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"Relatedness, external linkages and innovation"

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Abstract

This paper has two main objectives. First, it estimates the impact of related and unrelated variety of European regions' knowledge structure on their patenting activity. Second, it looks at the role of technological relatedness and extra-local knowledge acquisitions for local innovative activity. Specifically, it assesses how external technological relatedness affects regional innovation performance. Results confirm the strong relevance of related variety for regional innovation; whereas the impact of unrelated variety seems relevant only for the generation of breakthrough innovations. The study also shows that external knowledge flows have a higher impact, the higher the similarity between these flows and the extant local knowledge base.

JEL classification: O18; O31; O33; R11

Keywords: Variety; Patents; Patent citations; Relatedness; Knowledge production function.

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1. INTRODUCTION

It is now an established fact in the literature that the combination and recombination of previously unconnected ideas lead to new knowledge production, subsequent technological innovations, and ensuing economic growth and well-being (Aghion and Howitt, 1992; Jones, 1995; Weitzman, 1998). Further, knowledge diffusion in the form of knowledge spillovers is central to this literature as a cause of endogenous growth (Romer, 1990, 1986) and geographic agglomeration of firms (Audretsch and Feldman, 2004, 1996; Jaffe et al., 1993). This paper builds on different strands of literature and documents the influence of local diversity, i.e., related and unrelated variety, on regional innovation, for a large sample of European regions. We also assess whether the relation of the regional technological structure with external-to-the-region sources of knowledge boosts regions' innovation potential. The latter constitutes the main novelty of our analysis.

A recurrent theme in the knowledge externalities literature is whether firms located in agglomerations mainly learn from other local firms in the same industry or from other local firms in a range of other industries (Glaeser et al., 1992). The former dates back to Marshall's (1920) contributions on the benefits arising from spatial concentration. The latter relates to Jane Jacobs' contributions on cities, externalities and innovation (Jacobs, 1969; see also Glaeser et al., 1992). From her work we learn that a diversified economy brings benefits to local firms because it generates new knowledge and innovation steaming from the cross-fertilization of ideas across different industries. At the regional level, regions with a more diverse stock of knowledge have greater potential for innovation and growth. Since Frenken et al. (2007), several authors have argued that Jacob's concept of diversification needs to be more thoroughly elaborated, by differentiating between diversification of related industries and diversification of unrelated industries – or related versus unrelated variety. Regions hosting related industries, with different but connected knowledge bases, can more easily engage in recombinant innovation. On the contrary, the combination of previously unrelated industries or technologies is more difficult to succeed into the production of new ideas.

Besides, while much of the related literature assumes innovation production to draw on geographically localized knowledge (Audretsch and Feldman, 2004), a recent strand of studies has challenged this traditional view (Boschma, 2005). As these scholars posit, at some point, co-located agents may start to combine and recombine local knowledge that eventually becomes redundant and less valuable. As a result, processes of lock-in may begin to occur (Boschma, 2005; David, 1993). Conversely, firms looking for external sources of knowledge may find that the knowledge they require is available beyond the boundaries of the region where the firm is located (Bergman and Maier, 2009). Hence, the interplay between a vibrant 'local buzz' and more intentional 'global pipelines' is important to ensure an optimal regional rate of innovation adoption and further knowledge creation (Bathelt et al., 2004).

This paper contributes to these different strands of literature in several ways. First, within a regional knowledge production function (KPF) framework, we assess which diversified technological structure (related vs. unrelated variety) generates more knowledge spillovers which will ultimately enhance the regional innovation output. Second, we study how the internal technological structure of regions interacts with external sources of knowledge in the production of regional innovation. In particular, we assess (1) whether the more similar the internal and external knowledge structures, the larger the innovation outputs; and (2) whether different, but related, internal and external knowledge bases are more prone to innovation creation. Finally, our outcome variable distinguishes the effect of variety on regional innovation intensity versus quality-weighted regional innovation intensity. We expect the latter to draw more on unrelated and distant pieces of knowledge, as ideas with high impact tend to stem from knowledge cross-fertilization and the combination of unrelated technologies (Fleming, 2001; Saviotti and Frenken, 2008).

