Papers in Evolutionary Economic Geography

19.28

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

Roberto Antonietti and Sandro Montresor

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

Roberto Antonietti
"Marco Fanno" Department of Economics and Management
University of Padova
Via del Santo 33, 35123 Padova, Italy
E-mail: roberto.antonietti@unipd.it

Sandro Montresor
Gran Sasso Science Institute (GSSI)
Social Sciences Institute
Viale Francesco Crispi 7, 67100 L'Aquila, Italy
E-mail: sandro.montresor@gssi.it

Abstract

This paper investigates the role of Key Enabling Technologies (KETs) in the regional diversification of economic activities. We maintain that KETs drive different diversification trajectories, leading regions from the most conservative to the most radical pattern of diversification. Using an original dataset for Italian NUTS3 regions, we estimate a series of ordered logit models, in which a region's propensity to move across industry diversification patterns depends on its KETs endowment. We find regions with more KETs better able to move towards more 'unrelated' diversification patterns, but only when KETs are combined with other technologies, and only in densely populated regions.

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

JEL: R11, R58, O31, O33

Acknowledgments: We thank participants at the 2018 SMARTER Conference in Seville, the 2018 ENEF meeting in Brighton, the 2019 series of lunchtime seminars at the Department of Economics and Management, University of Florence, at the JRC-EC of Seville, and at the Parthenope University of Naples, the XXII 2019 Uddevalla Symposium in L'Aquila (GSSI), the 7th CONCORDi conference in Seville, and the Regional Innovation Policies conference in Florence.

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 into new activities and technologies (Boschma, 2016), and to grow through it (Frenken et al., 2007; Boschma and Iammarino, 2009; Boschma et al., 2011; Hartog et al., 2012). It has been claimed that the so-called "regional branching" is a pattern of regional diversification with lower search costs and a lower risk of failure than diversification in unrelated fields (Balland et al., 2018). On the other hand, relatedness can be a double-edged sword, limiting the exploration of novel growth opportunities and, at worst, locking a region in the domain of its extant activities (Saviotti and Frenken, 2008). Hence the interest in evidence of unrelated 'jumps' in industry-path creation (e.g. Isaksen, 2015; Isaksen and Trippl, 2014; Hassink et al., 2019), and the emerging need to focus more 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 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 (Boschma, 2016, p. 9). When regions enter new sectors their knowledge base evolves, adding a new technological dimension to the spatial dimension of their diversification, but this is unfortunately neglected by diversification studies. Like Boschma et al. (2017), we try to remedy this shortcoming by considering (for the first time in a systematic study) 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 across them.

The second gap 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 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 and we expect diversification patterns and trajectories will be affected by their regional endowment, though to a heterogeneous extent.

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

We look at such a role for KETs in an empirical application to Italian NUTS3 regions in two periods (2004-2007 and 2008-2010) for which patent and employment data could be merged. 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 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 unrelated regional diversification have generally treated it as a complement to the benchmark case of related diversification. Relatedness has been seen mainly as the similarity between new and previous regional activities in terms of 'capabilities' (Boschma, 2016). Evidence of unrelated diversification has largely been obtained indirectly, looking for factors that might attenuate the impact of relatedness on a region's capacity to diversify. While a variety of conditions for such diversification have emerged[2], there are some additional aspects to consider.

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). A second dimension refers to the 'socio-technical regimes' characteristic of the economic sectors in which regions operate and diversify (on which the transition literature has long concentrated [Geels, 2002; Kemp et al., 1998; Markard et al., 2012; Rip and Kemp, 1998]). At a certain point in time, these constitute an alignment of socio-technical elements (i.e. skills, artefacts and knowledge) that promotes incremental innovations, and makes sectors "resistant" to radical innovations. Radical novelty can still occur in the sector through the experimental creation and

[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).

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, 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 more or less prone to adopting one rather than another and, as we will argue, to move across them.

Insert Table 1 about here

Following the Schumpeterian theory of 'recombinant innovation' (Castaldi et al., 2015; Fleming, 2001; Weitzman, 1998), regional diversification according to the previous patterns, can be seen as a process in which regions (differently) recombine their already-combined (related) or un-combined techno-economic activities (unrelated). Both with respect to place- and path-dependence, this requires a certain complementarity, and not only similarity, between the capabilities underlying the activities to be combined (Boschma, 2016). Accordingly, the factors that enable or maybe reinforce such a complementarity represent a crucial driver of regional diversification. Among these factors,[4] an important complementarity enabler has been 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

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

[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).

