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

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1. Introduction

A large body of research has shown that relatedness to existing economic activities and technologies is an important driver of a region's ability to diversify (Boschma, 2016; Frenken et al., 2007; Boschma and Iammarino, 2009; Boschma et al., 2011; Hartog et al., 2012). However, relatedness is just one, albeit important, "place-dependent" dimension of regional diversification, which is also marked by the "path-dependent" evolution of the industries in which regions specialize and diversify. This multidimensional nature of regional diversification has recently led to the proposal of "augmenting" the juxtaposition between related and unrelated diversification developed within evolutionary economic geography with insights coming from transition studies, which point to the distinction between niche creation and regime adoption in the unfolding of socio-technical systems (Boschma et al., 2017).

In this "augmented" way of approaching regional diversification, the range of its trajectories expands, as well as that of "the risk, the institutional work, the key actors, and the spatial logic" that each of them involves (*ibidem* p. 39). In a "reduced" form of combination of these insights, four patterns of regional diversification have been theoretically identified in the "replication", "transplantation", "exaptation", and "saltation" of regional economic activities. Furthermore, a battery of empirical cases has been found to (simply) illustrate (so far) the more granular interpretative power of the relative taxonomy.

While it represents an important step towards a more comprehensive theory of regional diversification, the proposed augmented approach still lacks any operationalization. In particular, a methodology to proxy its constitutive patterns of regional diversification, and to inspect its drivers and consequences, has not been approached yet, posing a serious obstacle to the progress of the same research project. The present paper contributes to fill this gap by proposing an empirical methodology to address two issues in the regional diversification literature (see Boschma, 2016). The first concerns the relative disregard for the socio-technical evolution of the industrial sectors in which regions specialize and diversify. When regions enter new sectors their knowledge base evolves, adding a new technological dimension to the spatial dimension of their diversification. However, sticking to the "standard" domain of economic geography, this aspect has remained unfortunately neglected. Following Boschma et al. (2017), we try to remedy this shortcoming by drawing on transition studies and on their recent spatial development (Gibbs and O'Neill, 2017), by considering that the radical, rather than incremental nature of socio-technical development at industry level, can differently combine with the patterns of related and unrelated diversification at spatial level, leading to identify different diversification patterns and trajectories. For the first time ever, to the best of our knowledge, we propose a way to proxy the unfolding of these trajectories and to look at their determinants in an empirical application.

The second issue we address concerns the relatively scarce attention paid so far to the regional "bridging" factors (especially of a technological nature) that make local activities more complementary, with diversification purportedly deriving from their (re)combination (Boschma, 2016, p. 10). Going along with Montresor and Quatraro (2017; 2019), we suggest to make economics of innovation and new technology percolate more pervasively in economic geography and argue that Key Enabling Technologies (KETs), like the six recently identified by the European Commission (2012)[1], could have an important role in this respect. We propose that the regional endowment of these general-purpose kind of technologies could affect the diversification patterns and trajectories of regional economic activities, though to a heterogeneous extent.

We look at the role of KETs in an empirical application to Italian NUTS3 regions in two periods (2004-2007 and 2008-2010) merging patent and employment data. We estimate a set of ordered logit models, where the probability of a region entering increasingly diversified industries is regressed against its KET endowment, the extent to which technologies other than KETs draw on them, and several other regional characteristics. We find that regions with more KETs are better able to move

[1] These are: industrial biotechnology, nanotechnology, micro- and nanoelectronics, photonics, advanced materials, and advanced manufacturing technologies.

towards more 'unrelated' diversification patterns, but only if these KETs are used and combined with other technologies. These results hold for both periods examined, and for both types of diversification trajectories we consider, though to a heterogeneous extent, and they are robust to several checks.

The paper is developed as follows. Section 2 reviews the background literature. Section 3 describes the baseline empirical application. Section 4 discusses the results and some extensions. Section 5 presents the robustness tests. Section 6 concludes, presenting the research and policy implications.

2. Background literature

Empirical analyses of regional diversification have generally investigated it within the theoretical boundaries of evolutionary economic geography, by mainly contrasting related with unrelated diversification. Confirming the crucial role of the cognitive proximity between new and pre-existing regional activities in terms of 'capabilities' (Boschma, 2016), related diversification has generally emerged as a sort of positive and normative rule of the "diversification game" (Balland et al., 2019). Conversely, evidence of unrelated diversification has been obtained only scantly and mainly indirectly, looking for factors that might attenuate the impact of relatedness on a region's capacity to diversify.[2]

While much remains to investigate in this theoretical domain (for some perspectives, see Boschma, 2016), by strictly sticking to it some important aspects risk to remain unaddressed. Two of them appear relevant and suggest augmenting the analysis of regional diversification by enriching evolutionary economic geography with other theoretical perspectives.