Our methodological approach builds upon the large literature analysing the impact of variety (related and unrelated) on economic outcomes (see section 2 for a throughout review), with some differences. First, given our interests, we compute variety indexes using the technological classification provided in patent documents, which turns out to be more meaningful for our purposes. This is in contrast with the majority of studies, which define the variety variables using either employment or imports. We exploit technology information using the International Patent Classification (IPC) codes contained in patent applications to the European Patent Office (EPO) to build the diversity indexes, establishing a more direct link between regional diversification and its underlying technological nature.[i] Second, we make use of a large sample of European regions (261 NUTS2 regions, the largest coverage in Europe of studies of this kind) for several years, allowing us to introduce time and region fixed-effects (FE) to control for a large number of unobservables. Finally, and more importantly, our study is one of the few investigating cross-regional linkages and related variety, for which trade data has mostly been used to depict related linkages across regions (Boschma and Iammarino, 2009). Instead, we use citations to patents as a cleaner and more direct measure of knowledge flows across the space. Patent citations directly point to the prior knowledge to which the current innovations draw upon, and therefore represent a good proxy for cross-regional linkages and knowledge flows (Jaffe and Trajtenberg, 1999; Schoenmakers and Duysters, 2010).

The outline of the paper is as follows. Section 2 reviews the related literature and theoretical framework. Section 3 sets the empirical analysis and section 4 describes the data. We give the main results in section 5 and finally section 6 concludes.

2. RELATED LITERATURE AND THEORY

Much research on the geography of innovation and localized knowledge spillovers has addressed the question of whether specialization or diversity boosts local innovation. However, the concept of diversity is complex and subtle, as first signalled by Frenken et al. (2007). These authors pose the central question of whether it is related or unrelated diversity which is most relevant for growth. Related diversity, or variety, facilitates local knowledge spillovers across industries at a relatively low cost. This is because the cognitive distance across these industries is not too large so that complementarities exist among them in terms of shared competences, which enable effective connections as well as sharing knowledge and information. Conversely, unrelated variety may slow down the diffusion of ideas, given that they draw on very different and completely disconnected knowledge bases making it more difficult for them to engage in recombinant innovation, thereby hampering the production of new local innovation. However, unrelated variety protects a region against external asymmetric shocks in demand and thus against rising unemployment, since the risk is spread over unrelated sectors (Frenken et al., 2007) – known as the portfolio effect of variety.

Frenken's et al (2007) pioneering study shows how related variety impacts regional economic growth in the Netherlands. Results are confirmed by studies in other countries: Bishop and Gripaios (2010) for Great Britain, Boschma and Iammarino (2009) and Quatraro (2010) for Italy, Hartog et al. (2012) for Finland and Boschma et al. (2012) for Spain. The role of unrelated variety is more controversial: whereas Bishop and Gripaios (2010) find that unrelated variety affects employment growth in a larger set of industries than related variety, Boschma et al. (2012) and Hartog et al. (2012) do not find any growth effect. Meanwhile, Frenken et al. (2007) find that unrelated variety dampens unemployment growth, which the authors interpret as evidence of unrelated industries spreading risks of potential negative shocks – i.e., the portfolio effect of variety.

Yet, despite the emphasis put on earlier studies on related variety as knowledge spillovers facilitator, only recently scholars have investigated its direct links with knowledge production. For instance, Tavassoli and Carbonara (2014) and Castaldi et al. (2015) analyse the role of related and unrelated variety on the regional innovation output, for the Swedish and the United States (US) cases, respectively. Their findings suggest that when it comes to variety of knowledge within regions or US states, unrelated variety does not affect regional innovation output in general, whereas the impact is robust and positive for related variety. Conversely, Castaldi et al. (2015) also show that a high degree of unrelated variety do enhance technological breakthroughs – i.e., innovation with a high technological and economic impact.

In this paper we follow these latter contributions and regress regional innovative performance on regional knowledge variety. We expect variety of the knowledge within a region to play a key role in the generation of knowledge spillovers, as it is associated to the Schumpeter's notion of novelty by combination of previous ideas. In evolutionary thinking, the creation of new knowledge is often the result of novel recombinations of known pieces of knowledge or the reconfiguration of the way in which such knowledge pieces are connected (Aharonson and Schilling, 2016).

In this search for recombination, most of the firms and inventors tend to focus only on the technological pieces in which they have prior experience (related variety), since this previous expertise allows them to understand better the nature of the new knowledge and the relationships between different knowledge pieces. As a consequence, when a region presents a diversity of related technologies, connections are more effectively established given that related technologies are more easily recombined. On the other hand, if knowledge is originated in technologies that are very different from the each other (unrelated variety), regional actors would not be able to easily absorb it so that little spillovers would be generated. To put it differently, the different pieces of knowledge should be neither too close nor too far from each other, so that agents can develop interactions and ensure that new ideas rise and develop the innovation process.