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: 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. 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 (see Table 1): i) 'technology over place' (TOP) diversification via a 'transplantation' in which they first exploit an existing (global) regime to diversify their economic activities in unrelated regional domains, then "stretch" the novelty to the technology level by entering a new niche; or ii) 'place over technology' (POT) diversification via an '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 (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.

[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.

[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.

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 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").

[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.

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*.

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]

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

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.

[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.

Insert Figure 1 about here

Insert Figure 2 about here

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

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

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. 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] $Y_r^{2004/07} = \beta_0 + \beta_1 KETS_r^{95-04} + \beta_2 CITKETS_r^{95-04} + \beta_3 KETS_r * CITKETs_r + \boldsymbol{X}_{\boldsymbol{r}}^{\prime\mathbf{2004}} \boldsymbol{\beta}_{\mathbf{4}} + \varphi_R + \mu_j + \varepsilon_r$

[2] $Y_r^{2008/10} = \beta_0 + \beta_1 KETS_r^{95-08} + \beta_2 CITKETS_r^{95-08} + \beta_3 KETS_r * CITKETs_r + \boldsymbol{X}_{\boldsymbol{r}}^{\prime\mathbf{2008}} \boldsymbol{\beta}_{\mathbf{4}} + \varphi_R + \mu_j + \varepsilon_r$.

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

[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.

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

[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.

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 eventuality of a reverse causality in their relationship with regional diversification (Appendix B4); the presence of spatial correlation between the KETs endowment and/or diversification patterns of neighboring regions (Appendix B5); the scope of diversification available to regions with respect to the considered set of industries (Appendix B6). 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.

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.

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 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.

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.

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;

Cozza, C. and Schettino, F. (2015). Explaining the Patenting Propensity: A Regional Analysis Using EPO-OECD Data, in C. Mussida and F. Pastore (eds.). Geographical Labor Market Imbalances - Recent Explanations and Cures, Springer-Verlag Berlin Heidelberg 2015, p. 219-236.

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.

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.

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.

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

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., 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.
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.
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.
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.
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.
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-over-Place" (TOP) diversification"		**Space**	
		Related Place-dependent: known to the region	**Unrelated** "New to the region"
Technology	**Regime** Path-dependent: known to the world	*Replication*	*Transplantation*
	Niche "New to the world"	*Exaptation*	*Saltation*

Trajectory 2: "Place-over-Technology (POT)" diversification		**Space**	
		Related Place-dependent: known to the region	**Unrelated** "New to the region"
Technology	**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

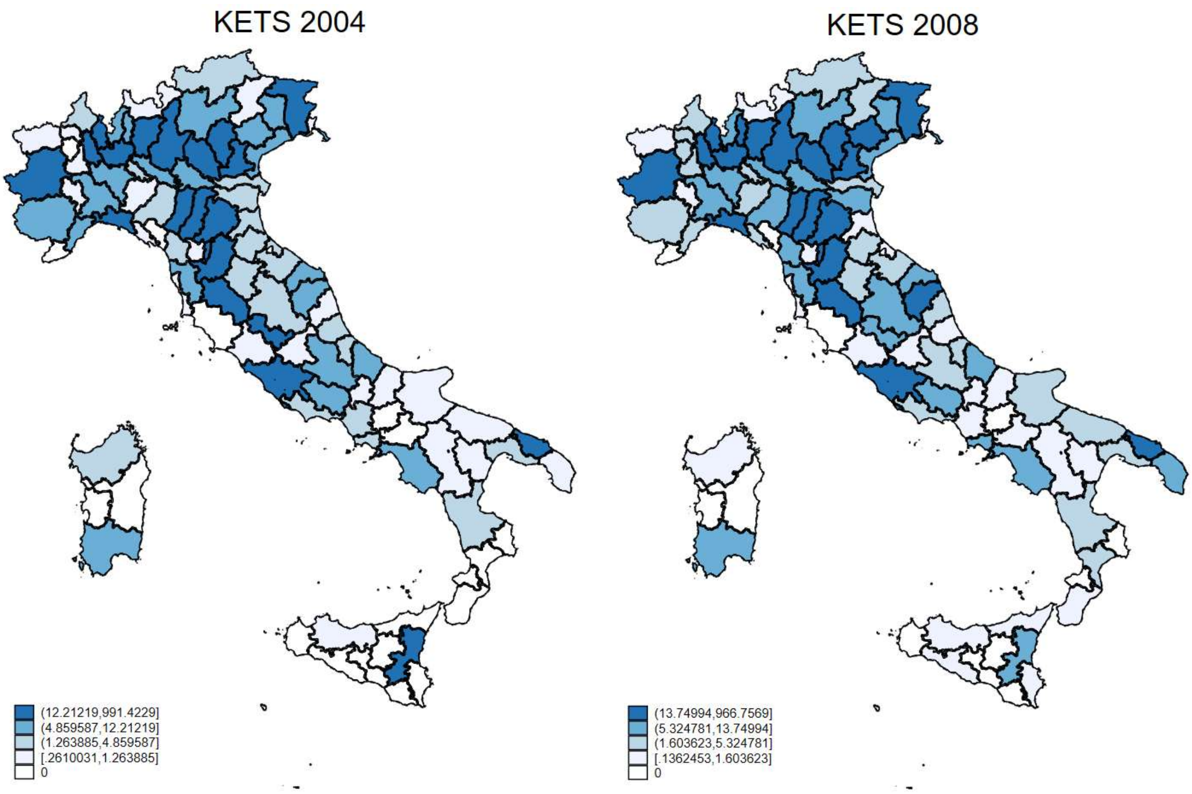
All the estimates also include a constant term and the following variables: ECI, DEN, DEN^2, GROWTH, HK, HK^2, BIRTH RATE, TRADE. Cluster (at NUTS3 region and 2-digit industry level)-robust standard errors in parentheses. *** p<0.01 ** p<0.05 * p<0.1.

