On the geography of radical innovations: Key Enabling Technologies (KETs) and technological novelty in European regions

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Abstract

This paper investigates the extent to which the local endowment of Key Enabling Technologies (KETs) can drive the regions' capacity to create technological novelty. Looking at innovations as re-combinations of pre-existing knowledge, we propose a new indicator of regional technological novelty, based on regional patents that originally draw (by citing) on still unexplored prior-art knowledge. We argue that KETs have inner knowledge re-combinatorial properties and that, consistently with the technological novelty approach we follow, the local endowment of KETs can be expected to drive its creation. We test this research hypothesis with respect to a sample of more than 1,200 NUTS3 regions in Europe over the period 2000-2014, and find general confirmation of it, although with some important nuances. The geography of radical innovations does significantly overlap with the geography of KETs, making the support of their development, use or eventually external acquisition an important policy priority.

Key-words: technological novelty; knowledge combination; Key Enabling Technologies (KETs).

JEL codes: R11, R58, O31, O33

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1. Introduction

The fact that knowledge creation and innovation could represent an important source of economic advantages and structural change at the regional level is nowadays widely recognized by different streams of academic literature and exploited by policy-makers (MacKinnon et al., 2002; Capello, 2013). On this basis, a research field in economic geography has flourished, which investigates the factors that account for an apparently uneven spatial distribution of innovation within and across countries in a global scenario (Feldman, 1994; Howells and Bessant, 2012; Clark et al., 2018). The state-of-art literature of the "geography of innovation" clearly reveals that the patterns through which it unfolds are highly heterogeneous in terms of both typologies of territories (e.g. core vs. peripheral places) and nature of innovation activities (e.g., formal vs. informal ones). Accordingly, more granular and finer investigations than those carried out so far appear necessary (Shearmur et al., 2016).

In this emerging need of a "geography of innovation*s*", particular attention is required by the regional distribution of 'technological novelty', meant as the brand-new technological knowledge, introduced by radical innovations with the most manifest economic impacts (Verhoeven et al., 2016). Indeed, while it has been recognized that "explaining regional performance in terms of breakthrough innovation requires different hypotheses than explaining regional innovative performance in more general terms" (Castaldi et al., 2016, p. 777), the geography of technological novelty has received only scanty attention so far (Castaldi and Los, 2012; Ejermo, 2009). In particular, two issues deserve to be addressed more carefully. First of all, the most recent studies have tried to detect local radical innovations by referring to regional residents' patents and by looking at the atypical knowledge combinations (Mewes, 2019), or at the combinations of unrelated knowledge (Castaldi et al., 2014), which their co-occurring classificatory codes (International Patent Classification (IPC) and/or Cooperative Patent Classification (CPC)) would reveal (Rigby, 2015). In so doing, only limited stock has been taken of the richness of methods, through which patent data have been used to inspect technological novelty in a-spatial framework so far. This leaves scope for further enrichments in the measurement of regional radical innovations, to which we aim at contributing with this paper. In particular, drawing on a recently developed patent-based measurement of "novelty in technological knowledge origins" (Verhoeven et al., 2016, p. 711), we propose a new regional indicator of technological novelty, based on the number of regional patents that originally rely on and combine (by citing) prior-art technological knowledge: that is, knowledge fields (proxied by patent codes), which were never previously used (cited) for purposeful inventions (again, proxied by patent codes), either in the region or in the entire world (as proxied by the focal patent office).

A second issue that requires further investigation concerns the determinants of the regional distribution of technological novelty. In accounting for it, previous studies have mainly followed a Jacobsian perspective (Jacobs, 1969) and looked at the economic scale and metropolitan nature of regions in favoring the higher degree of knowledge variety that radical innovations would entail (Mewes, 2019); similarly, attention has been also posed to the unrelated (rather than related) variety of the regional knowledge-base on which breakthrough innovations also draw (Castaldi et al., 2015). Conversely, still neglected appear the regional factors that could help the process of knowledge recombination itself from which, following a Schumpeterian perspective, technological novelty can be expected to follow (Uzzi et al., 2013; Kim et al., 2016). In contributing to fill this gap, the second aim of this paper is to investigate the role that local technologies marked by knowledge combinatorial properties can have in driving regional technological novelty. In particular, we draw on recent evidence about the effects that, because of these knowledge combinatorial properties, the six Key-Enabling-Technologies (KETs) recently put forward by the European Commission (EC, 2012a, 2012b) - i.e., i) industrial biotechnology, ii) nanotechnology, iii) micro- and nanoelectronics, iv) photonics, v) advanced materials, and v) advanced manufacturing technologies - have been shown to have in favoring explorative (i.e. less related, if not even unrelated) processes of regional diversification (Montresor and Quatraro, 2019; Montresor and Quatraro, 2017; Antonietti and Montresor, 2019). Indeed, we argue and expect these effects are the ultimate and indirect result of a more direct effect of KETs on the creation of technological novelty, which we look for in our empirical application.