The first aspect to consider is that regional diversification embraces at least one other dimension in addition to the spatial one, on which evolutionary economic geography has focused so far (Boschma et al., 2017). This second dimension refers to the 'socio-technical regimes' characteristic of the economic sectors in which regions operate and diversify: an issue on which transition studies have long concentrated (Geels, 2002; Kemp et al., 1998; Markard et al., 2012; Rip and Kemp, 1998), and whose insights thus need to be more comprehensively retained. In brief, at a certain point in time,

[2] These conditions have been identified at the macro-level – i.e. the socio-political conditions of diversifying countries, (Boschma and Capone, 2016) – at meso-level – such as the core vs. periphery status of the diversifying regions (Isaksen, 2015; Isaksen and Trippl, 2014) – and at micro-level – including the nature of the diversifying plants (Neffke et al., 2016).

these regimes constitute an alignment of socio-technical elements (i.e. skills, artefacts and knowledge) that promotes incremental innovations, and makes sectors "resistant" to radical innovations. On the other hand, radical novelty can still occur in the sector through the experimental creation and possible upscaling of 'niches', which protect the incubation of radical new technologies against the consolidating pressure of the regime (Coenen et al., 2010; Geels, 2002).

Having also and above all a socio-institutional nature (Smith and Raven, 2012), both regimes and niches have a spatial nature too, which means that regions have a technological 'path dependence' that interacts with the 'place dependence' of their capacity to diversify (i.e. relatedness). The combination of these two types of dependence yields different patterns of regional diversification, beyond the standard juxtaposition between relatedness and unrelatedness, which Boschma et al. (2017) identify as (Table 1): i) 'replication', with related diversification in an established socio-technical regime; ii) 'transplantation', with diversification in an unrelated industry, but still under the dominant regime; iii) 'exaptation', with a new sector niche developing in the presence of related diversification; and iv) 'saltation', with activities being developed that are new, in technological terms, both to the region and to the 'world'. These four configurations arguably differ in several respects[3], and different are the factors influencing them, making regions prone to adopting one rather than another and, as we will argue, to move across them.

Insert Table 1 about here

The second aspect that deserves more attention concerns the view of regional diversification as a process in which regions (differently) recombine their already-combined (related) or un-combined techno-economic activities (unrelated) (Castaldi et al., 2015; Fleming, 2001; Weitzman, 1998). Under the conventional umbrella of evolutionary economic geography, this re-combinatory process has been mainly read in terms of similarity vs. dissimilarity between the capabilities underlying the activities to be combined (Boschma, 2016). On the other hand, economics of innovation and new technologies suggests that, in order to lead to a successful inventive outcome, the Schumpeterian process of recombination of existing ideas and capabilities also requires complementarity between them and proper interfaces among them to build it up. Making these insights percolate more

[3] i.e. the risk, the institutional work, the key actors, and the local vs. global spatial logic they entail.

pervasively into economic geography, the factors that enable or maybe reinforce such a complementarity represent a crucial driver of regional diversification too. Among these factors,[4] an important complementarity enabler has been recently recognized in a region's endowment of 'general purpose technologies' (GPT), such as those recently identified by the EC as KETs for the transition towards a knowledge-based and sustainable economy (EC, 2002). Given their typical horizontal application pattern, which covers the whole spectrum of a region's economic activities, and the coincidence KETs entail between inventions and innovative applications (Bresnahan, 2010), KETs have been recently showed to make regional diversification less restricted by the relatedness between new and pre-existing activities (Montresor and Quatraro, 2017).

When these characteristics are matched with the regional diversification patterns that we identified above, the role of KETs appears more nuanced. For a start, the nature of KETs makes them more likely to enable non-replicative than replicative patterns of diversification, in general. KETs are also possibly more likely to enable a transplantation than an exaptation or saltation. This is because the latter depend on KETs being able to generate re-combinations of such novelty as to go beyond the regional boundaries, which is harder to achieve because of the regional specificity of their endowment.

Another role that KETs could have lies in prompting regions to shift from a replication to a saltation pattern (Boschma et al., 2017), along what could be considered an 'ideal' diversification strategy that escapes lock-in situations: an additional aspect of the "augmented" approach to regional diversification we are referring, which has not been addressed so far. Given the cumulative and path-dependent nature of regional dynamics, the same transition would be difficult and risky to achieve directly by simultaneously adding 'radicalness' to both the spatial and the technological dimensions. Regions could/should move gradually from replication to saltation, learning as they add one novel component at a time, and passing through one of the other two diversification patterns. They could thus go for one of two transition trajectories, which we originally propose to investigate (see Table 1): i) 'technology over place' (TOP) diversification, via 'transplantation', in which they first exploit an existing (global) regime to diversify their economic activities in unrelated regional

[4] An ample set of factors can help connect the activities that, once recombined, generate regional diversification, including: 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 (for a wider review, see Boschma, 2016).

domains, then “stretch” the novelty to the technology level by entering a new niche; or ii) ‘place over technology’ (POT) diversification, via ‘exaptation’, in which they first enter a new technological domain (niche) to diversify “around” their extant economic activities, then “expand” the new technology to unrelated regional domains too.

As both diversification trajectories entail an increasingly novel recombination of local activities, KETs could be expected to help in both respects thanks to their two GPT properties. As both place- and path-dependence are opposed during the transition (albeit following a different sequence), we have no reason to expect the impact of KETs to be greater for one trajectory than for the other. We leave this issue to emerge from our empirical application in the next section.