We contribute to the related variety literature in a critical way. An important debate within the geography of innovation literature that has emerged recently is the role of external knowledge in the process of regional knowledge creation. Indeed, the widely accepted assumption that agents usually source their innovations from their immediate vicinity might have limited our understanding of the ways in which knowledge flows across space and the way in which innovations are generated (Coe and Bunnell, 2003). Thus, it has been highlighted the increasing importance of agents' needs to access extra-local knowledge pools to overcome potential situations of regional 'entropic death' or 'lock-in' (Boschma, 2005; Camagni, 1991; Grabher, 1993; David, 1993). Otherwise, subsequent local interactions lead to the combination and recombination of the same pieces of knowledge, and firms would end up stuck in strong social structures that tend to resist social change (Boschma and Frenken, 2010; Morrison et al., 2011) and prevent them from recognizing opportunities in new markets and technologies (Lambooy and Boschma, 2001). Recent empirical works have extensively documented the influence of extra-local knowledge sources on firms' innovative performance and knowledge acquisition (Owen-Smith and Powell, 2004; Gittelman, 2007; Gertler and Levitte, 2005; Rosenkopf and Almeida, 2003; Zhou and Li, 2012; Bell and Zaheer, 2007).

However, inflows of extra-regional knowledge need to be understood by the local actors in order to transform it into new knowledge (Cohen and Levinthal, 1990). Yet, when the external knowledge basically integrates prior art from the same technologies, it can be easily absorbed but the new knowledge will not add much to the existing local one. On the contrary, when the external knowledge basically integrates prior art from technologies different from the local ones, it will be more difficult to understand but once it is integrated, the chances that they lead to more radical or breakthrough innovations are higher. Thus, not only the amount of knowledge flows coming from other regions is important, but also the degree of relatedness between the external knowledge that flows into the host region and the existing local one.

The scarce extant empirical literature on the role of relatedness of extra-regional knowledge flows has approached the issue using regional trade data –either imports or exports (Boschma and Iammarino, 2009, for Italian regional employment growth; Tavassoli and Carbonara, 2014, for Swedish regional innovation). Their findings suggest that it is not enough being connected to the outside world, but different, yet related, connections provide real learning opportunities and boost economic outcomes. In a similar vein, Boschma et al. (2009) look at labour mobility, workers skills' portfolio, and plant performance, for the Swedish economy. The authors show that inflows of workers with related, but different, skills do enhance plant performance. However, inflows of unrelated skills only contribute positively if they come from the same region. Meanwhile, when labour inflows come from other regions, only related skills have a positive effect on plant's productivity.

We depart from these latter contributions, but directly look at the actual knowledge flows, instead of using indirect ways to infer these flows across regions (such as the ones commented above). This is particularly appropriate in our framework, given our focus on the role of incoming flows for knowledge diffusion and recombination, and subsequent local innovation. We use patent citations as a proxy for knowledge flows. Patent citations point directly to prior art on which the patent is based (Trajtenberg, 1990) and, consequently, represent a "paper trail" worthwhile for the analysis of knowledge diffusion (Jaffe et al., 1993). Since Jaffe's et al. pioneering paper, patent citations have been considered to be useful to depict knowledge linkages between inventions, inventors and applicants along time, geographical space and technological fields, among other dimensions (Hall et al., 2005; Jaffe and Trajtenberg, 1999; Schoenmakers and Duysters, 2010). Jaffe et al. (2000), using a detailed survey of inventors and the relationship of their patented inventions to previous patents, confirm that citations do contain significant information on knowledge flows, albeit with a certain amount of noise. In our case, since patents record the residence of the inventors, they are an exceptional source for studying knowledge flows across regions.

We expect the degree of relatedness between the local knowledge base and external inflows of knowledge to be neither too small, to avoid lock-in in the same technology, nor too large, to facilitate the absorption of such extra-regional knowledge.