Overall, the aim of the paper is therefore to investigate the extent to which KETs allow regions to introduce radical innovations, whose technological novelty relies on the new combination (through citation) they make of the extant (local or global) knowledge space.

Using the OECD RegPat Dataset, and combining it with the Cambridge Econometrics European Regional Dataset, we carry out this analysis with respect to a sample of 1,255 NUTS3 regions in Europe over the period 2000-2014. The results of the econometric estimates generally support our argument about the role of regional KETs in driving our proposed measurement of technological novelty, although with some important nuances when regional technological novelty is distinguished from the absolute one.

The rest of the paper is structured as follows. Section 2 illustrates the background literature with respect to which we build up our indicator of technological novelty and our research hypothesis about the role of KETs in driving it. Section 3 presents our empirical application, and Section 4 discusses its results. Finally, Section 5 concludes.

2. Background literature

2.1. Searching for local technological novelty

As the literature review contained in Verhoeven et al. (2016) reveals, several methodologies have been proposed to identify radical innovations in "a-spatial" framework: that is, by looking at the inventors, firms and sectors in which they have been introduced, but without retaining the influencing and differentiating role of their geographical context. Among the alternatives,[1] patent-based measurements have emerged the most effective, given the rich information they provide about the technological profile of the focal inventions (classifying codes and descriptions), the origin of their ideas (backward citations) and the domain of their use (forward citations). In particular, the relative indicators look at the classes (IPC and/or CPC) into which patents are classified (by patent offices) as proxies of knowledge fields and, following a Schumpeterian perspective, consider a "new" combination of them as revealing a radical invention (Nooteboom, 2000; Nemet, 2009; Story et al., 2011). The way this knowledge combination has been captured is however heterogeneous, and different is the extent to which its geography has been investigated.

A first kind of addressed knowledge combination is revealed by the multiple classes into which individual patents can be, and generally are, cataloged. Upon their review, patents can actually be attributed a number of different technological classes (with different degrees of disaggregation), each of which captures the specific domain in which they bring novelty, starting from a primary class, in which the degree of novelty is the highest. The co-occurrence of classes with respect to which a patent claims to have brought original and relevant knowledge is of course, *per se*, a combination of knowledge "items" of the invention, and the extent to which this combination can be deemed unprecedent a signal of its eventual radicalness. This is the idea of a research stream based on the seminal papers by Fleming (2001) and Fleming and Sorenson (2001), which look at the "familiarity" (or, conversely, the atypicality) of the patent sub-classes and/or sub-classes combinations that occur in firms' patent portfolio to identify breakthrough inventions as "recombinant" ones, in line with seminal contributions by Evenson and Kislev (1976) and Weitzman (1998).

In addition to more recent developments with respect to non-geolocalized patents (Fleming, 2007; Strumsky and Lobo, 2015; Kaplan and Vakili, 2015), this measurement of radical inventions as "novelty in recombination" (Verhoeven et al., 2016, p. 710)[2] has recently found an interesting geographical application in the study by Mewes (2019). Using the z-scores methodology proposed

[1] These are numerous and span from ex-post, impact forecasting studies to ex-ante qualitative investigations, like surveys.
[2] As we will say, in Verhoeven et al. (2016) these inventions are proxied by patents that contain at least one pair of IPC groups that were previously unconnected.

by Teece et al. (1994) at the firm-portfolio level, comparing actual with stochastic patent class combinations at the local level, atypical combinations of (CPC) sub-classes are identified for Combined Statistical Areas in the US over about 170 years (1836-2010) and the role of urban size in their emergence is investigated: an issue on which we will return later.

While for sure expression of a particular kind of radical inventions, those based on the novel co-occurrence of classes in patents suffer from two limitations. The first one is general and regards the technical impossibility of considering as radical those patents that are assigned one class only (e.g. one IPC group or subgroup code only), which could still have an important impact in principle and are far from negligibly diffused (Verhoeven et al., 2016, p. 710; Cozza et al., 2019).[3] The second limitation concerns the geographical stance of the combination between technologies as accounted by the co-occurrence of the relative patent classes. In a sense, local radical inventions defined on their basis represent regional inventions that do not take stock of what has been called the "relatedness" of technological classes, at least by the studies that measure it with the frequency with which two classes appear on the same patent (Boschma et al., 2015; Balland et al., 2018). Indeed, while relatedness looks at typical combinations of knowledge fields in the ensuing "knowledge space", and predicts that regional innovations more easily develops on its basis (Quatraro, 2010; Neffke et al., 2011; Boschma et al., 2012; Colombelli et al., 2013; Koegler et al., 2013), radical inventions would unfold through atypical combinations in the absence of relatedness. On the other hand, as Rigby (2015) recognises, the relatedness that the co-occurrence of technological classes in local patents reveals could be due to "unspecified economic relationships that display positive spatial autocorrelation"; similarly, the absence of these economic relationships could mask the absence of relatedness they entail with actually spurious radical inventions.[4]