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.

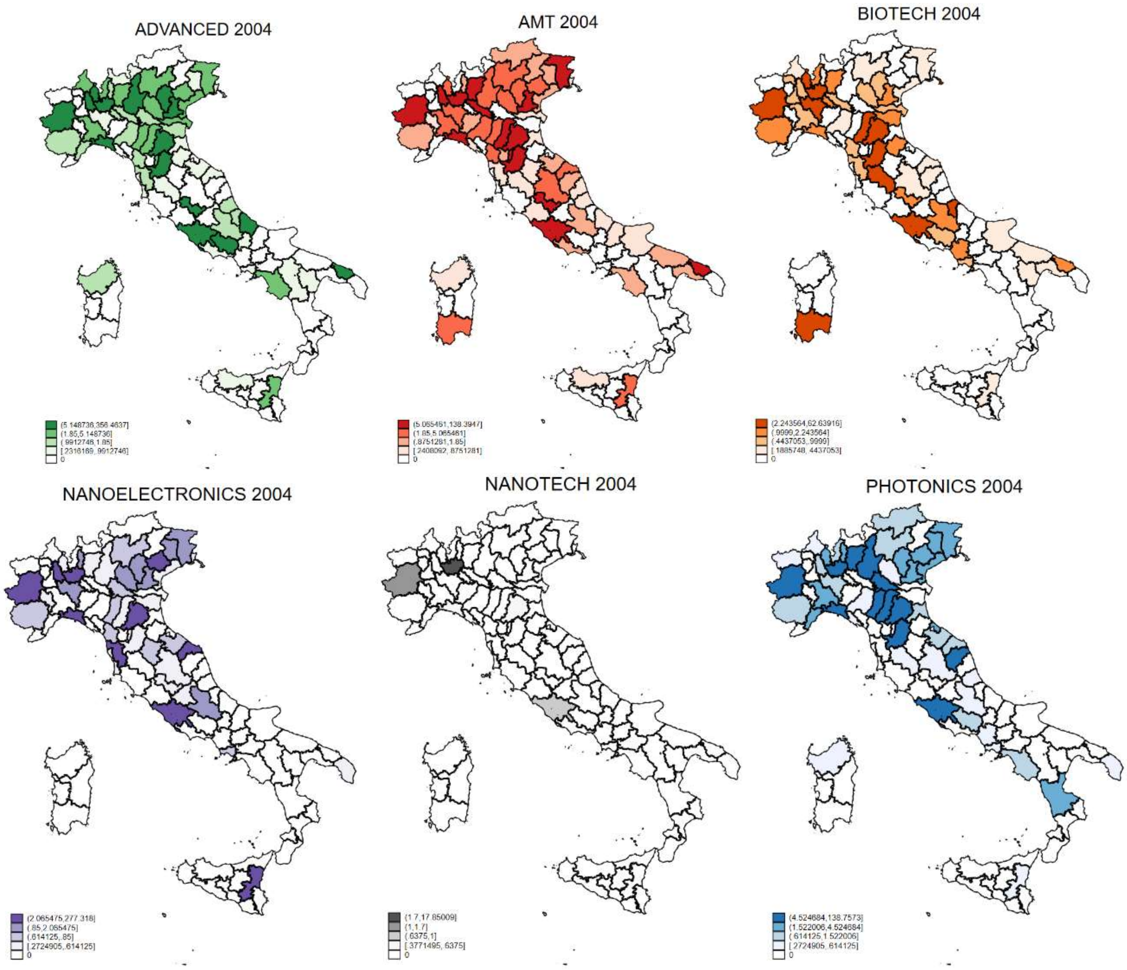
Figure 1. Geography of the KETS as a whole



