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Technological Novelty and Key Enabling Technologies: Evidence from European Regions

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Abstract

This paper investigates whether the local endowment of Key Enabling Technologies (KETs) drives the regions' capacity to create technological novelty. Looking at regional innovations as re-combinations of pre-existing knowledge, we propose two indicators of regional technological novelty (absolute and local), based on patents that originally draw on still unexplored prior-art knowledge connections. We argue that KETs have inherent re-combinatorial properties of the regional knowledge base and that their local endowment drives technological novelty. We test for this argument by focusing on a sample of 1,255 NUTS3 EU regions over the period 2000-2014 in an original instrumental variable setting. With some nuances, results confirm our main hypotheses. KETs do drive significantly the introduction of local technological novelty, but this mainly occurs for an absolute kind of novelty. The development, use or eventually external acquisition of KETs is thus an important policy priority for regions willing to compete at the technological frontier.

Technological Novelty and Key Enabling Technologies: Evidence from European Regions

1. Introduction

The fact that knowledge creation and innovation 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 widely exploited by policy-makers in diverse contexts (MacKinnon et al., 2002; Capello, 2013). On this basis, a research field in economic geography has flourished, which investigates the factors that may account for the possible uneven spatial distribution of innovation within and across regions 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) (Antonelli et al., 2020; Capello and Lenzi, 2014 and 2015). Accordingly, more granular and finer investigations than those carried out so far appear necessary (Shearmur et al., 2016).

In front of the emergence of different "*geographies* of *innovations*", particular attention is required by the regional distribution of 'technological novelty', meant as 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 limited attention so far (Ejermo, 2009; Castaldi and Los, 2012). 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 patents filed by regional residents and by looking at atypical knowledge combinations (Mewes, 2019; Berkes, and Gaetani, 2020), or at the combinations of unrelated knowledge (Castaldi et al., 2014), which their co-occurring technological classes 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, which points more directly than extant ones to the novelty in the knowledge recombination through which radical inventions can be expected to occur. This indicator is based on the number of regional patents that rely on and combine (by citing) prior-art technological knowledge in an original way: that is, knowledge fields (proxied by technological classes), which were never previously used (cited) for purposeful inventions, either in the region or worldwide (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; Berkes and Gaetani, 2020). Similarly, attention has been also paid to the unrelated (rather than related) variety of the regional knowledge-base on which breakthrough innovations would 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 nano-electronics, iv) photonics, v) advanced materials, and vi) 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, 2017; Antonietti and Montresor, 2019; Montresor and Quatraro, 2019). Indeed, we argue and expect these proved effects are the ultimate and indirect result of a more salient effect that KETs have 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 the analysis by focusing on a sample of 1,255 NUTS3 regions in Europe over the period 2000-2014. To provide robust causal evidence about the local endowment of KETs in the generation of novel technologies, we build up an original instrumental variable. By exploiting information on KETs-related patents that have been transferred in the US over the period 1995-2014, we obtain a measure of long-lasting regional exposure to non-KETs technologies likely to be substituted by KETs, which we use to instrument the local endowment of KETs in EU NUTS3 regions.

The results of the econometric estimates support our argument about the role of regional KETs in driving technological novelty and show an appreciable impact of them, more on "absolute" than on "local" technological novelty. In particular, a 1% increase in the number of KETs patents at the NUTS3 level leads to around 1.9% more patents whose technological re-combinations are novel to the technology space (i.e. they appear for the first time at EPO). Conversely, the same increase of KETs does only increase the share (and not the number) of patents whose combinatorial composition is novel just for the region (i.e. their combinations appear for the first time in the focal NUTS3 region, while already appeared elsewhere), and to a more modest extent (about 0.4%). Quite interestingly, KETs do not add (much) to the spectrum of drivers that extend the technology novelty of regions at the local margin, with respect to which their recombinant properties appear less essential and their role nearly neutral. On the contrary, the same KETs properties appear instead essential in allowing regions to extend the knowledge space in absolute terms going beyond their boundaries.

Inserting the development of KETs in the regional policy toolbox thus has an additional implication to that already recognized in their favoring an explorative pursuing of smart specialization strategies (Montresor and Quatraro, 2017). KETs do also favor regional innovation strategies with a high degree of novelty. However, KETs are more for "new-to-the-world" than for "new-to-the-region" radical innovations, representing a "high-power" policy-leverage to which regions are (not) recommended to resort when prioritizing the high (low) way to technological novelty.

The rest of the paper is structured as follows. Section 2 illustrates the background literature and discusses our research arguments. Section 3 presents our empirical application. Section 4 discusses its results. Section 5 concludes.

2. Background literature

2.1. Searching for technological novelty in space

To date, several methodologies have been proposed to identify radical innovations (see Verhoeven et al. 2016, for a review). However, so far this has mainly occurred in "a-spatial" framework: that is, by looking at the inventors, firms and industries by which innovations have been introduced, paying little attention to the conditioning role of their geographical context. Among the alternatives,[1] patent-based measurements have emerged quite effective, given the rich set of information they provide about the technological profile of the focal inventions (classifying codes and descriptions), the origin

[1] These are numerous and span from ex-post, impact forecasting studies to ex-ante qualitative investigations, like surveys.

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, in the few cases it has been done.

The multiple classes into which individual patents can be, and generally are, catalogued reveal a first kind of knowledge combination that has been addressed. Upon their review (in Europe, and upon their application too, in the US), patents can 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 claimed to be the highest. The co-occurrence of classes with respect to which a patent claims to have brought original and relevant knowledge is consequently understood as a combination of knowledge "items" of the invention, and the extent to which this combination can be deemed unprecedented as 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 in the modalities to identify the novelty of the co-occurring patent codes (see Fleming, 2007; Strumsky and Lobo, 2015; Kaplan and Vakili, 2015; Pezzoni et al., 2019), this measurement of radical inventions as "novelty in recombination" (Verhoeven et al., 2016, p. 710)[2] has recently found a first geographical application. Drawing on the z-scores methodology proposed by Teece et al. (1994) at the firm-portfolio level, comparing actual with stochastic patent class combinations at the local level, Mewes (2019) looks for "atypical combinations" of (CPC) sub-classes among Combined Statistical Areas in the US over about 170 years (1836-2010). The role of urban size in their emergence is then investigated: an issue on which we will return later. Yet, inventions based on atypical combinations of knowledge are indeed more prevalent in high-density urban centres.