In front of the previous difficulties, a second kind of patent-based knowledge combination that the literature on radical innovations has explored is rather represented by the citations that patents (even those with one IPC code) make backward, in so doing combining the technological classes (usually the primary ones) of citing and cited patents (Leten et al., 2007). Focusing on this kind of combination, different features have been considered for it, still in a-spatial framework, to identify technological novelty. For example, radical inventions have been searched by looking at the *number*

[3] As Verhoeven et al. (2016, p. 710, footnote 4) show: "Going to a more disaggregated IPC group level … when employing the IPC subgroups (lowest level of aggregation: 69,884 classes), …about 21 percent … belong to 1 IPC-code".
[4] This is in the spirit of what also Balland (2016) recognizes, by observing that the "co-production of knowledge" [captured through co-citations] can capture much more than knowledge relatedness understood as a reflection of cognitive proximity between organisations. …, [and] reflect the need for similar institutions, infrastructure, physical factors, technology or a combination of these factors. So, using such an outcome-based measure of relatedness for knowledge domains will not necessarily capture scientific or technological relatedness, but probably much more factors that lead to the co-production of knowledge domains" (p. 132)."

of citations made by the relevant patents, but with ambiguous results about their being few (Ahuja and Lampert, 2001; Banerjee and Cole, 2011) rather than many (Schoenmakers and Duysters, 2010). Radical inventions have thus been rather looked for on the basis of the *spread* of their citations, claiming that the relative patents would/should quote outside their attributed technological classes, or outside the coverage of the inventive firm's patent portfolio (Trajtenberg et al., 1997; Rosenkopf and Nerkar, 2001; Shane, 2001; Ahuja and Lampert, 2001). Alternatively, the *similarity* of the citation patterns revealed by different patent 'vintages' has been addressed, by expecting and finding that the among-classes distribution of citations showed by radical patents has a low or nil degree of overlapping with that of previous, concomitant and subsequent patents (Dahlin and Behrens, 2005).

While all useful in searching for a citation revealed kind of technological novelty, the previous approaches pose a computational burden that, by "exploding" in the search for its economic geography, make it more preferable referring to the inner idea of "novelty in technological knowledge origins". As Verhoeven et al. (2016) illustrate, radical inventions marked by this kind of novelty would be proxied by patents that make an unprecedent combination between their own IPC code and an IPC code of the patents they quote, that is, a combination that never occurred previously to their application year.[5] In comparison to the previous alternatives of the family, the present measurement has a number of advantages that make of it a good candidate for investigating the geography of technological novelty. First of all, at least in a-spatial framework, it has already been submitted to a scrupulous work of validation, confirming that the technological novelty it captures ex-ante is consistent with different sets of external information on their novelty ex-post (for this validation work, see Verhoeven et al. (2016, p. 715)). Second, as we have noticed in passing, it allows mono-IPC patents to potentially proxy for radical inventions and does not rule them out by construction. Third, it has some desirable features for its geographical translation. On the one hand, it somehow represents the "unrelated complement" of a more accurate measurement of relatedness between technological classes at the local level, based on the frequency of their correspondent citations, rather than of their co-occurrence (Rigby, 2015): in brief, inventions marked by the novelty of the technological knowledge origins are closer to inventions that develop in a truly unrelated manner. On the other hand, as we will say in the following, playing with the different domains with respect to which the focal knowledge combination can be deemed unprecedent, the indicator at stake actually forks into two, pointing to a relatively regional, rather than to an absolute kind of technological novelty. In both

[5] More precisely, patents marked by novelty in technological origins are identified in the following way: "We construct 'backward citation pairs' of IPC-codes, i.e. combinations between distinct IPC-codes from, on the one hand, all patents cited by the focal patent and, on the other hand, all distinct IPC-codes the focal patent belongs to. We compare each of the focal patent's 'backward citation pairs' to all citation pairs previously used to assess whether a certain pair is new (has never occurred before) (Verhoeven et al., 2016, p. 711).

respects, the search of the determinants of its geography represents a still unexplored issue, to which we turn in the following.