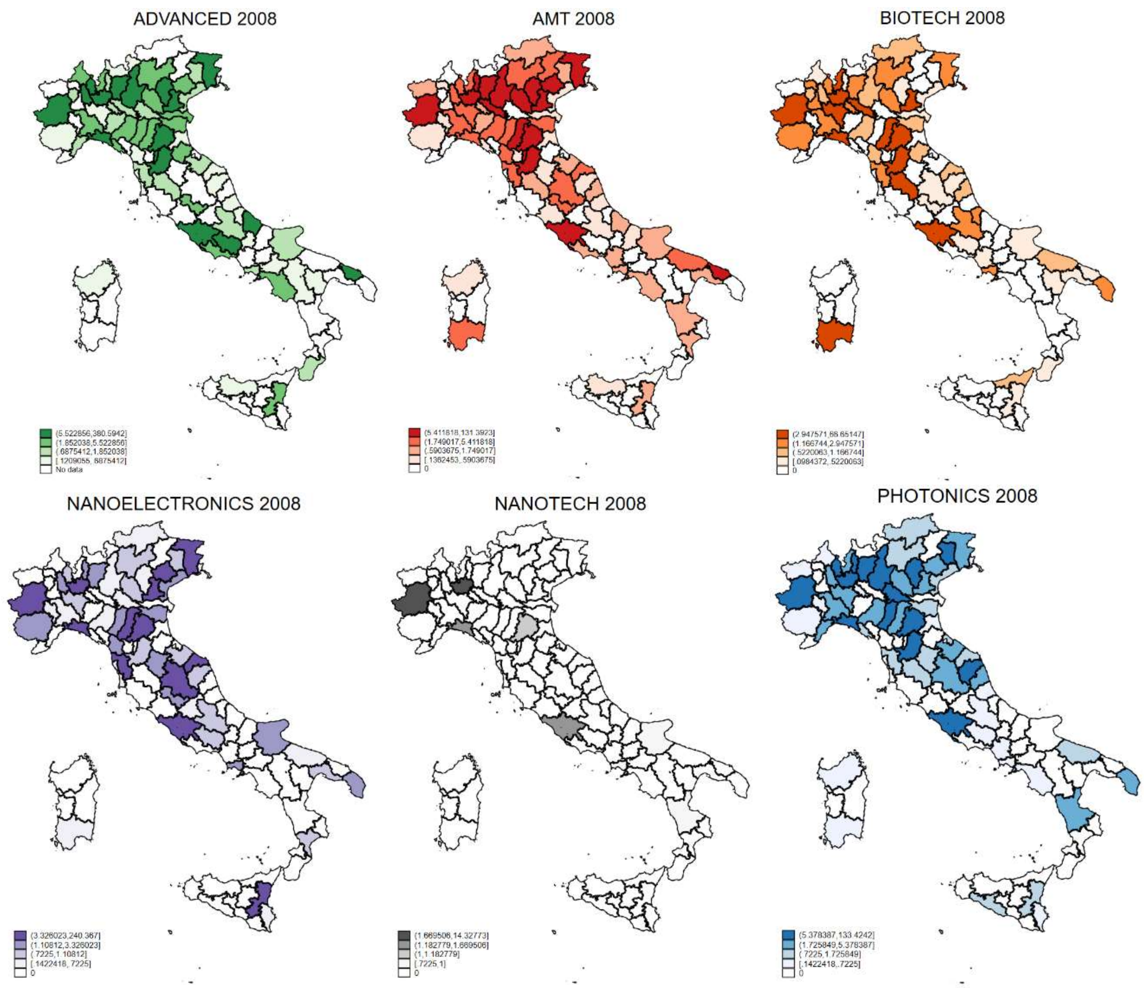
Source: author’s elaborations from OECD-Regpat data.