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

[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.

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., 2020).[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; Koegler et al., 2013; Colombelli et al., 2014), radical inventions would unfold through atypical combinations in the absence of relatedness. On the other hand, as Rigby (2015) recognizes, 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 to identify technological novelty. For example, radical inventions have been searched by looking at the *number* 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 searched based on the *spread* of their citations, claiming that radically new 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

[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).

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-based kind of technological novelty, the previous approaches pose a computational burden that, by "exploding" in the search of 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 unprecedented 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 this kind, the present measurement has several 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)).[6] 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 (Colombelli et al., 2014; 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 in which the focal knowledge combination can be deemed unprecedented, the indicator at stake forks into two: one pointing to an absolute kind of technological novelty, and the other to a relatively regional kind of it. 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).

[6] To be sure, the inner underlying idea of looking at citations (rather than patent codes co-occurrence) that the indicator proposes, has been just (at the time of this writing) applied also at the spatial level by Berkes and Gaetani (2020), who investigate the "geography of unconventional innovations" still with respect to the US (County Sub-Division (CSD) level between 2000 and 2010). Unlike that by Verhoeven et al. (2016), however, and of our own, their indicator relies on the methodology proposed by Uzzi et al. (2013) and, rather than focusing on an atypical combination of classes between cited and citing patents, "simply" considers the presence of atypical citations in the network of the local citations, looking at cited patents only. While using this different perspective, Berkes and Gaetani (2020) also find (like Mewes (2019) that unconventional ideas are mainly produced by high-density locations, pointing to an aspect on which we will return later by adding to the analysis the role of KETs.

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

2.2. Regional technological novelty and the geography of Key Enabling Technologies (KETs)

The scant research carried out so far about the determinants of an alleged uneven spatial distribution of technological novelty has mainly adopted a Jacobsian perspective and claimed that its main driver should be the diversity of the local knowledge base. In the recent study by Mewes (2019) "atypical" combinations of (co-occurring fields of) knowledge are deemed to be favored by explorative, rather than exploitative, combinations of pre-existing one (Schilling and Green 2011; Uzzi et al. 2013; Kim et al. 2016), and these combinations are in turned deemed helped by regional variety. Similarly, Ruben and Gaetani (2020) claim that "unconventional" innovations (associated to patents with unconventional tails of citation distributions) occur in more densely populated areas as the latter are more diversified pool of learning opportunities, where informal interactions are richer and help knowledge flows between diversified fields.

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 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 super-linearly with city size and show increasing returns to urbanization (Bettencourt et al., 2007; 2008): a result that Mewes (2019) finds focusing on the population of US metropolitan areas over a long time-span.

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 seminal distinction proposed by Frenken et al. (2007), they suggest and find that, more than the "related" variety of the local knowledge base, the "unrelated" one matters for technological novelty.[7] Considering radical inventions as the combination of previously unrelated bits/fields of knowledge (Section 2.1), their introduction is retained more probably fed by a local

[7] Extending Frenken et al.'s (2007) intuition, defined in terms of employment shares by industry, in Castaldi et al. (2015) related and unrelated variety refer to entropy-based measurements of the diversity shown by a region's patent portfolio at different levels of technological classification.

knowledge base, whose elements are not simply diverse but, as we claimed in the previous Section, so diverse to be not related yet.

Despite 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 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 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 over a certain temporal window: e.g., the steam engine, electricity and electronics, in the first wave of Industrial Revolutions. This kind of technologies reveal two properties that could favour 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 recombination 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 entire 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 favour the development of new socio-technical niches.

The role of these 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, for whose role Artificial Intelligence and related technologies are applying in the current era of the Fourth Industrial Revolution (Martinelli et al., 2019), KETs have the important advantage to have been already mapped in terms of diffusion, uses and patent classes in a consolidated manner (see the EC Feasibility Study on that (EC, 2012)).[8] Accordingly, they are 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 (Montresor and Quatraro, 2017; Antonietti and Montresor, 2019) and in different technological domains, like for example the green one (Montresor and Quatraro, 2019; Castellani et al., 2020). On the other hand, the results of all of these studies are interpreted and accounted by processes of knowledge re-combinations – 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 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 technological novelty and KETs is based on patent data from the OECD RegPat Dataset (2018 version). Additionally, we use the Cambridge Econometrics European Regional Dataset to retrieve further controls that help assessing the direction of our focal relationship, such as employment, GDP and population density.

[8] To the best of our knowledge, the geography of AI still hesitates to be investigated because of a set of methodological and data constraints (see Buarque et al., 2020).

As we will see in details, to deal with the endogeneity of our focal regressor, we will draw on information contained in patent transfers data at the USPTO between 1995 and 2014 to propose an original instrumentation method.

3.1. Dependent variables

Our focal dependent variables are two measures of regional technological novelty: absolute ($ABSNOV_{r,t}$) and local technological novelty ($LOCNOV_{r,t}$), proxied by the number of absolutely and locally novel patents invented in the focal region, respectively. As we said, their rationale lies in the fact that patent citations are references to prior technology on which the current patent builds or which it uses, i.e. prior art (Trajtenberg, 1990; Jaffe et al., 1993; Jaffe and Trajtenberg, 1999; Maurseth and Verspagen, 2002).[9] Therefore, if the technology in which the patent is classified relies on a novel bit of prior art, this signals an original combinatorial attempt that, possibly, enriches the technology space, opening rooms for new technological trajectories (Fleming, 2001).