2.2. The geography of technological novelty and that of Key Enabling Technologies (KETs)

The little research carried out so far about the determinants of an alleged uneven distribution of technological novelty has mainly adopted a Jacobsian perspective and claimed that its main driver should be the knowledge diversity of the local knowledge base. In the recent study by Mewes (2019), once depicted as "atypical" combinations of (co-occurrent fields of) knowledge, radical inventions are supposedly favored by explorative, rather than exploitative, combinations (Schilling and Green 2011; Uzzi et al. 2013; Kim et al. 2016), and these combinations in turned mainly helped by regional variety. This is Jacobs' (1969) core idea, according to which places engaged in different industries, like metropolitan areas or cities, would host people with heterogeneous background, from whose knowledge interaction technological novelty would descend. In particular, firms based in diverse regions, marked by large and heterogeneous pools of knowledge, could benefit from the cross-fertilization of ideas between different industries – the so-called Jacobsian externalities (Glaser et al., 1992) – and take stock of them to innovate more radically. As this regional diversity naturally grows with the urban size of an area, atypical combinations leading to radical inventions can be expected to scale superlinearly with city size and show increasing returns to urbanization (Bettencourt et al., 2007; 2008): a result that Mewes (2019) actually finds with respect to population for US metropolitan areas over a long period of time.

In their analysis of "breakthrough innovations" in US states over the period 1977–99, this time proxied by the local share of "superstar patents" – i.e. marked by high forward citations (Castaldi and Los, 2012) – Castaldi et al. (2015) use a refined version of the classical Jacobsian argument about regional variety. Following the distinction proposed by Frenken et al. (2007), they suggest and find that, more than the "related" variety of the local knowledge-base, it is the "unrelated" one that matters for technological novelty.[6] Indeed, considering radical inventions as the combination of previously unrelated bits/fields of knowledge (Section 2.1), their introduction is more probably fed by a local knowledge-base, whose elements are not only diverse but, as we claimed in the previous Section, so diverse to be not related yet.

In spite of this important specification, regional variety is however only one part of the story in the regional distribution of radical innovations. As Mewes (2019) notices, "regional diversity […] is not

[6] As is well-known, related and unrelated variety refer to the entropy-based measurements of the diversity shown by a region's patent portfolio at different levels of technological classification.

sufficient to actually explore new combinations [as it] rather indicates the *potential* that could be explored", while other factors are required to make the exploration *effective*. Among these factors, the author mainly points to elements that are still related to the urban size of the regions, like the local availability of skills, creative and/or R&D employment. These are actually retained crucial to recognize, and often entrepreneurially discover, the opportunities of explorative combinations that diverse regions offer, and to set them in action through products and processes marked by new properties and operations. While they are already combinatorial factors, rather than combinatorial opportunities, these regional elements have also been found to scale with city size (Florida, 2002; Bettencourt et al., 2007; Combes et al., 2008) and thus reinforce Mewes' (2019) main conclusion about the metropolitan location of radical (atypical) innovations. On the other hand, additional factors could help the implementation of recombinant innovations, which do not necessarily correlate with the regional size. Among these, an important role can be played by the local availability of technologies with knowledge combinatorial properties: that is, technologies that can work as 'interfaces' among the knowledge domains of whose atypical combination radical inventions consist.

In innovation studies, these technologies have been since long identified as General Purpose Technologies (GPT), that is, technologies that the evolution of techno-economic paradigms render capable of multiple and transformative applications with respect to a certain temporal window: e.g., the steam engine, electricity and electronics, in the last set of Industrial Revolutions. This kind of technologies actually reveal two properties that could favor the combination of unrelated knowledge, and thus radical inventions, also and above all at the local level (Bresnahan, 2010). First of all, they are marked by a typical co-invention-application pattern of development; thanks to it, the regional activities that are based on the applicative path of an extant technology becomes connectable, not only to the complementary activities of related technologies, but also to the non-complementary ones based on the new inventive path the GPT has created. In other words, by co-creating new regional inventions and applications, the development of GPT can allow the region to implement recombinations of local activities that the simple branching of the extant application would not have made possible (Frenken et al., 2012). To a similar conclusion leads the second property of GPT, that is, their horizontal nature and their capacity to move the regional technological frontier ahead. Because of that, GPT can attenuate the constraints that the ruling socio-technical regimes pose to a radically new recombination of existing ideas (Olsson and Frey, 2002). In other words, the development of GPT could provide regions with an extra buffer of knowledge and ideas, which can be combined in such an afresh way to reach an even extra-regional kind of novelty and eventually favor the development of new socio-technical niches.