3. EMPIRICAL ANALYSIS

3.1 Empirical model

We test our hypotheses under a KPF framework at the regional level. Our point of departure is the simplest specification of this model:

$$Y_{it} = f(RD_{it}, Z_{it}), \tag{1}$$

Where Y is the innovative output of a given region, which depends on regional R&D expenditures (RD) as well as Z, a number of time-variant controls that account for specific features of the region i at time t. Among them, we include measures of variety and relatedness, as explained in the following subsections. Note that regional differences in size are accounted for by dividing the dependent and explanatory variables by total population. All in all, the following model is suggested:

$$\mathbf{ln} Ypc_{it} = \beta \cdot \mathbf{ln} RDpc_{it} + Z_{it} + \delta_i + \delta_t + \varepsilon_{it}, \tag{2}$$

where $ln\, Ypc_{it}$ is the log-transformation of the annual number of patent applications per million inhabitants in region i and year t, $ln\, RDpc_{it}$ is the log-transformation of R&D expenditures per capita in region i and year t, and Z are a number of focal variables – as explained below – and controls. For the latter, we include a proxy for human capital, measured as the share of human resources devoted to science and technology (HRST), as well as a variable accounting for differences in the economic structure of regions, proxied by the share of manufacturing employment (ShareInd). In addition, δ_i and δ_t stand for, respectively, regional FE and time FE. In order to consider deviations from the theory, a well-behaved error term is also introduced, ε_{it}.

3.2 Related and unrelated variety

We first aim to analyse the impact of knowledge diversification on regional patenting activity. In line with previous papers, as a proxy for this diversified knowledge we measure variety as well as related and unrelated variety with entropy measures (Frenken et al., 2007). We borrow from Castaldi et al. (2015) the use of the technological classification of patents in order to construct the measures of regional knowledge variety. Our entropy indicators are computed using information retrieved from applications to the EPO. In particular, we use the IPC system, which provides a hierarchical system of codes for the classification of patents according to the different areas of technology to which they pertain – directly assigned by the patent office, the EPO in this case. These codes are grouped into eight sections, which are the highest level of hierarchy of the classification. Each section is divided into three-digit classes and four-digit subclasses. The current version of the IPC classification contains 635 technological subclasses.[ii] Scholars have reorganized these technological subclasses in meaningful fields and broad fields of technology, similar to the grouping of products or economic activities into sectors (such as the Standard International Trade Classification used in trade or International Standard Industrial Classification of All Economic Activities). The aim of this grouping is to allow time and cross-country comparisons of innovation activities, and it is based on minimizing technological heterogeneity within technology fields and broad fields. Here we use the classification built by Schmoch (2008), which grouped subclasses into 35 technology fields (35-field), which are further grouped into 5 broad fields (5-field), namely: Electrical engineering, Instruments, Chemistry, Mechanical engineering, and Other fields.[iii]

Using the IPC codes and Schmoch's (2008) classification of technological fields, the variety variable measures the degree of knowledge diversification through the computation of an entropy measure at the four-digit level (subclasses), where p_j is the share of the four-digit sector j:

$$Variety = \sum_{j=1}^{J} p_j log_2 \left(\frac{1}{p_j}\right) \qquad (3)$$

The value of this index will by higher in regions characterized by a high diversified sectoral composition in its knowledge base.

We break down this measure in two different indicators. Following Frenken et al. (2007), if all four-digit subclasses j fall under a 35-field technology S_g, where g=1,…, G, it is possible to derive the 35-field shares, P_g, by summing the four-digit shares p_j

$$P_g = \sum_{j \in S_g} p_j \qquad (4)$$

Related variety is then measured by the weighted sum of the entropy at the four-digit within each 35-field technology:

$$RV = \sum_{g=1}^{G} P_g H_g \qquad (5)$$

where:

$$H_g = \sum_{j \in S_g} \frac{p_j}{P_g} log_2 \left(\frac{1}{p_j / P_g} \right) \qquad (6)$$

Equation (6) measures the diversity of a region's portfolio at the most fine disaggregation. Thus, it assumes that knowledge in sectors that belong to the same 35-field technology are technologically related to each other and, as a consequence, can learn from each other through knowledge spillovers.

Unrelated variety is proxied by the entropy of the 5-field distribution. Formally, being K the total number of 5-field sectors (k=1,…, K), the unrelated variety index is given by

$$UV = \sum_{k=1}^{K} p_k log_2 \left(\frac{1}{p_k} \right) \qquad (7)$$

Thus, equation (7) measures the extent to which a region is diversified in very different types of activities. This measure assumes that knowledge in technologies that do not share the same broad field (5-field) are unrelated to each other. Theoretically, high levels of this variable are associated to less knowledge spillovers.