Before moving on, an important point should be retained. In principle, knowledge of KETs could have the above-described recombinant effects on regional diversification for the ‘simple’ fact of being produced locally and somehow available - through local inventive efforts and their possible “pure knowledge spillovers”. We argue, however, that the diversification-driving role of KETs increases the more their knowledge is purposely used in other technological domains. Such a use could facilitate the direct ‘exposure’ of these technological domains to the work of GP technologies like KETs, and thus increase the chances of prompting novel knowledge re-combinations as a result. So, a region’s ‘use’ of KETs[5] can be expected to positively influence the impact of KETs on the regional diversification trajectories that we identified.

3. Empirical application

Our empirical application refers to 103 Italian NUTS3 regions (i.e. provinces), for which we could combine two sources of data. One is the Statistical Archive on Active Firms (*Archivio Statistico Imprese Attive – ASIA*) managed by the Italian Statistics Institute (ISTAT), from which we obtained data on the numbers of plants and employees by industry (up to five-digit level) and region (at NUTS3 level) to measure our diversification patterns and trajectories (see Section 3.1). The second source is the OECD-REGPAT database, from which we drew regional patent data (Acs et al., 2002; Nagaoka et al., 2010) to build up our core regressor, that is, KETs knowledge available in the region

[5] In the patent-based metrics adopted in our empirical application, such a use could be interpreted in terms of number of citations KETs patents receive by non-KETs ones.

(see Section 3.2). KET-related patents were identified as those labelled with at least one International Patent Class (IPC) and/or Cooperative Patent Classification (CPC) identified by the EC feasibility study on KETs (EC, 2012b). The same data source was used to retrieve the number of citations of KET-related patents by non-KETs regional patent applications to measure the extent to which they are used at local level. Finally, we drew on other ISTAT regional statistics to measure additional characteristics of Italian regions to use in testing our relationship.

While data from previous sources are available from 2004 to 2010, a "statistical break" occurred in the ASIA dataset in 2008, so the observation period had to be split in two: 2004-07 and 2008-10[6]. This prevented us from running a dynamic analysis, but enabled us to test our arguments across the business cycle before (2004-07) and during the financial crisis of ten years ago (2008-10). In the end, we had 756 five-digit industries in 103 provinces, for a total of 63,449 observations for the former period (Industries are not evenly distributed across NUTS3 regions), and 805 five-digit industries and 67,485 observations for the latter.

3.1 Variables

3.1.1. Dependent variables

To conduct our analysis, we define *Tech-Place-Diver*$_{rT}$ (TOP) and *Place-Tech-Diver*$_{rT}$ (POT) 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 to either 'transplantation' (for TOP) or 'exaptation' (for POT). As explained below, this also enables us to look at our first research question, i.e. the determinants of the individual diversification patterns comprising the ordered variables, and the role of KETs across them.

Following the literature on regional diversification (see, for example, Neffke et al., 2016), the constitutive values of these two ordered variables are built up by looking at regions' involvement in

[6] In 2008 the ISTAT followed EUROSTAT recommendations and revised its industry classification system, switching from ATECO 2002 (i.e. NACE Rev. 1.1) to ATECO 2007 (i.e. NACE Rev 2). As a result, industries cannot be merged across 2008 without a marked loss of disaggregated data.

new economic activities based on the jobs created over our two periods (2004-07 and 2008-10), and by classifying the relative industry “entries” in the region as follows:

- *replication*: a 5-digit entry at *T*, in a 3-digit industry that already existed (still in employment terms) at *t*, both in the region and in Italy (new neither to the region, nor to the world[7]);

- *transplantation*: a 5-digit entry at *T*, 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*, in a 3-digit industry that already existed in the region, but not in Italy at *t* (new to the world, but not to the region);

- *saltation*: a 5-digit entry at *T*, in a 3-digit industry that did not exist at *t*, neither in the region nor in Italy (new to the region and to the world).[8]

Table 2 shows the distribution of all these variables across our two periods. Before the economic crisis (2004-07), the Italian provinces show all four types of diversification, though *saltation* is rare and concentrated in a single 3-digit industry (ATECO code 652, “other financial intermediation”). We therefore opt not to include it in the first period, and to construct our dependent variables using the other two diversification patterns (in addition to no diversification). In the aftermath of the economic crisis (2008-10), the number of entries drops substantially, and we find no cases of exaptation or saltation. We consequently cannot identify the corresponding *Place-Tech-Diver* variable, so we only use *Tech-Place-Diver*.

[7] Of course, referring to the country regions belong as the technological world of reference is a gross simplification, we were forced to make because of data availability. Still, being a forerunner in a new industry in the country presumably exposes the region to at least some of those processes of experimentation and radical innovation that a new ‘real’ niche would entail.

[8] To avoid the effect of spurious entries (e.g., temporary jobs), an employment threshold for industry entries is set at the median employment level for the whole sample of newly created five-digit industries, i.e. 3.5 in 2004-07, and 2.13 in 2008-10. As a robustness check, we also compute the employment medians for each and every new five-digit industry. Tables B1.1 and B1.2 in Appendix B1 show that the results are mainly robust to the use of these different employment thresholds.

Insert Table 2 about here

3.1.2. Focal regressors

Our focal explanatory variable is the region *r*'s endowment of KETs at the beginning of each sub-period ($KETs_{rt}$). Following innovation studies, we proxy this with the regional stock of KET-related patent applications in our two focal periods, applying the perpetual inventory method to the flows of said patents (*PATKETst*) over the years 1995-2004 and 1995-2008, respectively. We thus use the following formula:[9]

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

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

To disentangle the role of the six KETs identified by the EC, we repeat the same procedure and obtain the separate stocks of patents for: 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 stocks of KETs-related patents in total and by type, respectively.