The role of the previous GPT properties has been recently investigated with respect to what can be considered one of their last generations, that is, the six technologies that the EC has identified as Key Enabling Technologies (KETs) for “a competitive, knowledge-based and sustainable economy” (EC, 2009, 2012): i) industrial biotechnology; ii) nanotechnology; iii) micro- and nano-electronics; iv) photonics; v) advanced materials; and vi) advanced manufacturing technologies. While possibly not the very last GPT generation, more readily represented by the enabling technologies of the Fourth Industrial Revolution (Artificial Intelligence, *in primis*), KETs have the important advantage to have been already mapped in terms of patent classes (see the EC Feasibility Study on that (EC, 2012)) and are thus easily geo-localizable and investigable at the regional level. By exploiting this advantage, some recent studies have found that the local availability of KETs can help processes of unrelated technological diversification in different geographical contexts (Antonietti and Montresor, 2019; Montresor and Quatraro, 2017) and in different technological domains, like for example the green one (Montresor and Quatraro, 2019; Castellani et al., 2019). On the other hand, the results of all of these studies are interpreted and accounted by processes of knowledge recombinations - that is, of creation of technological novelty in the spirit of the previous Section - which are not directly observed and rather assumed to drive the observed phenomena of less related and unrelated diversification. Using the indicator of regional technological novelty that we have proposed, these direct effects of KETs can however also be addressed and represent the subject of the empirical application we are going to present in the next Section.

3. Empirical application

Our empirical analysis is conducted at the EU NUTS3 level and refers to a sample of 1,255 regions observed over the period 2000-2014. The investigation of their recombinant innovations and KETs is based on patent data from the OECD RegPat Dataset. Additionally, the Cambridge Econometrics European Regional Dataset is used to retrieve suitable controls in investigating our focal relationship, such as employment, GDP and population density.

Dependent variables – We propose two measures of recombinant innovations, based on the novel co-occurrence of patent IPC classes between citing and cited patents: pure novelty and local novelty. As we said, the rationale for exploiting links between patents and their citations to measure novelty is that patent citations are references to prior technology on which the current patent builds or which it uses (prior art) (Trajtenberg, 1990; Jaffe et al., 1993; Jaffe and Trajtenberg, 1999; Maurseth and

Verspagen, 2002).[7] Therefore, if the technology in which the patent is classified relies on a novel bit of prior art, this signals for an original combinatorial attempt that, possibly, enriches the technology space opening rooms for new technological trajectories (Fleming, 2001). As we also said, this, in turn, may contribute to the enhancement of local technological variety and to less related, if not even, unrelated diversification (Montresor and Quatraro, 2017; 2019; Antonietti and Montresor, 2019), a key driver for regional growth (Frenken et al., 2007; Boschma and Iammarino, 2009; Boschma et al., 2012; Hartog et al., 2012).

Precisely, we define as purely novel a patent that links, for the first time at EPO, a specific IPC class with another IPC (cited).[8] Similarly, we define as locally novel a patent that shows an IPC link never observed before in the NUTS3 region in which it is invented. Hence, if a patent is purely recombinant it will be also recombinant at the local level, while the opposite does not necessarily hold.[9] To assign novel patents to local areas (i.e. NUTS3), we rely on information contained in inventor addresses.

Explanatory variable and controls – As we said, our hypothesis is that the regional endowment of KETs, given their GPT features, could boost novel combinations across the knowledge space. Our main regressor of interest is therefore the local number of KETs-patents. In order to individuate EPO patents related to KETs we exploit the IPC classification. More precisely, we retrieve the list of KETs-related IPC classes from the "KETs Feasibility Study" (EC, 2012b).[10] As for novel patents, KETs-related patents are assigned to local areas according to the inventor address.[11]

In order to address other sources of heterogeneity of regional recombinant innovations, we include a list of controls at the local level, such as: the stock of non-KETs patents ($SNOKETS$), that controls for the local level of general innovativeness that may influence both the emergence of novel combinations and the local innovation activity in KETs; the level of GDP to account for the local economic size (GDP); the level of employment in industry (manufacturing and energy sectors, $empl\ ind$), and the level of population density ($dens$), as proxies of concentration that may impact both our dependent variable and our regressor of interest. Finally, we include NUTS3 fixed effects to

[7] For a recent survey about the use of patent citation data in social science research, see Jaffe and de Rassenfosse (2017).
[8] We consider 4-digits IPC classes. Importantly, we exclude KETs-related classes when measuring combinatorial novelty.
[9] A novel combination may appear simultaneously in more than one patent, as well as in more than one region. We indeed take the patent priority year as time reference to assign patents to local areas.
[10] https://ec.europa.eu/growth/tools-databases/kets-tools/sites/default/files/library/final_report_kets_observatory_en.pdf
[11] Alternatively, we substitute the local KETs stock ($SKETS$) for the KETs flow, applying the perpetual inventory method, as it follows:

$$SKETS_{i,t} = KETS_{i,t} + (1 - \delta) * SKETS_{i,t-1}$$

Where $KETS_{i,t}$ is the number of KETs patents invented in region i at time t, and δ is the 15% obsolescence rate.

control for all possible time-invariant local characteristics and year dummies to account for shocks common to all the regions included in the analysis, such as for example business cycle.

