)	(4)	(5)	(6)
NON-KETS	-0.001**	-0.020	-0.000	-0.016	-0.0003**	-0.015
	(0.000)	(0.013)	(0.000)	(0.012)	(0.000)	(0.010)
CITNONKETS		0.373		0.073		-1.557
		(1.730)		(1.868)		(1.396)
NONKETS*CITNONKETS		-0.021		-0.017		-0.015
		(0.013)		(0.013)		(0.010)
ECI	-0.330	-0.259	0.072	0.167	0.182	0.225
	(0.359)	(0.359)	(0.373)	(0.375)	(0.595)	(0.593)
POPDEN	-0.001**	-0.001**	-0.001*	-0.001*	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$POPDEN^2$	0.000*	0.000*	0.000*	0.000*	0.000**	0.004**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GROWTH	0.537	0.438	0.690	0.589	-0.192	-0.229
	(0.742)	(0.738)	(0.785)	(0.783)	(0.382)	(0.387)
HK	-24.28	-23.50	-18.88	-18.68	-0.730***	-0.702***
	(16.08)	(16.14)	(14.50)	(14.72)	(0.207)	(0.210)
HK^2	30.07	28.79	27.93	27.76	0.366***	0.354***
	(24.95)	(25.06)	(21.64)	(21.98)	(0.113)	(0.115)
BIRTH RATE	0.024	0.016	0.056	0.035	0.106	0.120
	(0.226)	(0.225)	(0.241)	(0.239)	(0.153)	(0.155)
TRADE	0.003***	0.002***	0.001*	0.001	0.001*	0.001*
	(0.001)	(0.000)	(0.000)	(0.001)	(0.0010	(0.000)
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	63449	63449	63449	63449	67485	67485
Pseudo R^2	0.256	0.256	0.199	0.200	0.082	0.083

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 14. Moran-I test: 2004-07

Band	0<*d*<5	0<*d*<3
$KETS_{1995\text{-}2004}$	0.009	0.009
	(0.440)	(0.491)
$CIT_{1995\text{-}2004}$	0.001	0.009
	(0.264)	(0.215)
KETS*CITKETS	-0.012	-0.014
	(0.376)	(0.348)
Replication	0.034	0.057
	(0.007)	(0.003)
Transplantation	0.045	0.048
	(0.001)	(0.009)
Exaptation	-0.005	-0.001
	(0.389)	(0.352)

Table 15. Spatial regressions: 2004-07

Dep. Var.	Replication		Transplantation	
	Direct	Indirect	Direct	Indirect
KETS	-0.077**	-0.598	-0.050***	0.044
	(0.033)	(0.645)	(0.015)	(0.158)
CITKETS	12.96	144.4	-2.495	-198.3
	(13.77)	(172.7)	(7.193)	(209.9)
KETS*CITKETS	2.024**	17.50	1.334***	-1.456
	(0.963)	(18.86)	(0.459)	(4.665)
N	103		103	
Pseudo R^2	0.142		0.243	
Wald test spatial terms (p-value)	0.496		0.028	