Operationally, we follow Verhoeven et al. (2016) and define as *absolutely novel* ($ABSNOVPAT_{p,r,t}$) a region *r*'s patent, *p*, that links, for the first time at EPO in *t*, a specific IPC class with another IPC (cited).[10] Similarly, we define *locally novel* ($LOCNOVPAT_{p,r,t}$) a patent *p* of region *r* that shows an IPC link at *t*, never observed before in the NUTS3 region in which it is invented, irrespectively from whether it was observed elsewhere.[11] Hence, if a patent shows an absolute novelty, it will be also novel at the local level, while the opposite does not necessarily hold.[12]

In order to capture the role of KETs more "purely", and have a less confounded evidence about their role in driving technological novelty, we do not consider IPC classes related to KETs when measuring novelty: in brief, our technological novelty measures do not consider novel combinations driven by KETs related patent citations. Finally, to assign novel patents to NUTS 3 regions, we rely on information contained in inventor addresses reported in patent documents using the standard fractional counting method.[13] Each patent p is thus assigned to a NUTS 3 region r according to the fraction of inventors listed in the patent document that reside in region r at the time of the patent filing.

[9] For a recent survey about the use of patent citation data in social science research, see Jaffe and de Rassenfosse (2017). On a more critical view of the implications of patent citations, see also Kuhn et al. (2020).
[10] This measure replicates the measure proposed by Verhoeven et al. (2017) that they define as "*Novelty in technological knowledge origins*".
[11] We exploit the International Patent Classification (IPC) and we consider 4-digits IPC classes.
[12] It is worth to notice that a novel combination may appear simultaneously in more than one patent, as well as in more than one region. Accordingly, we take the patent priority year as time reference to assign patents to local areas.
[13] In spite of the debate about the pros and cons of choosing the inventor vs the applicant address (see for example, Santohala, 2019), this is widely considered as a good approximation of local innovative outcomes.

Drawing on the previous positions, we build up the following two measurements of technological novelty:

$$\mathrm{ABSNOV}_{\mathrm{r,t}} = \sum_{\mathrm{p}} \mathrm{ABSNOVPAT}_{\mathrm{p,r,t}} \qquad \text{[Equation 1]}$$

$$\mathrm{LOCNOV}_{\mathrm{r,t}} = \sum_{\mathrm{p}} \mathrm{LOCNOVPAT}_{\mathrm{p,r,t}} \qquad \text{[Equation 2]}$$

where $ABSNOVPAT_{p,r,t}$ is the (fraction) patent p filed in region r at time t that shows an absolutely novel citation link and $0 \leq ABSNOVPAT_{r,t} = {\sum i_{p,r}}/{\sum i_p} \leq 1$, where ${\sum i_{p,r}}/{\sum i_p}$ is the share of inventors i listed in patent p that reside in region r.

Similarly, $LOCNOVPAT_{p,r,t}$ is the (fraction) patent p filed in region r at time t that shows a citation link novel for the region and $0 \leq LOCNOVPAT_{r,t} = {\sum i_{p,r}}/{\sum i_p} \leq 1$, where ${\sum i_{p,r}}/{\sum i_p}$ is the share of inventors i listed in patent p that reside in region r.

Let us notice that, first of all, while obtained by counting novel regional patents, by assigning them to regions through fractional counting, the two variables are non-negative continuum ones and do not require the resort to count-data models. Secondly, as they are the (fractional) sum of locally invented patents of a special kind, both the dependent variables are arguably sensible to the economic and inventive size of the focal region, which will have to be controlled for.

3.2. Explanatory variable and instrument

Our main regressor of interest is the local endowment of KETs knowledge ($KETS_{r,t}$). As we are not interested in the regional capacity of diversifying and/or specializing into brand new technologies, but rather of "producing" and adding technological novelty to the knowledge space, we coherently proxy the local endowment of KETs by counting the number of KETs patents ($KETSPAT_{p,r,t}$). 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).[14] As we have done for novel patents, we assign also KETs-related patents to a NUTS3 r according to

[14] https://ec.europa.eu/growth/tools-databases/kets-tools/sites/default/files/library/final_report_kets_observatory_en.pdf

the fraction of inventors that reside in r as listed in patent documents. Formally, we measure $KETS_{r,t}$ in the following way:

$$\mathrm{KETS}_{\mathrm{r,t}} = \sum_{\mathrm{p}} \mathrm{KETPAT}_{\mathrm{p,r,t}} \qquad \text{[Equation 3]}$$

where $KETPAT_{p,r,t}$ is the (fraction) patent p filed in region r at time t that is classified in at least one of the IPCs related to KETs and $0 \leq KETPAT_{r,t} = {\sum i_{p,r}}/{\sum i_p} \leq 1$, where ${\sum i_{p,r}}/{\sum i_p}$ is the share of inventors i listed in patent p that reside in region r.

As previous works on the role of KETs in regional technological diversification have alerted (e.g. Montresor and Quatraro, 2017, 2019), though by not going beyond such an alert, the regional endowment of KETs could be affected by endogeneity issues in the usual respects (i.e. reverse causality and unobserved heterogeneity). In order to provide a causal estimate of the relationship between the local endowment of KETs and novel technological combinations, we frame the analysis in an instrumental variable setting. Concisely, we instrument the KETs endowment of our focal regions with the "exposure" they show to a specific set of non-KETs patents: that is, non-KETs patents that can be claimed to be replaced (at least partially) by the development of KETs. On the one hand, we expect that the higher the exposure of the regional knowledge base to such a substitutional development between KETs and non-KETs technologies, the lower the production and endowment of local KETs. On the other hand, we do also expect that the same exposure is not capable, *per se*, to directly affecting the local production of radical innovations. Indeed, such an exposure does not simply amount to the local production of non-KETs technologies, which could actually hamper regional technological novelty, but rather represents a trait of the regional knowledge base that could possibly affect it.