The indices of related and unrelated variety are not opposites. One region can have both a high related variety (diversified into many specific subclasses in each field) and a high unrelated variety (diversified into unrelated broad 5-field technologies). In fact, they tend to correlate positively (Frenken et al., 2007; Boschma et al., 2012), although it is not always the case. In addition, given the decomposable nature of the entropy measure, variety calculated at different digit levels can be included in a regression analysis without necessarily generating collinearity.

Following with the empirical model sketched above, we include now the indices proxying for related and unrelated variety in the Z vector including controls that account for specific features of the region,

$$Z_{it} = g(RV_{it}, UV_{it}), \tag{8}$$

which once inserted into the main equation yields to:

$$\ln Ypc_{it} = \beta \cdot \ln RDpc_{it-1} + \lambda_1 HRST_{it-1} + \lambda_2 ShareInd_{it-1} + \omega_1 RV_{it-1} + \omega_2 UV_{it-1} + \delta_i + \delta_t + \varepsilon_{it} \tag{9}$$

Note that we introduce the subscript t-1 to all the explanatory variables in order to indicate that they have been time lagged one period to lessen endogeneity concerns due to system feedbacks. Section 4 includes further details regarding the construction of all the variables used in the present analysis.

3.3 Relatedness and external interactions

As sketched in section 2, we aim to evaluate the role of external knowledge in the process of regional knowledge creation. Although some studies, at the level of European regions, have consistently shown the importance of cross-regional interactions to the process of regional innovation (Maggioni and Uberti, 2009; Ponds et al., 2010), little attention has been paid to which kind of external interactions may be more beneficial. We conjecture that, even if new variety may enter a region thanks to the interactions with other regions – in the form of, e.g. trade linkages, FDI, research collaboration or labour mobility, extra-regional knowledge flows should be related to the technological base of a region in order to positively impact the region's outcomes.

To build our variables, we use citations made by inventors resident in the focal region to EPO applications of inventors living outside the region. In particular, we look at backward citations listed in patents produced in a given region and collect the cited patents (alongside their technology codes) with all inventors living outside the region. Patent citations are widely used as a proxy for knowledge flows since they signal the previous knowledge, or prior art, on which the patents are based, and represent a "paper trail" useful for studying knowledge diffusion (Jaffe et al., 1993; Schoenmakers and Duysters, 2010; Trajtenberg, 1990). Even though the use of patent citations does not come without limitations – e.g., some citations are added by the examiner, and not the applicant (Alcacer and Gittelman, 2006), they have been widely used in innovation economics as a proxy for knowledge flows (Criscuolo and Verspagen, 2008; Jaffe et al., 1993; Jaffe and Trajtenberg, 1999). Moreover, as citations relate cited patents with citing ones, they include detailed descriptions of technological characteristics and classification into technical domains (Popp et al., 2011) allowing the computation of the indexes measuring the degree of relatedness between the local knowledge base and the inflows of external knowledge.

To determine the similarity between the external knowledge entering a region and its existing knowledge base, we use a SIMILARITY index, as in Boschma and Iammarino (2009). In our case it is computed as the sum of the products of the absolute sizes of the four-digit subclass patents ($PAT_4(j)$), as a proxy of the knowledge stock in a region, and the four-digit subclass extra-regional patents the former have cited ($CIT_4(j)$):

$$SIMILARITY = log \sum_j PAT_4(j)\, CIT_4(j) \tag{10}$$

This measure gets a maximum when the region is specialized in just one technology and this technology coincides with the extra-regional patents cited. The lowest values are obtained when the more diverse the region is in its patent portfolio as well as in the extra-regional patents it cites, and at the same time the less similar both profiles are.

When a region gets knowledge from other regions, but such knowledge comes from the same technologies that are present in the region, the knowledge base of the economy will be able to absorb it but it will not add much to the existing knowledge. Therefore, it can also be of interest to use a more subtle measure of the degree of relatedness between the knowledge base in the region and the incoming knowledge flows from other regions as measured through the indicator RELATEDNESS, which is built in a similar fashion to Boschma and Iammarino (2009):

$$RELATEDNESS = \sum_j CIT_4^M(j)\, PAT_4(j) \tag{11}$$

where $CIT_4^M(j)$ is the entropy measure obtained with data for extra-regional backward citations in four-digit technologies (subclasses) other than j, but within the same 35-field technology, and $PAT_4(j)$ is the relative size of the four-digit patent technology j in the total regional patenting. The idea is that for each four-digit patent technology in a region (e.g., technology C07G), we measured the entropy of the citations to patents from the other four-digit subclasses (e.g., C07K, C12M, C12N, C12P, C12Q, C12R, and C12S) pertaining to the same 35-field sector (e.g., the biotechnology field), excluding the focal four-digit subclass itself (i.e., subclass C07G).