Empirical model – The estimated models take the following forms:

$$\mathrm{PN}_{i,t} = \vartheta_i + \tau_t + \beta_1 KETS_{i,t-1} + \boldsymbol{X}'_{\boldsymbol{i,t-1}}\beta_2 + \varepsilon_{i,t}$$

$$\mathrm{LN}_{i,t} = \vartheta_i + \tau_t + \beta_1 KETS_{i,t-1} + \boldsymbol{X}'_{\boldsymbol{i,t-1}}\beta_2 + \varepsilon_{i,t}$$

Where $\mathrm{PN}_{i,t}$ and $\mathrm{LN}_{i,t}$ are, respectively, the number of purely and locally novel patents invented in region i at time t; ϑ_i are region fixed effects; τ_t are year fixed effects; $KETS_{i,t-1}$ is the number of KETs-patents invented in region i at time $t-1$; $\boldsymbol{X}'_{\boldsymbol{i,t-1}}$ is a vector of lagged local controls such as the stock of non-KETs, employment in manufacturing and energy, GDP, and population density; $\varepsilon_{i,t}$ is the error term. Standard errors are clustered at the NUTS2 level to account for possible spatial correlation across NUTS3 regions.

4. Results

Before presenting our preliminary results, we provide some descriptive statistics of the variables of interest. Table 1 reports descriptive statistics, while Figures 1, 2 and 3 provide a geographical representation of the distribution of recombinant (purely and locally) and KETs patents across EU NUTS2 regions over the period 2000-2014.

Table 1. Summary statistics

	Obs.	mean	sd	min	max
Pure recomb pat	17,570	2.583	5.681	0	103
Local recomb pat	17,570	32.262	58.477	0	724
KETS	17,570	1.775	5.129	0	180
SNOKETS	17,570	372.658	770.064	0	9,129.07
GDP	17,570	9,303.734	14,935.820	105	208,042
Empl ind	17,570	29.480	32.081	.1	617.1
dens	17,570	591.209	1,428.914	2	21,317.9

As Figures 2 and 3 show, there is large overlapping between the two variables of interest. The two figures plot the quintile distribution (weighted by population density) of, respectively, purely recombinant and locally recombinant patents. Regions in which the highest number of patents with novel and local recombination is concentrated are, not surprisingly, German regions, regions in the

south-east of France and in the north-west of Italy, in the south of the UK and in the south of the Scandinavian area.

Figure 3 reports the geographical quintile distribution (weighted by population density) of the number of KETs patents. The KETs distribution appears strongly spatially correlated with the number of novel patents in the recombinant way we measure them.

Figure 1. Geography of pure recombinant innovations by NUTS-2 (2000-2014)

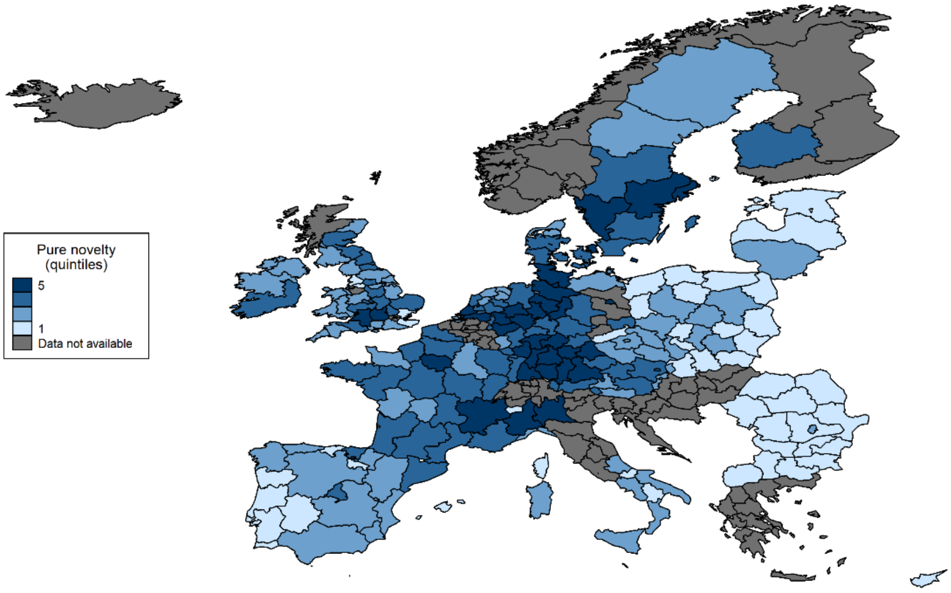


Figure 2. Geography of local recombinant innovations by NUTS-2 (2000-2014)