Figure 2 – Geography of the six KETs

1995-2004



1995-2008



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

Appendices

Appendix A – Methodological notes

ECI Index

The ECI index is based on 3-digit industries in which each province has revealed a comparative advantage. We compute this 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} is the value of exports by province *p* in (3-digit) industry *i*; and the province has an RCA 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 an RCA in a given industry; the latter to the number of industries in which a province has an RCA. Putting the 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 is 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.

Appendix B – Additional results and robustness checks

B1. Testing different thresholds

In order to check for the sensitivity of results to the threshold adopted for identifying industry entries, estimates are repeated with respect to a nil-employment threshold and to the employment medians for each new five-digit industry.

Tables A1.1 and A1.2 show that the results are mainly robust to the use of different employment thresholds.

Table B1.1 KETs and regional diversification:
Industry entries for emp>0 and emp>industry_median, 2004-07

	TOP				POT			
	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 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 B1.2 KETs and regional diversification:
Industry entries for emp>0 and emp>industry median, 2008-10

	TOP			
	emp_{2010}>0		emp_{2010}>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 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 B2. Ordered logit estimates, by single KET (2008-10)

TSD	(1)	(2)	(3)	(4)	(5)	(6)
CITKETS	1.833	1.632	2.538*	2.308	2.119	2.311
	(1.428)	(1.455)	(1.379)	(1.388)	(1.390)	(1.389)
AMT	-0.050***					
	(0.018)					
AMT*CITKETS	1.314***					
	(0.524)					
ADV		-0.037***				
		(0.012)				
ADV*CITKETS		1.015***				
		(0.319)				
BIOTECH			-0.023			
			(0.030)			
BIOTECH*CITKETS			0.403			
			(0.956)			
NANOEL				-0.065		
				(0.028)		
NANOEL*CITKETS				1.786**		
				(0.781)		
NANOTECH					-0.675**	
					(0.288)	
NANOTECH*CITKETS					17.06**	
					(8.148)	
PHOTO						-0.027**
						(0.012)
PHOTONICS*CITKETS						0.584
						(0.412)
			omitted			
N	67485	67485	67485	67485	67485	67485
Pseudo R^2	0.082	0.082	0.082	0.082	0.082	0.082

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.

B3. Self-selection for KETs

Regions may not be fully comparable due to some intrinsic characteristics that are not observable. For instance, 19 out of 103 regions register no KET-related patent applications, and only 25 regions have more than 10 KET-related patents. To make regions easier to compare, we proceed as follows. First, we estimate a logit model on our sample of NUTS 3 regions using as the dependent variable a dummy that takes the value of 1 if the region is endowed with a positive amount of KETs patents between 1995 and 2004. Since the process of KETs production, and accumulation is mainly science-driven, as an explanatory variables we use the proportion of university professors per million population ($PROF/POP_{1996}$) in 1996, and the number of universities per million population ($UNIV/POP_{1996}$), which is the first year available in the ASTI database (data provided by the Italian Ministry of Education and Research).

We expect regions more endowed with university personnel and facilities to be better able to accumulate KETs over time.

After running this first probit estimation, we omit 23 regions with a propensity score falling outside the common support (CS). In fact, these regions are not comparable with the rest in terms of the regressor selected, i.e. the proportion of university professors out of the total population. Looking at the propensity score distribution in Figure B3.1, they are regions with some of the oldest universities in Europe (e.g. Bologna, Padova and Siena), and a particular concentration of university professors. They are also among the regions with the largest KETs endowment in Italy. Table B3.1 shows the results of the first stage probit estimates.

Figure B3.1 Propensity score distribution

Table B3.1 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%)

We also adopt an alternative strategy, omitting from the sample all regions where *KETS*=0, and re-estimating equations [1] and [2] only for the regions with at least some KETs endowment in 1995-2004. Table B3.2 shows the results of the ordered logit estimates for 2004-07.

Columns 1 and 2 show that the baseline results concerning TOP hold both for regions with KETS>0 and for those on the common support (i.e. where CS=1). As for POT, the results are the same as in Table 4 for regions with KETS>0, but the estimated coefficients of *KETS* and *KETS***CITKETS*, despite having the same sign, are not statistically significant for regions on the common support. This implies that, unlike the case of TOP, the role of KETs in promoting a region's unrelated diversification via POT relies on the presence of a large endowment of these technologies.