The instrumentation procedure consists of two steps. In the first step, we try to identify the set of non-KETs patent classes that are likely to be substituted by KETs over time because of the inner nature of the same technologies. We claim that a way to identify these non-KETs technologies can be that of looking at non-KETs patents in the patent portfolios of companies that acquire KETs patents for reasons other than technological diversification and/or survival. The underlying logic is that, when firms are not involved in this kind of processes, in which technology acquisitions (hence also patent acquisitions) arguably have low (if not even, no) connection to internal technology development, the former can generate substantial substitutive effects on the latter across different technological domains. In general terms, through technology acquisitions firms aim at reducing costs by minimizing uncertainty related to the process of internal technology development and at facilitating access to technological assets developed externally (Karim & Mitchell, 2000; Phillips & Zhdanov, 2012). Firms also use technology acquisitions to outsource internal R&D and match complementary resources (Cassiman & Veugelers, 2006; Higgins & Rodriguez, 2006). Technological acquisitions create value by bringing together related knowledge bases, overlapping patent portfolios, or necessary complementary assets (Ahuja & Katila, 2001; Gans & Stern, 2003; Sears & Hoetker, 2014; Chondrakis, 2016). Finally, firms may even enter an innovation path through technological acquisitions (Tsai and Wang, 2009). When this happens, and one or more of the previous mechanisms are set at work, firms may decide to not investing further in extant R&D projects and definitively substitute previous technologies with new ones.

While referring to technology acquisitions by firms can be a channel to identify non-KETs patents that are substitutive of KETs ones, in order to use the relative regional exposure to instrument the KETs patents of our European regions – the second step of our analysis – we need both spatial and temporal exogeneity. In order to satisfy these two criteria, we refer to technology acquisitions by exploiting information contained in patent transfer data at the USPTO. In particular, we retrieve information on changes of patent ownerships at the USPTO from the Patent Assignment Database (PAD, version 2017).[15] Using these data, we isolate the non-KETs patents, together with their IPC classes (4-digits level), j, that form the patent portfolios of innovative US companies purchasing KETs at the USPTO between 1995 and 2014. In trying to be conservative, among the US buyers of US-invented KETs patents,[16] we only consider innovative companies that did not produce KETs before acquiring their first KETs-related patent.[17] Moreover, we also exclude companies whose patent acquisitions extends beyond KETs (i.e. companies that acquire both KETs and non-KETs patents).[18] Finally, we consider only companies that, while acquiring KETs, keep going innovating in the same sector over time.[19] This last restriction aims at excluding both cases in which patent acquisitions are a mean to switch sector and cases in which the company exits the (technological) market, i.e. that stop patenting. Overall, the imposed restrictions allow us to isolate non-KETS technologies likely to be substituted by KETs over time in the US. The companies included in the sample used to build the

[15] See Marco et al. (2015) and Graham et al. (2018) for a precise description about the data on USPTO patent transfers.

[16] US buyers are companies whose registered address is in the US, as for the information reported in PAD. Similarly, US-invented patents are patents whose inventors reside in the US.

[17] We define innovative the companies that filed at least one patent before acquiring a KET-patent. We exclude companies that already filed a KET patent before acquiring a KET patent to minimize cases of merely strategic patent acquisitions within the KETs domain.

[18] This restriction serves the goal of excluding cases in which substitution takes place between technologies not related to KETs.

[19] We assign sectors to patent applicants using the concordance tables proposed by Lybbert and Zola (2014). Precisely, we merge IPC 4-digit classes contained in US patents with NAICS 2-digit sectors. Each patent applicant in year t is assigned to the NAICS 2-digit sector that includes the largest part of the IPCs contained in its patents filed in that year (or in the last year in which it patented).

instrument are indeed companies that innovate over time in the same sector but, through patent acquisition, can be claim to substitute (at least partially) their technologies with KETs.

Let us notice that calculating the "exposure" of European regions to a set of technologies identified with respect to innovative US companies purchasing KETs at the USPTO should guarantee spatial exogeneity. Focusing on US companies acquiring US-invented patents should indeed eliminate the risk of our instrument being influenced by EU local features. In other words, our aim here is to isolate technological dynamics behind the substitution of specific technologies with KETs, cleaned by local factors that might be confounding.

As far as the temporal exogeneity of the instrument is concerned, we look at such an exposure in 1995 to have a measure sufficiently distant in time from the beginning of our reference period.[20] In the same respect, as we will see, we allow this 1995 composition across NUTS3 European regions to vary over time according to the IPC-specific yearly rate of growth in the US between 1996 and 2014. We avoid, in this way, the growth of those technologies, again, to depend from local features.

The previous choices are at the basis of the second step of our instrumentation procedure, which calculates the "exposure" that each and every European region r reveals at time t to the non-KETs technologies j that are substitutive of KETs ones. In order to do so, we take the relative incidence, W_j, that (the non-KETs) technology j patents have in the aggregate patent portfolio of KETs US buyers – coming from step one – as unitary measure of such an exposure. We then obtain the total regional exposure to j in the initial year (1995) by using W_j to weight the number of patents in each technology j invented in region r in the same year. The initial regional exposure to j is then updated at time t by using the rate of growth of technology j in the US from 1996 to t, $G\_US_{j,1996:t}$. Finally, we add up all of these j stocks of non-KETs patents to which region r is exposed and define our instrument as follows:

$$\mathrm{IV\_KETS_{r,t}} = \sum_{\mathrm{j}} \mathrm{W_j} \times \mathrm{S_{j,r,1995}} \times \left(1 + \mathrm{G\_US_{j,1996:t}}\right) \qquad \text{[Equation 4]}$$

where $S_{j,r,1995}$ is the number of patents in technology j invented in region r in 1995, W_j is the weight of technology j in the aggregate portfolio of KETs US buyers, and $G\_US_{j,1996:t}$ is the rate of growth of technology j in the US from 1996 to t.

3.3. Control variables

[20] We run several robustness checks, moving back the starting year of exposure to 1990 and 1985. Results, available upon request, are consistent with the main analysis.