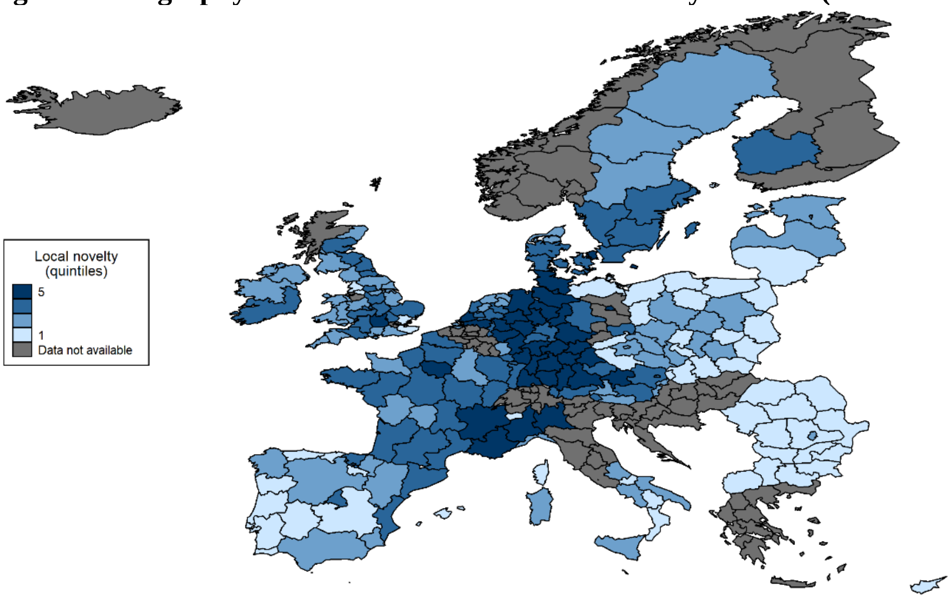
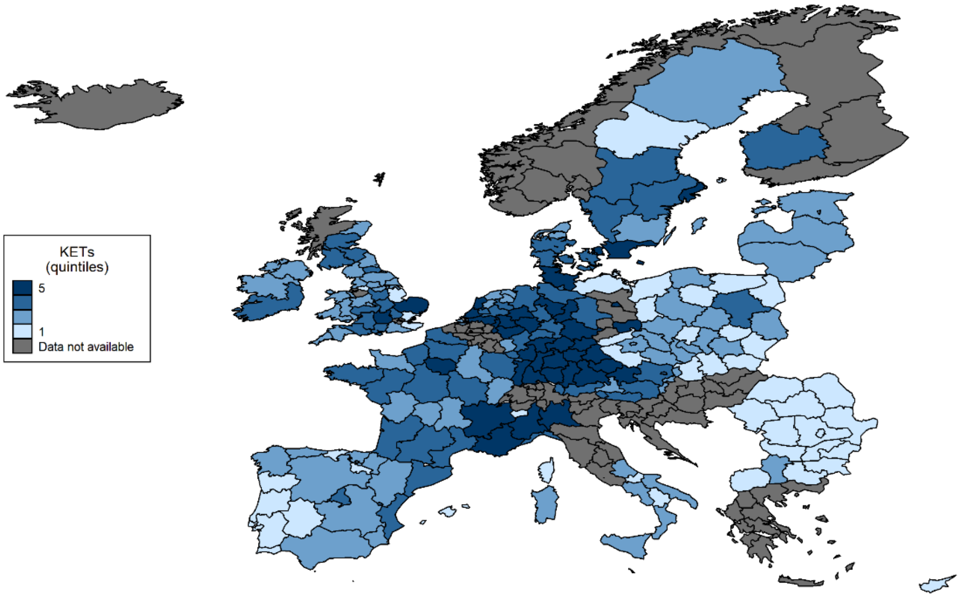


Figure 3. Geography of KETs by NUTS-2 (2000-2014)



Tables 2 and 3 report our preliminary empirical results. In Table 2 we estimate the impact of the local endowment of KETs on the generation of patents showing pure combinatorial novelty. Columns from I to V report the results obtained saturating the model by adding the control variables one by one. The coefficient for the variable KETs is always positive and significant, ranging between around .2. and .18. Since the model is estimated in a log-log form, we can interpret the result as a 1% increase in the local number of KETs patents at time t leads to a .18% increase in the local generation of patents showing a purely novel recombination (i.e. patents citing at least one IPC class never previously related to their IPCs) at time $t + 1$.