Insert Figure 1 about here

Insert Figure 2 about here

[9] Although regionalizing patent data by inventor is usually preferred, this method has just as many weaknesses as considering applicants, as we did (Cozza and Schettino, 2015). The main results tend to be robust when using inventors' addresses.

As for the ‘use’ made of KETs in other local technologies, following the patent literature (Trajtenberg, 1990), we proxy this by looking at the extent to which KET-related patents are cited by non-KET patents. We thus obtain the variable $CITKETs_{rt}$ from the sum of these citations per year, divided by the total number of citations for region in our two focal periods (1995 – 2004 and 1995 – 2008).[10] 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 from considering the stock of non-KET-related patents among the regressors, as it would be collinear.

3.2.3. Other regional characteristics and controls

The diversification trajectories that regions follow might also depend on characteristics other than KETs. Looking at previous studies on the determinants of related vs. unrelated diversification, we maintain that three regional factors should be salient.

i) The level of economic complexity of the region (Pinheiro et al. 2018; Petralia et al., 2016: Balland et al., 2018). Following Hidalgo and Hausmann (2009), and using regional export data from the Coeweb archive provided by ISTAT, we calculate an indicator, ECI_{rt}, which combines the diversity of the industries in which the region has shown a comparative advantage, and the ubiquity of these industries (see Appendix A for more details).

ii) The regional human capital (Gilbert & Campbell, 2015; Lester, 2007; Tanner, 2016; Consoli et al., 2019). The region’s stock of human capital at the beginning of each period, HK_{rt}, is measured as the number of university graduates (with bachelor’s and master’s degrees) in the resident population, using ISTAT data from ASTI (*Atlante Statistico Territoriale delle Infrastrutture*).

iii) Agglomeration economies are proxied with the population density of the region, $POPDEN_{rt}$, in terms of its resident population per km^2.

Two further sets of regressors are considered. First of all, using data from the Business Register of the Italian Chambers of Commerce (available through Infocamere), we obtain and include the number of newly active companies out of all companies registered in 1995 in each NUTS 3 region (*BIRTH RATE*). This should control for a problem of reverse causality, descending from the fact that more KETs-endowed regions are also those where the rate of firm creation is traditionally higher.

[10] Considering the cumulative number of citations of KET-related patents in other patents provide robust result.

Second, as results could be affected by the business cycle and the international climate regions operate in, we control for the rate of growth in regional per capita added value (*GROWTH*$_{rt}$) over the three years before *T* (i.e. 2001-2004 and 2005-2008), and for regional trade openness (*TRADE*$_{rt}$), given by the sum of imports and exports out of the regional added value, respectively.

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

Insert Table 3 about here

3.3. Econometric strategy

We estimate the following two models:

$$[1]\ Y_r^{2004/07} = \beta_0 + \beta_1 KETS_r^{95-04} + \beta_2 CITKETS_r^{95-04} + \beta_3 KETS_r * CITKETs_r + \boldsymbol{X_r'^{2004}\beta_4} + \varphi_R + \mu_j + \varepsilon_r$$

$$[2]\ Y_r^{2008/10} = \beta_0 + \beta_1 KETS_r^{95-08} + \beta_2 CITKETS_r^{95-08} + \beta_3 KETS_r * CITKETs_r + \boldsymbol{X_r'^{2008}\beta_4} + \varphi_R + \mu_j + \varepsilon_r\ .$$

where, Y_{rT} refers to our two ordinal diversification variables (*TOP* and *POT*) for the region *r, KETs*$_{rt}$ and *CITKETs*$_{rt}$ are our two focal regressors, and the vector $\boldsymbol{X_{rt}}$ includes the other regional characteristics and selected controls. The terms φ_R and μ_j respectively represent the NUTS2 region and the NACE 2-digit industry dummies, while ε_r is the stochastic error component. The interaction between *CITKETs*$_{rt}$ and *KETS*$_{rt}$ is considered to test for the moderating role of the use of KETs on the impact of KETs on *Y*. As we said, the two models are estimated first with the generic stock of KETs, then with the single regional endowments of *AMT*$_{rt}$, *ADV*$_{rt}$, *BIOTECH*$_{rt}$, *NANOEL*$_{rt}$, *NANOTECH*$_{rt}$ and *PHOTO*$_{rt}$, inputed separately due to their strong correlation.

Since Y_{rT} is constructed as an ordered variable, we estimate equations [2] and [3] using an ordered logit model and clustering the standard errors at NUTS3 region and 2-digit industry level. We test for the validity of the parallel lines (or proportional odds) assumption using both a likelihood ratio (LR) and a Brant test. If the null hypothesis of correct specification of the model is rejected, we use the Bayesian Information Criterion (BIC) to compare one model where the estimated coefficients are equal across outcomes, and one where the coefficients can vary across outcomes (Williams, 2016).