In order to address other sources of heterogeneity, we include several controls at the local level. First, we include the stock of non-KETs patents ($SNOKETS$). This stock, net of KETs patents (and of patents belonging to the set of technological classes used in the instrumentation), controls for the local technological size that may influence the emergence of novel combinations.[21] Second, in the light of the previous studies about the "metropolitan" geography of "unconventional/atypical" innovations (Mewes, 2019; Ruben and Gaetani, 2020), and given the absolute nature of our dependent variables, we need to include the local level of GDP, to account for the local economic size (GDP), and the level of population density ($DENS$), as proxy of agglomeration economies. Third, we also control for the average technological variety (IE) of the region, as a proxy of the heterogeneity of the local knowledge base in terms of breadth of its constitutive ideas (patent codes).[22] Let us notice that, while referring to the opportunities of recombination from which regional novelty could benefit, the same regressor is also expression of the extent to which the region has already occupied the knowledge space and could thus reflect a saturation dynamics in developing radical innovations. Finally, we include NUTS3 fixed effects, to control for all time-invariant local characteristics, and year fixed effects, to account for shocks common to all the regions in the sample, such as, for example, those due to the business cycle.

3.4. Methodology

Using the two measures of regional technology novelty proposed above (Equations [1] and [2]), we estimate two versions of a two-stage model, whose second stage takes the following form:

$$\mathrm{Y_{r,t}} = \vartheta_\mathrm{r} + \tau_\mathrm{t} + \beta_1 \widehat{\mathrm{KETS}}_\mathrm{r,t} + \mathbf{X}'_{\mathbf{r,t-1}}\beta_2 + \varepsilon_\mathrm{r,t} \qquad \text{[Equation 5]}$$

where $Y_{r,t}$ is, alternatively, the (log transformed) number of absolute or local novel patents invented in region r at time t (i.e. $ABSNOV$ and $LOCNOV$); ϑ_r are NUTS3 fixed effects; τ_t are year fixed effects; $\widehat{KETS}_{r,t}$ is the instrumented (log transformed) number of KETs-patents invented in region r at time t; $\boldsymbol{X}'_{\boldsymbol{r,t-1}}$ is a vector of lagged local controls such as $SNOKETS$ (log transformed), GDP (log transformed), $DENS$ and IE; $\varepsilon_{r,t}$ is the error term. Standard errors are clustered at the NUTS2 level to account for possible spatial correlation across NUTS3 regions.

The first stage of the two models takes the following form:

[21] We apply the perpetual inventory method to calculate $SNOKETS$, with a decay rate of 15%. Formally, $SNOKETS_{r,t} = NOKETS_{r,t} + (1-d) \times SNOKETS_{r,t-1}$, where d is the decay rate and $NOKETS_{r,t}$ is the number of non-KETs patents filed in region r at time t.

[22] Following Quatraro (2010), we calculate the local level of technological variety using the information entropy index (Attaran and Zwick, 1987). The index measures the degree of disorder (or randomness) of the regional knowledge base from the probability of co-occurrences of patent technological classes contained in local patents. For its formal construction, please refer to Quatraro (2010).

$$\mathrm{KETS}_{r,t} = \vartheta_r + \tau_t + \beta_1 \mathrm{IV\_KETS}_{r,t} + \mathbf{X}'_{\mathbf{r,t-1}}\beta_2 + \varepsilon_{r,t} \quad \text{[Equation 6]}$$

where $IV\_KETS_{r,t}$ is the instrumental variable (see Equation 4) and the rest of the variables are the same as in Equation 5.

Table 1 reports summary statistics and the correlation matrix of the variables used. The dependent variables of both Equations [5] and [6] are non-negative continuum variables, so that the choice of a 2SLS model for their estimation reveals adequate. Since the models are estimated in a log-log form, as usual, the focal coefficients can be interpreted as elasticities.

[TABLE 1 HERE]

[FIGURE 1 HERE]

Figure 1 provides a geographical representation of the distribution of novel (absolute and local) and KETs patents across EU NUTS3 regions over 2000-2014.

Panels a) and b) plot the geographical quintile distribution (weighted by population density in 2014) of, respectively, the number of absolute novel and the number of local novel patents. The NUTS 3 regions in which the highest number of patents with absolute and local novelty are concentrated are, not surprisingly, continental regions of Germany, north and south-east of France, Austria, north of Italy, Denmark, the Netherlands, regions in the south of the UK and regions in the Scandinavian area. The peripheral European regions do not show remarkable contribution in terms of novelty, with few exceptions in Spain and Ireland.

Panel c) of Figure 1 plots the geographical quintile distribution (weighted by population density in 2014) of the number of KETs patents. The KETs distribution appears spatially correlated with the distribution of novel patents in the way we measure them, suggesting a relationship to whose closer scrutiny we now move in Section 4.

4. Results

Starting with the first stage of our 2SLS models, which is common to the two specifications of the dependent variable, $ABSNOV$ and $LOCNOV$, Panel A in Table 2 reassures us about the selected instrument. Columns I to V report the first stage results obtained saturating the model by adding the main control variables one by one (the coefficients of the control variables are not reported in Panel

A). The coefficient for our instrument (IV_KETS) is always negative and significant, ranging between -.279 and -.328. This confirms our claim that a higher local exposure to technologies substituted by KETs is significantly associated with a lower generation of KETs. Precisely, a 1% increase in the number of technologies that are likely to be substituted by KETs leads to around 0.28% decrease in the local generation of KETs (according to the estimate of the full model reported in column V). Finally, F-statistics of excluded instruments are above the threshold of 10 confirming that our instrument is not weak. Overall, the evidence reported in Table 2, Panel A supports the idea that local areas highly exposed to technologies substituted by KETs are less likely to generate KETs over time.

Coming to the second stage of the model, Panel B of Table 2 reports the estimates of the impact that the (instrumented) local endowment of KETs has on the generation of patents showing absolute combinatorial novelty ($ABSNOV$). Columns 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, confirming our argument about the effect that their knowledge re-combinatorial properties can have on the introduction of technological novelty. The relative coefficients range between around 1.797 and 1.906, revealing an impact that is modest, but not negligible. Since the model is estimated in a log-log form, looking at column V (full model) we can interpret the result as a 1% increase in the local number of KETs patents leads to around 1.87% increase in the local generation of $ABSNOV$.