Table2. Effect of KETs on pure recombinant innovation

	(I) Pure recomb innovation	(II) Pure recomb innovation	(III) Pure recomb innovation	(IV) Pure recomb innovation	(V) Pure recomb innovation
KETs (log)	0.196***	0.184***	0.182***	0.181***	0.181***
	(0.019)	(0.018)	(0.018)	(0.018)	(0.018)
SNOKETs (log)		0.170***	0.133***	0.143***	0.143***
		(0.032)	(0.033)	(0.033)	(0.033)
GDP (log)			0.215***	0.276***	0.276***
			(0.065)	(0.065)	(0.065)
empl ind (log)				-0.323***	-0.322***
				(0.085)	(0.084)
dens					0.000
					(0.000)
NUTS3 FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.290	0.296	0.298	0.300	0.300
Obs.	17,570	17,570	17,570	17,570	17,570

Dep. Var.: Number of pure novel patents (log). KETs, SNOKETs, GDP, empl industry and dens lagged 1-year. Robust standard errors, in parentheses, clustered at the NUTs2 level. * $p < .1$, ** $p < .05$, *** $p < .01$

We then replicate the same analysis but focusing on the number of recombinant patents that show novelty only at the local level. Results are reported in Table 3. Similar to the effect on pure recombinant novelty, the local endowment of KETs is positively and significantly related also with the generation of patents showing local novelty. The coefficient for the variable KETs ranges between .26 and .23, meaning that a 1% increase in the number of KETs patents increases by around a quarter of a percentage point the number of patents showing combinatorial attempts never observed before in the region.

Table 3. Effect of KETs on local recombinant innovation

	(I) Local recomb innovation	(II) Local recomb innovation	(III) Local recomb innovation	(IV) Local recomb innovation	(V) Local recomb innovation
KETs (log)	0.263^{***}	0.235^{***}	0.232^{***}	0.231^{***}	0.230^{***}
	(0.019)	(0.018)	(0.018)	(0.018)	(0.018)
SNOKETs (log)		0.415^{***}	0.366^{***}	0.380^{***}	0.382^{***}
		(0.044)	(0.042)	(0.043)	(0.043)
GDP (log)			0.285^{***}	0.367^{***}	0.367^{***}
			(0.088)	(0.083)	(0.083)
empl ind (log)				-0.434^{***}	-0.422^{***}
				(0.107)	(0.108)
dens					0.000
					(0.000)
NUTS3 FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.581	0.597	0.598	0.601	0.601
Obs.	17,570	17,570	17,570	17,570	17,570

Dep. Var.: Number of locally novel patents (log). KETs, SNOKETs, GDP, empl industry and dens lagged 1-year. Robust standard errors, in parentheses, clustered at the NUTs2 level. * $p < .1$, ** $p < .05$, *** $p < .01$

As for the control variables, the local stock of patents in technological fields that do not refer to KETs is positively associated with the generation of novel patents, as well as the local level of GDP. Interestingly enough, we find a negative association between the local level of employment in manufacturing and energy sectors and the number of novel recombinant patents, both pure and absolute. While somehow unexpected, this result may suggest that the recombinant process of innovation that we are addressing is possibly more capital than labor intensive, leading to substitution effects between the two factors.

Overall, this preliminary analysis suggests that, as expected, the local endowment of KETs, due to their GPT properties, is an important driver for the local generation of technologies that emerge out of novel combinatorial attempts. Should these preliminary findings be confirmed, important policy implications could be drawn in terms of regional policy. As the EC envisaged upon their identification (EC, 2002), KETs appear actually "enabling" regions to embark in technological transitions that are breakthrough and thus possibly leading to more knowledge intensive and sustainable patterns of

growth. On the other hand, providing a more direct confirmation to the indirect results obtained by recent studies about the role of KETs in driving unrelated diversification, KETs seem to be the leverage through which regions can eventually "stretch" their smart specialization strategies in order to avoid the risk of being locked in their pre-existing competencies.

5. Conclusions

The results that we have presented above are preliminary and require further investigation to be robustly confirmed. Future analysis has been prospected in testing /dealing with the endogeneity of our focal regressor and to take better care of unobserved heterogeneity. Fixed effects estimate and the lag structure built on our regressors attenuate possible endogeneity issues. However, an instrumental variable setting may be required to better capture causality between KETs and local combinatorial novelty dynamics. Moreover, we are planning to test for heterogeneous effects that different KET types may have on local novelty. Finally, further investigating geographical heterogeneity may enrich our understanding of the phenomenon under scrutiny.

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