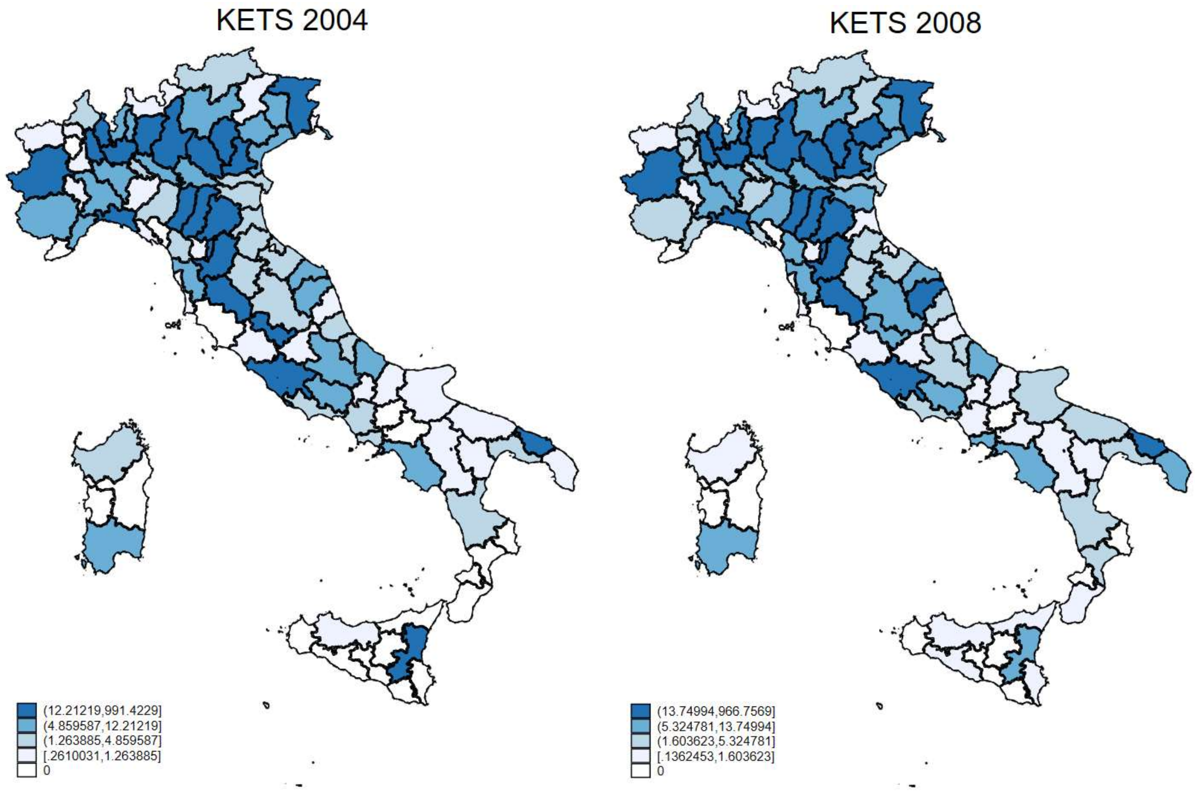
All the estimates include also a constant term. *** p<0.01 ** p<0.05 * p<0.10.

Table 16. KETs and regional diversification in 2004-07: accounting for industry saturation

	TSD	STD
KETS	-0.011**	-0.007
	(0.006)	(0.006)
CITKETS	-0.067	-0.025
	(1.751)	(1.890)
KETS*CITKETS	0.288**	0.197
	(0.155)	(0.160)
INDUSTRY SATURATION	0.004***	-0.001
	(0.001)	(0.001)
ECI	-0.491	0.063
	(0.344)	(0.369)
POPDEN	-0.000	-0.001
	(0.000)	(0.000)
$POPDEN^2$	0.000	0.000*
	(0.000)	(0.000)
GROWTH	0.263	0.427
	(0.761)	(0.812)
HK	-3.739	-13.54
	(17.36)	(15.50)
HK^2	1.305	21.13
	(26.92)	(23.23)
BIRTH RATE	-0.005	0.030
	(0.220)	(0.239)
TRADE	0.001	0.001
	(0.001)	(0.001)
Regional dummies	Yes	Yes
Industry dummies	Yes	Yes
N	63449	63449
Pseudo R^2	0.257	0.200