4. Results

Table 4 shows the ordered logit and OLS estimates for *TOP* (Columns 1-3) and *POT* (Columns 4-6) the first period, 2004-2007. For each trajectory, the first column (1 and 4, respectively) refers to the specification that includes only the stock of KETs as the main regressor, while in the other columns (2-3 and 5-6, respectively) the results include the interaction between *KETs* and *CITKETs*.[11]

The stock of regional KETs alone never affects the probability of a region diversifying into increasingly unrelated industries.[12] A significant effect only emerges for the interaction between the stock of KETs and their citation in other technologies available in the region. Columns 2-3 and 5-6 show that, in the absence of any citations (i.e. when *CITKETS*=0), the stock of KETs even reduces the region's propensity to diversify through new entries, apparently being more functional to preserving its existing economic structure. In the presence of citations, however, its propensity for diversification increases (especially for TOP, and less so for POT), thus counteracting the negative effect of the sole KETs regressor. Therefore, its total net marginal effect needs to be considered, as we do below.

This is a first interesting result. The sole creation of KETs knowledge is not enough to make regions follow the diversification trajectories we are investigating. For that to happen, KETs need to be combined with local non-KET-related knowledge. 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 the risk of lock-in as they move towards the new knowledge-based economy,

[11] LR and Brant tests confirm the parallel lines assumption is valid in the case of TOP, whereas this does not happen in the case of POT. However, the BIC statistics show that a model where the coefficients of our variables are equal across the ordered classes is preferable to a model where they are not (Williams, 2016).

[12] Among the other regressors, some of which have been squared to check for non-linear effects, Table 4 shows that the probability of (increasingly) unrelated diversification rises with trade openness and, albeit non-linearly, with population density. No significant effect is seen for the other control variables.

but rather an *effective use* made of them by the players involved in the production of the region's 'normal' knowledge base.

Insert Table 4 about here

Table 5 shows the marginal effects related to the estimates in Table 4. For the TOP trajectory (Column 2 in Table 4), the positive marginal effect of *KETS*CITKETS* is always larger than the negative effect of *KETS*, so 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 of a region diversifying and shifting from replication to transplantation. Just to make an example, increasing the stock of KETs from 0 to 991 (the highest value, corresponding to the province of Milan) would raise this probability by almost 700%.

As for the POT diversification trajectory (Column 5 in Table 4), the marginal effect is consistently lower, amounting to 0.003% (0.011%). As expected, the role of KETs in regional diversification varies, being more effective when further radicalness is achieved in an existing technological regime (TOP) than in the creation of a new niche (POT).

Insert Table 5 about here

Moving on to the second period of the analysis, 2008-2010, Table 6 confirms the results obtained for the previous period for POT (the only trajectory we are able to observe). Quite interestingly, the citation-weighted influence of KETs on a region's diversification is also confirmed in a negative phase of the business cycle, appearing as a sort of 'structural' driver of it.

Insert Table 6 about here

This result is confirmed in Table 7, which shows the corresponding marginal effects (Column 2), as they are in line with those in Table 5.

Insert Table 7 about here

Finally, Table 8 shows the ordered logit estimates when the endowment of each type of KET is input separately. Columns 1, 3, 5, 7, 9 and 11 reveal that only two of them, when combined with other non-KET technologies, significantly affect the TOP trajectory, i.e. advanced manufacturing technologies, and advanced materials. Similarly, Columns 2, 4, 6, 8, 10 and 12, show that the only KET affecting POT is advanced manufacturing technology. The same results (Table B2 in the Appendix) hold for TOP in the second period 2008-10. This is an important result, showing that only the two more GPT-like KETs can affect a region's propensity to transit through diversification.

Insert Table 8 about here

4.1. Non-linearities and the role of densely populated regions

Table 9 shows the ordered logit and OLS estimates, where we include *KETS* and $KETS^2$ among the main regressors, in order to control for possible non-linearities in their diversification impact. For reasons of space, we omit the estimated coefficients of the other covariates, which remain the same as in Table 4. Columns 1 and 2 confirm that the relationship between KETs and TOP is non-linear: it is negative up to a minimum threshold of 547 (522) KET-related patents, beyond which it turns positive. The same holds for 2008-10 (Columns 5 and 6), and for POT (Columns 3 and 4). Interestingly, we find only one province, Milan, with such a high KETs endowment, meaning that only Milan has enough KETs to stimulate the region's diversification without any interaction with non-KETs through citations. For this to happen elsewhere, the KETs need to be combined with the non-KETs.

Insert Table 9 about here

This result prompts us to investigate how densely populated areas might support the role of KETs in a region's diversification. To do so, we re-estimate equations [1] and [2] on two different subsamples, one including and the other excluding the most densely populated regions.[13] We thus 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 both types of regional diversification, the baseline results on KETs hold only for densely populated regions, implying that the accumulation and effective use of KETs are largely an urban phenomenon, requiring a critical socio-economic mass.

Insert Table 10 about here

4.2. The role of other technologies

In order to be sure the effect we observe is due to the intrinsic features of KETs, we use a sort of placebo test and re-estimate equations [1] and [2] omitting the KETs related variables and using an alternative set of explanatory ones: the stock of non-KET technologies (*NON-KETS*), and the number of citations that non-KET-related patents make to them (*CITNONKETS*).