Table B3.2 KETs and regional diversification, 2004-07: common support and positive KETs

	TOP		POT	
	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 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.

B4 Reverse causality

The relationship between KETs endowment and regional diversification can be affected by unobserved heterogeneity and simultaneity. For instance, an unobserved shock may affect both variables, altering the density of KET-related patents in a region and the region's ability to generate new industries. Or unobserved local characteristics could make new and unrelated industries emerge in regions more endowed with KETs, but without these technologies having a clear role. While the structure of our econometric strategy can already deal with these problematic issues to a certain extent,[14] we address them by adopting an instrumental variable approach, as proposed by Lewbel (2012).

This method uses the conditional second moments of our potentially endogenous variables (*KETS, CITKETS* and *KETS*CITKETS*) to address the endogeneity issue. Identification occurs when the residuals of the first-stage regression are heteroskedastic and at least a subset of the regressors used for estimating equations [1] or [2] correlates with the variance of these residuals, but is independent of the covariance between these first-stage residuals and those emerging from the second-stage regression. If this condition is satisfied, instruments are computed by multiplying the first-stage residuals by the mean-centered 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. We also 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 B4.1 shows two interesting results. First, the sign and significance of the estimated coefficients of *KETS* and *KETS*CITKETS* remain the same as in Tables 4 (2004-07) and 6 (2008-10). Second, the difference in the Sargan test (statistics) 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 judging from the Hansen J test.

[14] 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.* Then, by construction, we estimate our relationship in two periods, 2004-07 and 2008-10, which refer to a positive and a negative phase of the business cycle, respectively.

Table B4.1 IV-GMM regressions: Lewbel's (2012) approach

	2004-07		2008-10
	TOP	POT	TOP
	(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		
No. of instruments excluded	222		
Hansen J (p-value)	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 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.

B5 Spatial autocorrelation

Given the possible presence of knowledge spillovers across Italian NUTS3 regions, the diversification pattern of one region *r* could be affected by the KETs endowment of neighboring regions. In order to address this issue, referring to the first of our periods,[15] we test for the presence of spatial autocorrelation in KETs. After summing KETs at the level of each of the 103 provinces, we run a

[15] Results for the second period are available from the authors upon request.

Moran-I test on *KETS, CITKETS* and *KETS*CITKETS*, using the latitude and longitude of the NUTS 3 region to compute the distance matrix. The upper part of Table B5.1 shows that the test never rejects the null hypothesis of spatial autocorrelation.

Then we test for the spatial autocorrelation in our dependent variables. Since *Y* is measured at (5-digit) industry-NUTS 3 region level, we first sum the number of entries by diversification pattern (i.e. replication, transplantation, and exaptation) at 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 B5.1, the test rejects the null hypothesis for *Replication* and *Transplantation,* but not for *Exaptation.*

Table B5.1 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)

Taking stock of these findings, we estimate a spatial Durbin model to check whether the single number of entries involving replication and transplantation in the region *r* in 2004-07 is affected by the entries and KETs in the same region *r* (direct effect) and/or in neighboring regions (indirect effect). Table B5.2 shows that, for both types of diversification, only the direct effect is significant, in line with the results in Table 4. We conclude that our results are not affected by spatial autocorrelation.

Table B5.2 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 also include a constant term. *** p<0.01 ** p<0.05 * p<0.10.

B6 Industry saturation

Since the entry of new industries in the region is measured in terms of new 5-digit industries based on the NACE Rev. 2 classification, it may be that the chances of a region creating further new, and unrelated industries depends on the maximum number of industries that can be coded by ISTAT. To check this, we re-estimate equations [1] and [2] including a variable that measures the difference between the maximum number of industries and the actual number of industries in a region (*INDUSTRY SATURATION*), assuming that a higher number coincides with higher chances of a region further generating new industries, and vice versa.

Table B6.1 shows the ordered logit results, still with respect to 2004-07,[16] confirming the baseline results in Table 4: the higher the stock of citation-weighted KETs, the greater the propensity of a region to diversify following a *technology over place*, rather than a *place upon technology* pattern.

Table B6.1 KETs and regional diversification in 2004-07: accounting for industry saturation

	TOP	POT
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 2-digit industry level) standard errors in parentheses. All the estimates include a constant term. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[16] And available from the authors for the second one (2008-2010).