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

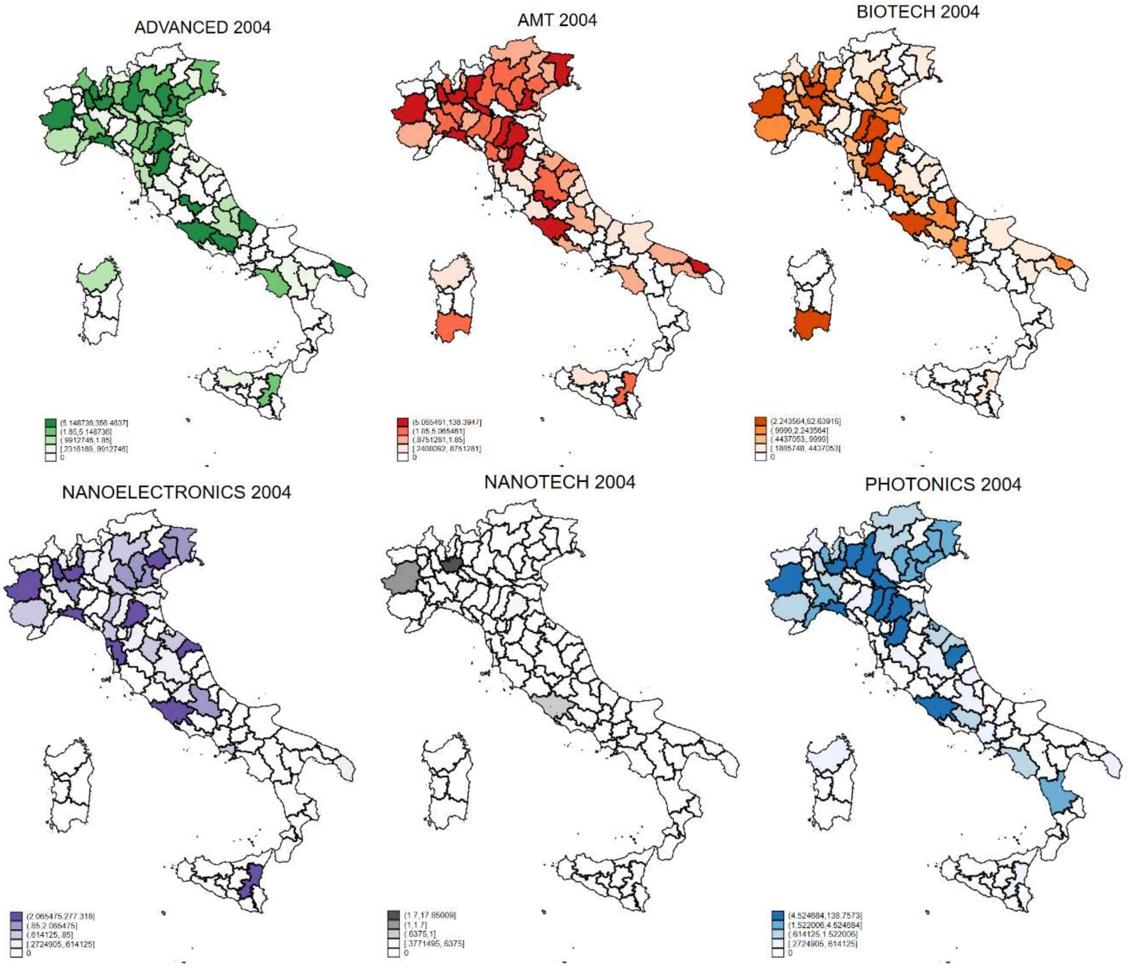
Figure 1. The