Table 11 shows the ordered logit results for both periods. Columns 1 (2004-07) and 5 (2008-10) show that, as for KETs, the regional stock of non-KETs does not *per se* raise the probability of regions developing new, and increasingly unrelated activities. However, as expected, Columns 2, 3, 4 and 6 show that, as expected, the estimated coefficient of the interaction term never differs statistically from zero: we thus surmise that a region's unrelated diversification is driven only by the KETs-related knowledge base of the region.

Insert Table 11 about here

4.3 Robustness checks

A set of robustness checks are carried out in order to consider: the presence of selection mechanisms in the region capacity to develop KETs knowledge (Appendix B3); the presence of spatial correlation between the KETs endowment and/or diversification patterns of neighboring

[13] We define these regions with a dummy taking the value of 1 when a region's population in 1996 is higher than the median (i.e. 383,075), and 0 otherwise. We achieve the same results if we define as densely populated a NUTS 3 region with a population of more than 500,000.

regions (Appendix B4); the scope of diversification available to regions with respect to the considered set of industries (Appendix B5). Although with some sensible variations, the results reported in the relative Appendices confirm the main outcome of our empirical application, which thus can be retained robust.

6. Conclusions

Regional diversification is a complex phenomenon that combines cumulativeness and path-dependence at both spatial and technological levels. When both dimensions are considered, the options of diversification increase and the opportunity emerges for regions to move gradually and differently across them in escaping the risk of getting locked into their extant specializations, opting either for a 'technology-over-place' (TOP) diversification, or for a 'place-over-technology' (POT) one. As these patterns and trajectories of diversification occur through the recombination of existing activities, the regional availability of factors that can favor their complementarity reveals crucial, and this is especially the case for general purpose kind of technologies, like KETs.

Our empirical analysis of Italian (NUTS3) region actually confirm that a region's capacity for creating new industries using increasingly varied patterns of diversification is influenced by its endowment of KETs knowledge. Unless a large critical mass of technological activities is reached, this is not because of pure knowledge spillovers that the KET-related inventive activity creates in the region, but because other technologies make use of these KETs. This is largely a case of a TOP type of diversification trajectory, where regions switch from replication to transplantation. The evidence for a POT type of diversification trajectory is less robust.

Our results hold in two distinct phases of the business cycle, in 2004-07 and 2008-10, and reveal less heterogeneous diversification patterns after the crisis. What is more, they vanish with respect to low populated urban areas, suggesting that a critical socio-economic mass is also crucial for KETs to enable diversification. Finally, results are robust to regions' self-selection for accumulating KETs and endogeneity, and to the role of other technologies, spatial autocorrelation, and industry saturation.

These results suggest that KETs are an important tool in a region's policy box for diversifying, providing that support for their creation is combined with support for their use. Such a policy implication is particularly important for the most urbanized regions, which emerged in our Italian empirical application as drivers of the overall results. While these regions presumably reach the critical mass of KETs (inventive activities) needed for the relationship between these technologies and a region's diversification to be apparent, this relationship does not emerge in the absence of their effective use.

Our analysis also shows that, as expected, KETs have a different impact on the various patterns of diversification that emerge, when their place and technology path-dependence are both considered. KETs help regions to extend the scope of their local economic activities (transplantation) more than they can do with respect to the socio-technical regime that embraces these activities on a global (or, in our case, national) scale (exaptation). Accordingly, if regions are willing to prioritize the creation of a radically new technological niche, or to add such an exaptation strategy to a transplantation strategy based on unrelatedness, then KETs 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 suggesting a set of interesting regional policy implications, our results are not without their limitations. As we said, the most important concern the methodological choices that the available dataset necessitated: in capturing the technological world with which regional economies deal, which was limited to their reference country in our case; and in addressing the dynamics of regional patterns of diversification over time, which was restricted to two sets of cross-sectional analysis. As is usually the case, a search for additional datasets, possibly enabling comparisons with other countries, will be the next step in our future research agenda to address these limitations.

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TABLES AND FIGURES

Table 1. Regional diversification patterns

Trajectory 1: "Technology-over-Place" (TOP) diversification"		**Space**	
Technology		**Related** Place-dependent: known 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: "Place-over-Technology (POT)" diversification		**Space**	
Technology		**Related** Place-dependent: known 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-digit industries	%	N. of 5-digit 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

	TOP			POT		
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 2-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 Brant test of the parallel lines assumption are based on a model with no 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. KETs and regional diversification: 2008-10

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

Table 10. Ordered logit estimates: densely populated regions (DPR)

	2004-07				2008-10	
	TOP (DPR=0)	TOP (DPR=1)	POT (DPR=0)	POT (DPR=1)	TOP (DPR=0)	TOP (DPR=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