[TABLE 2 HERE]

Table 3 reports the results of the second stage of the analysis but focusing on the number of patents that show novelty only at the local level ($LOCNOV$). The coefficients for the local endowment of KETs is positive and significant only in column I, while it is not significant (even if still positive) when we include the control variables (columns II to V). This result leads to a relevant implication, on which we will return showing the robustness check of the analysis: enhancing the local endowment of KETs fosters novel technological attempts that may benefit the overall (global) technological advance, while their role for local technological catching-up is lower or even not significant. Somehow expectedly, technological advances that extend only (and, as Table 1 reveals, mostly) the local knowledge bases possibly unfold through knowledge combinatorial processes that require less “interfacing” work among ideas than those at the basis of absolute technological novelty, so that their role is neutral with respect to local novelty.

Differences between the estimates for $ABSNOV$ and $LOCNOV$ emerge with respect to the control variables too. The local stock of patents, in technological fields that do not refer to KETs ($SNOKETs$), is negatively and significantly associated with the generation of patents showing absolute combinatorial novelty (Table 2), while we find the opposite for local novelty (Table 3). This asymmetry might suggest that by increasing their level of innovativeness, regions could find less crucial to explore the knowledge space and thus reduce the number of absolute novel attempts in innovative processes. On the contrary, by enriching the local knowledge base the incentive/need appears to remain in fostering the adoption of novel attempts already introduced in other regions.

As for GDP, we do not find a significant coefficient for absolute novelty, while it is positively associated with local novelty. This suggests that larger regions in economic terms are only more prone to introduce innovations that are locally "unconventional", but not globally so. This represents an important specification of the recent evidence about the metropolitan gains in this kind of innovations (Mewes, 2019; Ruben and Gaetani, 2020), which apparently reduce when technological novelty is absolute. In the same respect, let us also notice that we observe no effect of population density on both absolute and local novelty. Finally, while non-significant with respect to $LOCNOV$, IE appears negatively associated with the number of absolute combinatorial novelties, pointing to the saturation dynamics to which we have alluded in introducing this variable.

[TABLE 3 HERE]

4.1. Robustness checks

As a first robustness check, in order to further neutralise the presence of scale effects, which are already controlled for by $SNOKETS$ and GDP, we re-define our two dependent variables, $ABSNOV$ and $LOCNOV$, and consider, rather than their regional fractional counts, their shares with respect to total regional patents. Results are reported in Tables 4 and 5.

In Table 4, focusing on the share of patents showing absolute combinatorial novelty, the coefficient for the variable $KETS$ is always positive and significant, ranging between around 0.051 and 0.063. Since the model is estimated in a level-log form, looking at column V (full model) we can interpret the result as a 1% increase in the local number of KETs patents leads to around 0.00053 increase in the local share of absolutely novel patents. The sample mean of the local share of absolute novel patents is ≈0.0345 (with SD≈0.07), meaning that a 1% increase in KETS increases the share of novel patents by 1.54% for the average region (i.e. from ≈0.0345 to ≈0.0350). This result, largely in line with Table 2, confirms the positive role of KETs in fostering the local capacity of introducing absolute novelty at the local level. In other words, a higher local endowment of KETs is a driver for the generation of first-time combinatorial attempts, never observed before, at a higher rate than inventions with lower levels of novelty.

[TABLE 4 HERE]

In Table 5, focusing on the share of patents that are only locally novel, the coefficient for the variable $KETS$ is now always positive and significant, while it was so only in the first specification of Table 3. Quite interestingly, while incapable to increase their absolute number, KETs are at least capable to increase the relative incidence of this kind of patents, that is, their relative weight with respect to the size of the regional knowledge base. On the other hand, the effects of KETs remains largely lower with respect to that on absolute technological novelty. A 1% increase in the local number of KETs patents leads to around 0.00347 increase in the share of locally novel patents. The sample mean of the share of locally novel patents is ≈0.475 (with SD≈0.317), meaning that a 1% increase in $KETS$ increases the share of local novel patents by ≈0.7% for the average region (i.e. from ≈0.475 to ≈0.478).

Although with this important specification, and with some other changes among the controls, the results about the role of KETs in driving the geography of technology novelty appear confirmed.[23]

[TABLE 5 HERE]

As a second robustness check, we redefine our focal dependent variables of technological novelty by imposing further restrictions in the identification of novel combinations of citing-cited patent classes. In Tables 2 to 5 we defined a patent as (absolutely or locally) novel if it showed at least one combination between its IPC classes and its cited classes, never observed before (overall or just in the region, respectively). Here we put three different thresholds to the share of novel combinations to define a patent as novel (either absolute or local). More precisely, we consider a patent (absolutely or locally) novel if it shows at least 10%, 25% or 50% of (absolutely or locally) novel combinations over the total number of combinations in its citation flow.

Table 6 presents the second stage results when the dependent variables are the (log transformed) number of novel patents, calculated according to the three mentioned thresholds. Columns I to III

[23] We find a significant coefficient for GDP in Table 4 (while in Table 2 this variable was not significant); a negative and significant coefficient for SNOKETS in Table 5 (while in Table 3 this variable was positive); and a negative and significant coefficient for IE in Table 5 (while in Table 3 the coefficient for this variable was not significant).

report the second stage results for absolute combinatorial novelty. Columns IV to VI focus on local combinatorial novelty. The first stage, common to all models, is the same reported in Table 2, Panel A. All the models in Table 6 include the full set of control variables.

The results of this further set of robustness checks appear confirmatory of the main analysis, showing a significant and positive impact of the local endowment of KETs on the generation of new technological combinatorial attempts in the region, especially on the number of absolutely novel patents. Interestingly, when we narrow down the measure of novelty to the largest extent, by imposing that at least one over two of the focal patent's citations does not show previous records in the technology (column III) and in the regional knowledge space (column VI), two important specifications of the previous results emerge. On the one hand, the size of the KETs effect on very intensively novel patents in absolute terms reduces substantially, suggesting that their combinatory power might be bounded with respect to the scope of possible recombinations. On the other hand, KETs regain a significant and sizeable effect also on very intensively novel patents in local terms, which is even larger than that on the correspondent novel patents in absolute terms. When the scope of combinations that qualifies a relative advancement of the regional knowledge base increases, the combinatorial properties of KETs stop being neutral and actually help it substantially.