geography of KETS



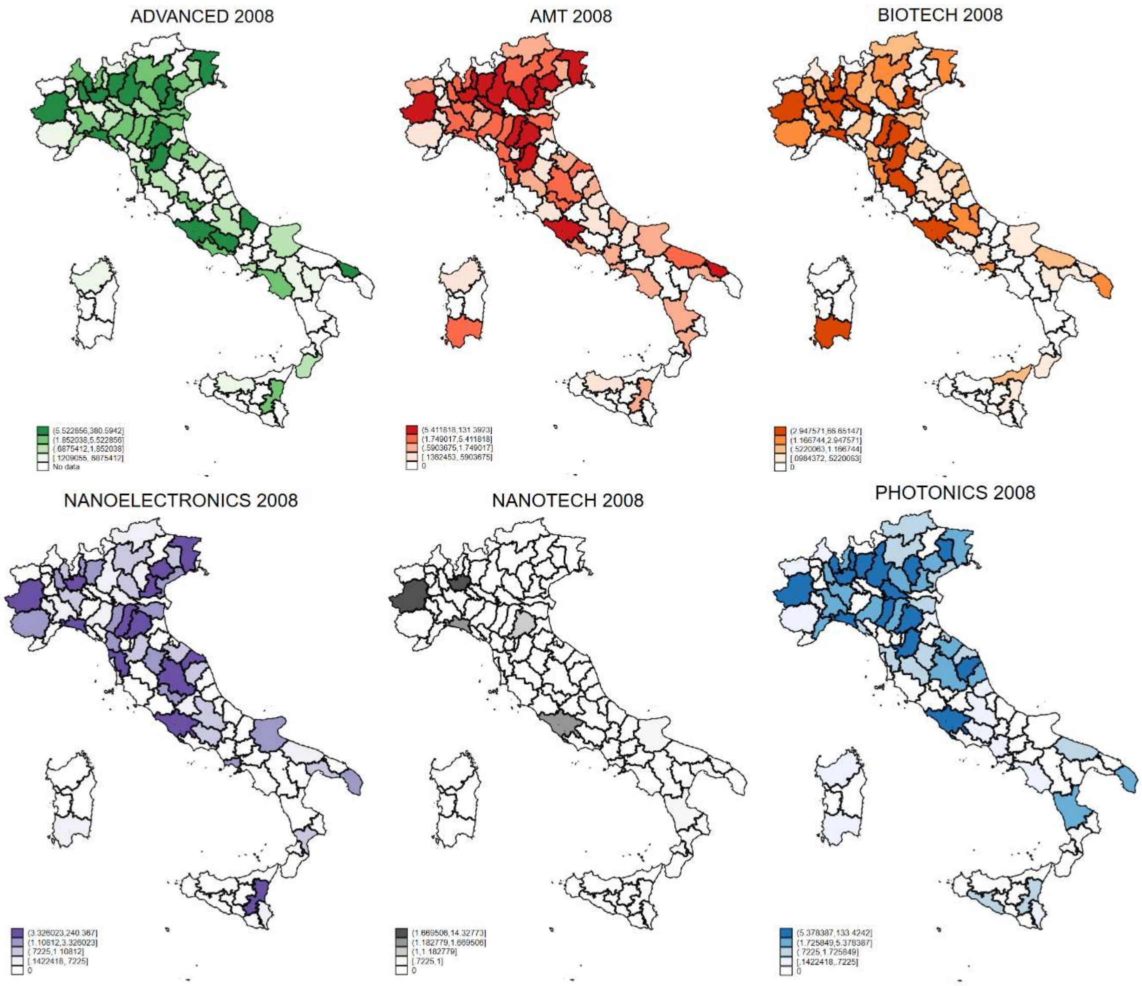
Source: author’s elaborations from OECD-Regpat data.