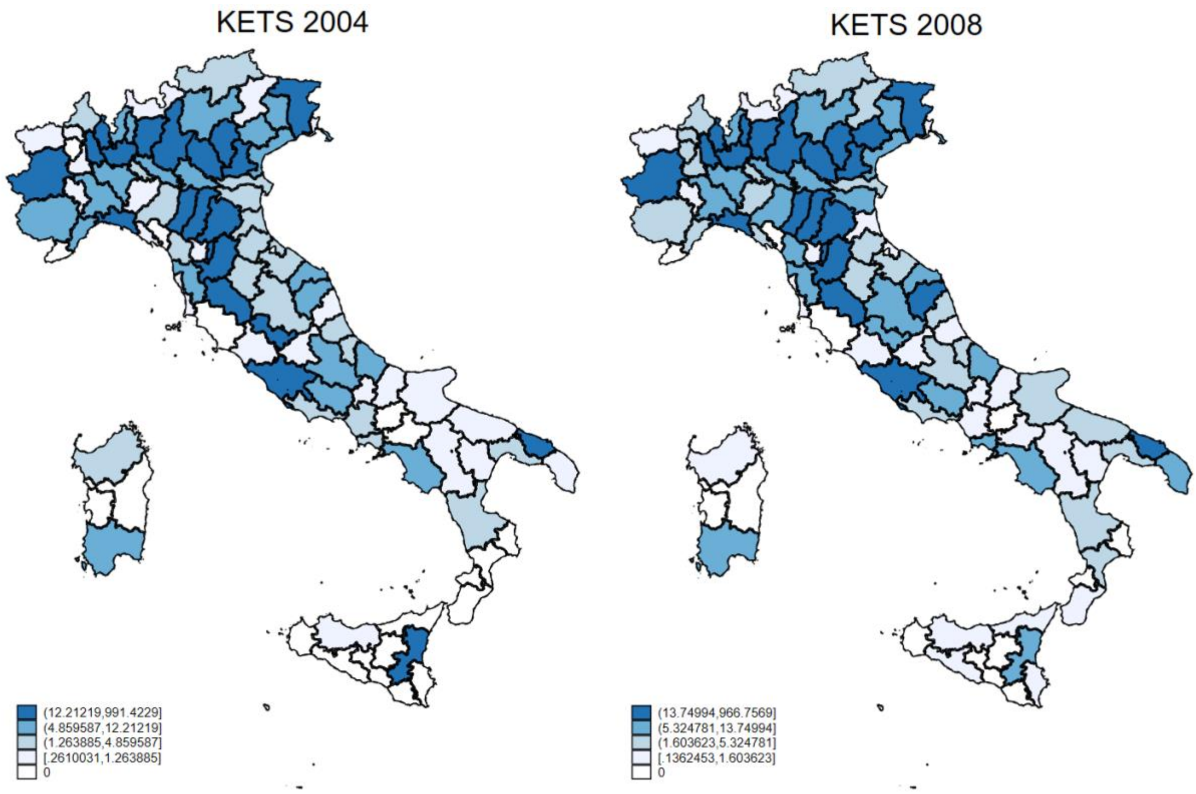
All the estimates also include a constant term and the following variables: ECI, DEN, DEN^2, GROWTH, HK, HK^2, BIRTH RATE, TRADE. Cluster (at NUTS3 region and 2-digit industry level)-robust standard errors in parentheses. *** p<0.01 ** p<0.05 * p<0.1.

Table 11. The role of other technologies

	2004-07				2008-10	
	TOP		POT		TOP	
	(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 also include a constant term. Cluster (at NUTS3 region and 2-digit industry level)-robust standard errors in parentheses. *** p<0.01 ** p<0.05 * p<0.1.

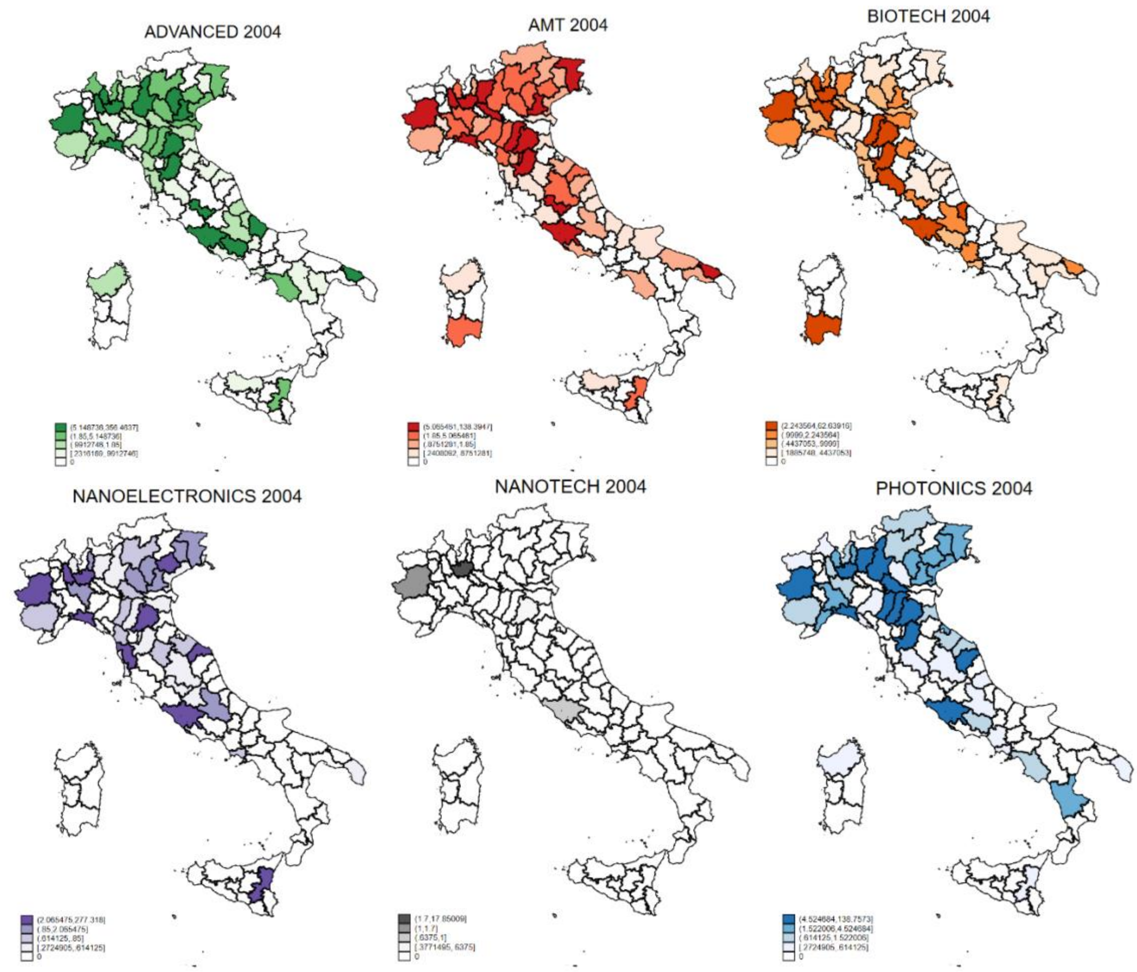
Figure 1. Geography of the KETS as a whole