[TABLE 6 HERE]

5. Conclusions

The paper tested empirically the hypothesis that, given the knowledge combinatory properties that descend from their General Purpose Technology (GPT) nature, the local endowment of Key Enabling Technologies (KETs) could work as a driver for regions to introduce both absolute and local technological novelty.

The analysis has been conducted at the NUTS3 regional level in Europe over the period 2000-2014. KETs do actually increase regional technological novelty, but with nuances that depends on its scope. In particular, unless the spectrum of defining novel patent combinations is restricted, KETs do not add (much) to the spectrum of drivers that extend the technology novelty of regions at the local margin, with respect to which their recombinant properties appear less essential and their role nearly neutral. On the contrary, the same KETs properties appear instead essential in allowing regions to extend the knowledge space in absolute terms going beyond their boundaries.

The paper contributes to academic research in two main respects. On the one hand, we add to the still scant literature about the identification and measurement of technological novelty in space (Mewes, 2019; Ruben and Gaetani, 2020), by extending to the regional level recent advancements in its "a-spatial" patent-based analysis (Verhoeven et al., 2016). On the other hand, we also contribute to the still limited investigation of the drivers of breakthrough regional innovations (Castaldi et al., 2016): not only by pointing to the role of regional KETs, as already done in previous studies (Montresor and Quatraro, 2017), but also by addressing for the first time their arguable endogeneity.

The results that we have obtained have important policy implications. Inserting the development (or the acquisition) of KETs in the regional policy toolbox has an additional implication to that already recognized in their favoring an explorative pursuing of smart specialization strategies (Montresor and Quatraro, 2017). KETs appear also "enabling" regions to embark in technological transitions that are breakthrough and thus possibly leading to more knowledge intensive and sustainable patterns of growth. However, KETs are more for "new-to-the-world" than for "new-to-the-region" radical innovations, representing a "high-power" policy-leverage to which regions are (not) recommended to resort when prioritising the high (low) way to technological novelty.

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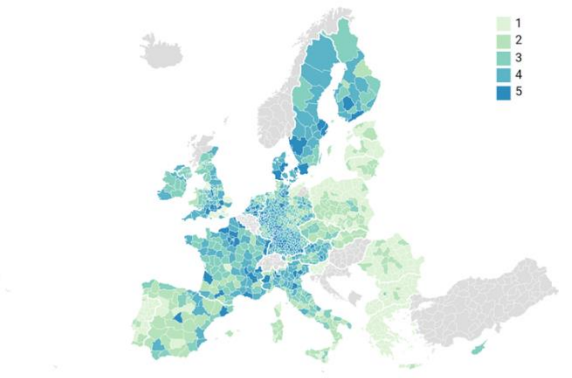
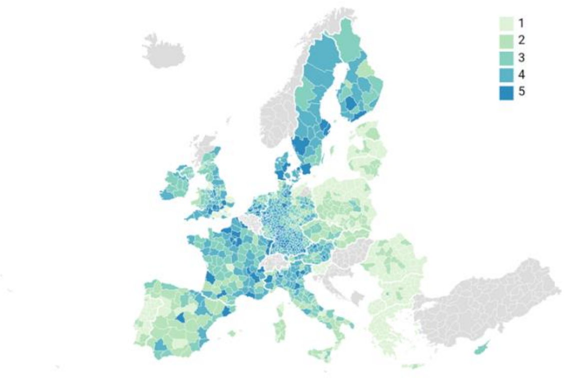
FIGURES AND TABLES

Figure 1. Geography of technological novelty and KETs by NUTS-3

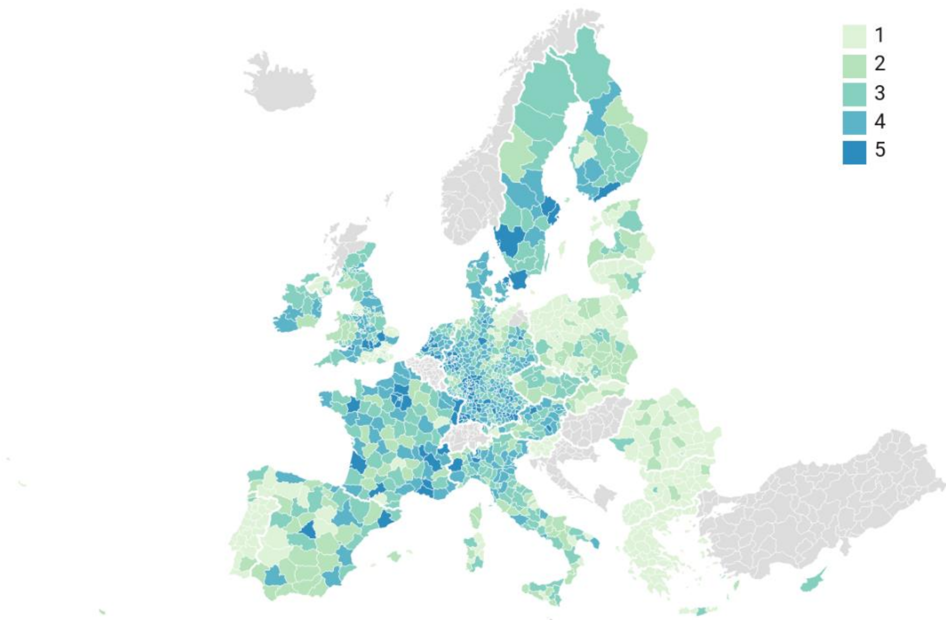
a) Geography of absolute novel patents by NUTS-3 (2000-2014)



b) Geography of local novel patents by NUTS-3 (2000-2014)



c) Geography of KETs by NUTS-3 (2000-2014)



Tables

Table 1. Descriptive statistics

Panel A – Summary Statistics					
	Obs.	mean	sd	min	max
ABSNOV	17,570	2.556	5.607	0	107
LOCNOV	17,570	30.955	56.058	0	692
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
DENS	17,570	591.209	1,428.914	2	21,317.9
IE	17,570	3.262	2.306	0	8.839