Figure 2 – The geography of the six KETs

1995-2004

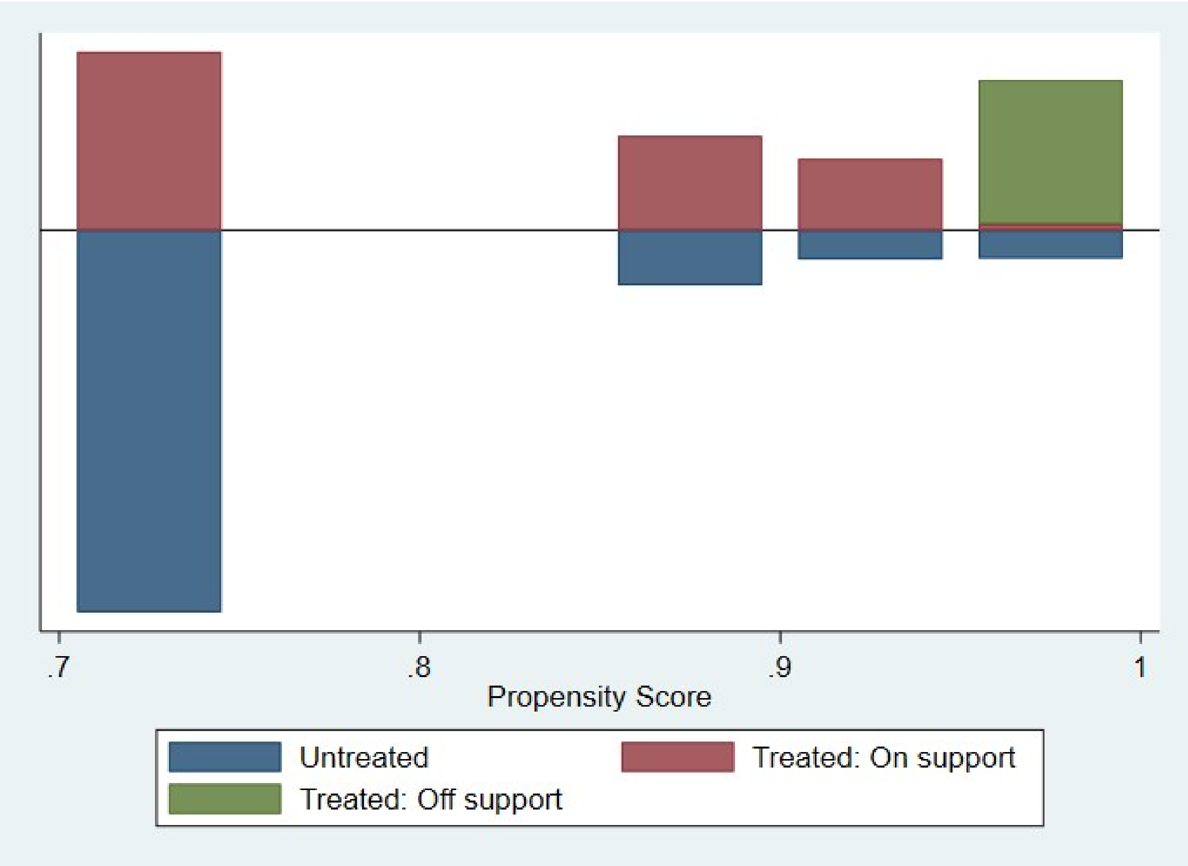


1995-2008



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

Figure 3. Propensity score distribution



APPENDIX

Table A1. Testing different thresholds, 2004-07

	TSD				STD			
	$emp_{2007}>0$		$emp_{2007}>median$		$emp_{2007}>0$		$emp_{2007}>median$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
KETS	-0.001	-0.020***	-0.001	-0.016***	-0.000	-0.014***	-0.000	-0.011
	(0.001)	(0.004)	(0.001)	(0.005)	(0.001)	(0.004)	(0.001)	(0.007)
CITKETS		-2.864**		-2.544		-2.050		-1.811
		(1.262)		(1.822)		(1.335)		(1.787)
KETS*CITKETS		0.539***		0.421***		0.382***		0.300*
		(0.111)		(0.145)		(0.127)		(0.187)
ECI	0.195	0.278	0.114	0.178	0.453*	0.522**	0.420	0.471
	(0.240)	(0.239)	(0.329)	(0.329)	(0.244)	(0.346)	(0.323)	(0.325)
POPDEN	-0.001***	-0.001***	-0.000	-0.001	-0.001***	-0.001***	-0.000*	-0.001
	(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	0.287	0.198	0.754	0.663	0.825	0.7699	0.788	0.733
	(0.528)	(0.524)	(0.692)	(0.688)	(0.551)	(0.550)	(0.699)	(0.702)
HK	-31.29***	-31.52***	-4.723	-5.174	-27.48***	-27.50***	-13.33	-13.43
	(10.34)	(10.39)	(10.34)	(10.39)	(10.39)	(10.50)	(14.28)	(14.50)
HK^2	38.04**	41.02**	2.475	5.292	36.63**	38.76**	18.52	20.34
	(15.83)	(15.92)	(18.42)	(18.66)	(15.60)	(15.85)	(21.64)	(22.13)
BIRTH RATE	-0.033	-0.063	0.039	0.000	-0.070	-0.106	0.035	-0.003
	(0.134)	(0.135)	(0.182)	(0.183)	(0.146)	(0.145)	(0.184)	(0.185)
TRADE	0.004***	0.003***	0.003***	0.002***	0.003***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	63449	63449	63449	63449	63449	63449	63449	63449
Pseudo R^2	0.158	0.159	0.106	0.107	0.128	0.129	0.099	0.100
LR test (p-value)		0.420		0.406		0.000		0.000
Brant test (p-value)								
All var		0.067		0.293		0.000		0.000
KET		0.077		0.861		0.001		0.006
CIT		0.318		0.942		0.350		0.374
KETS*CITKETS		0.832		0.160		0.001		0.006
BIC (pl)						20440.6		13515.6
BIC (npl)						20480.1		13546.4