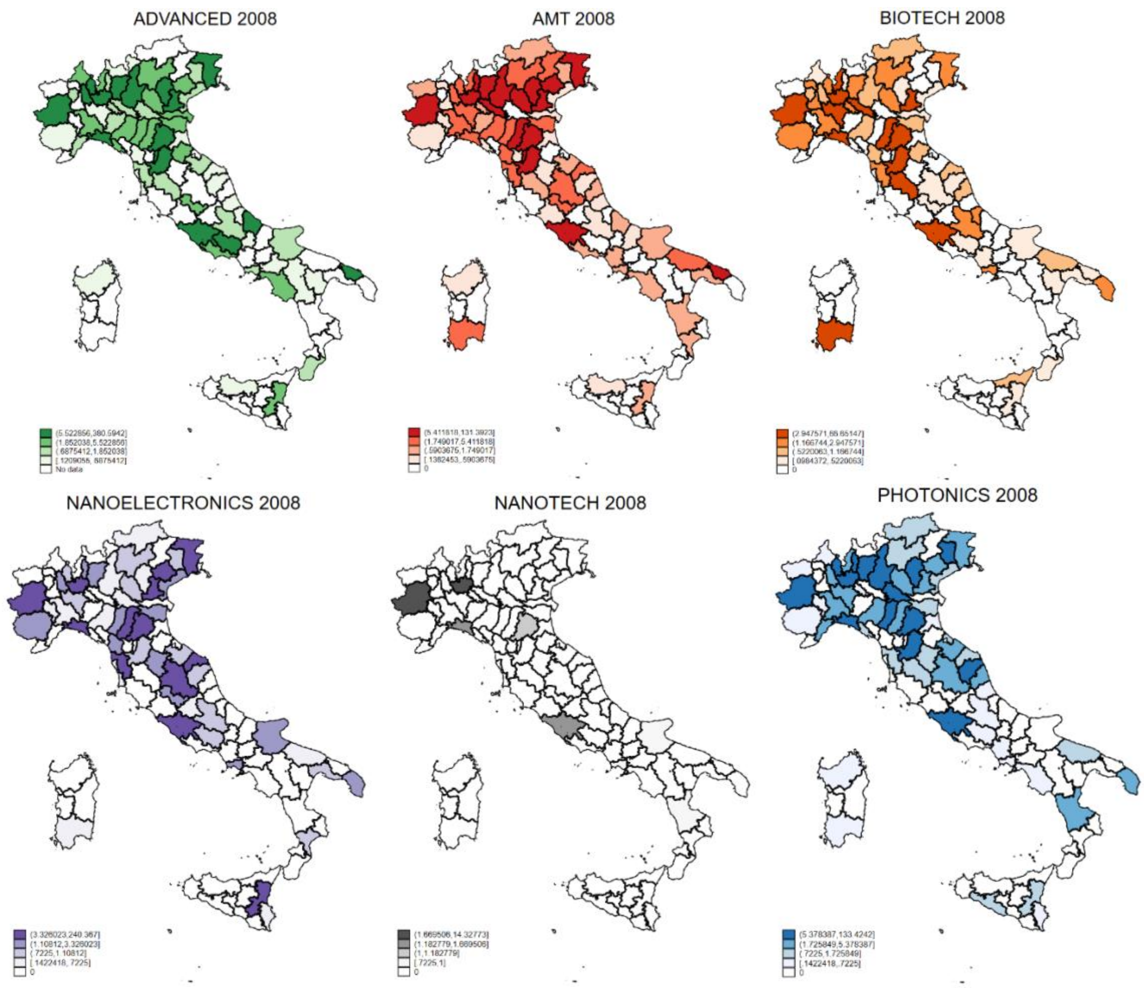
Source: author’s elaborations from OECD-Regpat data.

Figure 2 – Geography of the six KETs

1995-2004



1995-2008



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