Panel B – Correlation Matrix							
	ABSNOV	LOCNOV	KETS	NOKETS	GDP	DENS	IE
ABSNOV	1						
LOCNOV	0.830*	1					
KETS	0.742*	0.713*	1				
NOKETS	0.676*	0.872*	0.594*	1			
GDP	0.429*	0.475*	0.402*	0.527*	1		
DENS	0.067*	0.016	0.106*	-0.024*	0.326*	1	
IE	0.710*	0.841*	0.631*	0.876*	0.549*	0.023*	1

* p<0.01

Table 2. Effect of KETs on absolute novelty (*ABSNOV*): IV estimates

Panel A – First stage results (dep. var.: KETS (log))					
	(I)	(II)	(III)	(IV)	(V)
IV_KETS (log)	-0.328***	-0.290***	-0.279***	-0.280***	-0.284***
	(0.075)	(0.072)	(0.072)	(0.072)	(0.072)
F-stat	19.23	16.37	15.01	15.03	15.47

Panel B – Second stage results (dep. var.: Absolute novel patents (log))					
	(I)	(II)	(III)	(IV)	(V)
KETS (log)	1.797***	1.904***	1.901***	1.906***	1.874***
	(0.349)	(0.420)	(0.438)	(0.439)	(0.423)
SNOKETS (log)		-0.128*	-0.128**	-0.129**	-0.110*
		(0.069)	(0.065)	(0.065)	(0.061)
GDP (log)			0.007	0.007	0.016
			(0.076)	(0.076)	(0.074)
DENS				0.000	0.000
				(0.000)	(0.000)
IE					-0.021**
					(0.009)
NUTS3 FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Obs.	17,570	17,570	17,570	17,570	17,570

Dep. Var.: ABSNOV. KETs, SNOKETs, GDP, DENS and IE lagged 1-year. Robust standard errors, in parentheses, clustered at the NUTS 2 level. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 3. Effect of KETs on local novelty (*LOCNOV*): IV estimates

	Second stage results (dep. var.: Local novel patents (log))				
	(I)	(II)	(III)	(IV)	(V)
KETS (log)	0.579***	0.287	0.192	0.220	0.235
	(0.178)	(0.176)	(0.199)	(0.201)	(0.196)
SNOKETS (log)		0.351***	0.328***	0.326***	0.318***
		(0.044)	(0.042)	(0.041)	(0.040)
GDP (log)			0.245**	0.245**	0.241**
			(0.096)	(0.096)	(0.095)
DENS				0.000	0.000
				(0.000)	(0.000)
IE					0.010
					(0.007)
NUTS3 FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Obs.	17,570	17,570	17,570	17,570	17,570

Dep. Var.: LOCNOV. KETs, SNOKETs, GDP, DENS and IE lagged 1-year. Robust standard errors, in parentheses, clustered at the NUTS 2 level. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 4. Effect of KETs on absolute novelty, *ABSNOV* (shares): IV estimates

	Second stage results (dep. var.: Share of absolute novel patents (log))				
	(I)	(II)	(III)	(IV)	(V)
KETS (log)	0.051***	0.063***	0.056***	0.057***	0.053***
	(0.018)	(0.021)	(0.021)	(0.021)	(0.020)
SNOKETS (log)		-0.014***	-0.016***	-0.016***	-0.014***
		(0.005)	(0.005)	(0.005)	(0.005)
GDP (log)			0.017*	0.017*	0.018**
			(0.009)	(0.009)	(0.009)
DENS				0.000	0.000
				(0.000)	(0.000)
IE					-0.003***
					(0.001)
NUTS3 FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Obs.	17,570	17,570	17,570	17,570	17,570

Dep. Var.: Share of absolute novel patents. KETs, SNOKETs, GDP, DENS and IE lagged 1-year. Robust standard errors, in parentheses, clustered at the NUTS 2 level. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 5. Effect of KETs on local novelty (shares): IV estimates

	Second stage results (dep. var.: Share of local novel patents (log))				
	(I)	(II)	(III)	(IV)	(V)
KETS (log)	0.347***	0.399***	0.373***	0.375***	0.363***
	(0.098)	(0.121)	(0.120)	(0.120)	(0.115)
SNOKETS (log)		-0.063***	-0.070***	-0.070***	-0.063***
		(0.023)	(0.022)	(0.022)	(0.022)
GDP (log)			0.068**	0.068**	0.071**
			(0.031)	(0.031)	(0.030)
DENS				0.000	0.000
				(0.000)	(0.000)
IE					-0.008***
					(0.003)
NUTS3 FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Obs.	17,570	17,570	17,570	17,570	17,570

Dep. Var.: Share of local novel patents. KETs, SNOKETs, GDP, DENS and IE lagged 1-year. Robust standard errors, in parentheses, clustered at the NUTS 2 level. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 6. Effect of KETs on absolute and local novelty: IV estimates, robustness

	Second stage results					
	Absolute (10%)	Absolute (25%)	Absolute (50%)	Local (10%)	Local (25%)	Local (50%)
	(I)	(II)	(III)	(IV)	(V)	(VI)
KETS (log)	1.787***	1.467***	0.360***	0.257	0.418**	0.641***
	(0.410)	(0.372)	(0.122)	(0.187)	(0.195)	(0.203)
SNOKETS (log)	-0.141**	-0.159***	-0.040**	0.308***	0.260***	0.178***
	(0.060)	(0.054)	(0.017)	(0.038)	(0.037)	(0.037)
GDP (log)	-0.024	-0.077	-0.019	0.249***	0.266***	0.285***
	(0.071)	(0.068)	(0.020)	(0.092)	(0.085)	(0.074)
DENS	0.000	-0.000	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IE	-0.019**	-0.018**	-0.003	0.009	0.006	0.000
	(0.008)	(0.007)	(0.002)	(0.006)	(0.006)	(0.006)
NUTS3 FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	17,570	17,570	17,570	17,570	17,570	17,570

KETs, SNOKETs, GDP, DENS and IE lagged 1-year. Robust standard errors, in parentheses, clustered at the NUTS 2 level. * $p < .1$, ** $p < .05$, *** $p < .01$