Clustered (at NUTS3 region and two-digit industry level) standard errors in parentheses. All the estimates include a constant term. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The likelihood-ratio (LR) and the Brant test of the parallel lines assumption are based on a model without regional and industry dummies.

Table A2. Testing different thresholds, 2008-10

	TSD			
	$emp_{2007}>0$		$emp_{2007}>median$	
	(1)	(2)	(3)	(4)
KETS	-0.001***	-0.001***	-0.0004**	-0.001***
	(0.000)	(0.000)	(0.0001)	(0.000)
CITKETS		0.411		-0.332
		(0.986)		(1.359)
KETS*CITKETS		0.082***		0.069**
		(0.031)		(0.030)
ECI	1.165***	1.191***	1.232**	1.302**
	(0.438)	(0.431)	(0.567)	(0.560)
POPDEN	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
$POPDEN^2$	0.000***	0.000***	0.000***	0.005***
	(0.000)	(0.000)	(0.000)	(0.001)
GROWTH	-0.070	-0.068	0.184	0.201
	(0.276)	(0.278)	(0.395)	(0.398)
HK	-0.713***	-0.702***	-0.663***	-0.658***
	(0.156)	(0.158)	(0.205)	(0.205)
HK^2	0.339***	0.336***	0.309***	0.313***
	(0.090)	(0.091)	(0.119)	(0.119)
BIRTH RATE	0.170	0.173	0.128	0.114
	(0.113)	(0.113)	(0.143)	(0.143)
TRADE	0.001**	0.001**	0.001*	0.001
	(0.000)	(0.000)	(0.000)	(0.000)
Regional dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
N	67485	67485	67485	67485
Pseudo R^2	0.081	0.081	0.067	0.068
LR test (p-value)	0.272	0.231	0.135	0.116
Brant test (p-value)	0.247	0.181	0.097	0.166

Clustered (at NUTS3 region and two-digit industry level) standard errors in parentheses. All the estimates include a constant term. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The likelihood-ratio (LR) and the Brant test of the parallel lines assumption are based on a model without regional and industry dummies.

Table A3. Propensity score estimates: first stage

Dep. Var.	(1)
Dummy KETS=1	LOGIT
$UNIV/POP_{1996}$	0.938^{***}
	(0.024)
$PROF/POP_{1996}$	0.323^{***}
	(18.12)
Constant	0.875^{***}
	(0.013)
N	63449
Pseudo R^2	0.125
NUTS 3 regions on the common support	80 (77.67%)
NUTS 3 regions off the common support	23 (22.33%)
Observations on the common support	15453 (24.35%)
Observations off the common support	47996 (75.65%)