With these two indices (SIMILARITY and RELATEDNESS) we aim to measure how related the knowledge that flows into a region is to the current regional knowledge stock of a given region, in order to infer the role of such relatedness in the creation of new knowledge.

4. DATA

We use a sample of 261 NUTS2 European regions of 27 countries – EU-27 (except Cyprus and Malta) plus Norway and Switzerland, to estimate a regional KPF from 1999 to 2007. Our dependent variable, innovation output, is measured by patent applications, a variable widely used in the literature to proxy innovation outcomes. As widely documented, this proxy presents serious caveats since not all inventions are patented, nor do they all have the same economic impact, as they are not all commercially exploitable (Griliches, 1991). In spite of these shortcomings, patent data have proved useful for proxying inventiveness as they present minimal standards of novelty, originality and potential profits, and as such are a good proxy for economically profitable ideas (Bottazzi and Peri, 2003). We retrieve patent data at the regional level from the OECD REGPAT database – July 2013 edition (Maraut et al., 2008). When patents have been produced by inventors resident in different NUTS2, they have been fractionally assigned to the different regions, according to the number of inventors out of all inventors listed in a patent living there – fractional counting.

As for the explanatory variables, R&D expenditures data (both private and public expenditures in regions) were collected from Eurostat and some National Statistical Offices. Data for human resources devoted to science and technology (HRST) and the share of manufacturing employment (ShareInd) are collected also from Eurostat.

As mentioned above, variety indexes are constructed using the information of IPC codes listed in patent documents (again from the OECD REGPAT database – July 2013 edition). Again, based on the available data, there are 635 four-digit patent classes, 35 technological fields and 5 broad fields. Knowledge flows are proxied through patent citations as explained in section 3. We use unit-record data retrieved from EPO patents – OECD REGPAT database, July 2013 edition – to construct the patent citation variables (OECD Citations database, July 2013 edition; see Webb et al., 2005). All the patent data used to build the focal explanatory variables are retrieved for moving time windows of five years.

Table 1 provides summary statistics of the variables used in the present analysis.

Table 1. Summary statistics

Variable	Obs.	Mean	Std.Dev	Min.	Max.
PATpc	2,235	111.65	131.32	0	1,017.78
Weighted PATpc	2,235	263.90	323.62	0	2,575.42
Variety	2,235	5.84	1.50	0	7.78
Related Variety	2,235	1.78	0.77	0	3.20
Unrelated Variety	2,235	1.96	0.35	0	2.31
Similarity	2,235	6.31	3.37	0	13.68
Relatedness	2,235	0.03	0.03	0	0.43
Similarity Int'l	2,235	6.15	3.30	0	13.60
Relatedness Int'l	2,235	0.03	0.03	0	0.43
R&Dpc	2,235	0.40	0.41	0	2.88
HRST	2,235	14.16	4.73	3.90	34.40
ShareInd	2,235	19.16	6.75	5.21	38.55
GDPpc PPP	1,835	21,291.66	8,807.90	3,400	84,600

Note: Variables in this table are expressed without taking the logarithmic transformation.

5. RESULTS

5.1 Local variety and innovation

We estimate an unbalanced panel FE model of 9 periods (from 1999 to 2007, both inclusive). Table 2 provides the two-way FE estimates for the regional KPF model, including all the controls listed in section 3. Columns (i) and (ii) use as dependent variable the logarithmic transformation of the number of patents per million inhabitants. Because of the existence of zero patents in some cases, a small constant, 1, is added before the logarithmic transformation.

Table 2. Related/unrelated variety and regional innovation

	(i) Patents pc	(ii) Patents pc	(iii) Quality-weighted patents pc	(iv) Quality-weighted patents pc
Variety	0.104***		0.159***	
	(0.0308)		(0.0374)	
Related Variety		0.240***		0.292***
		(0.0653)		(0.0784)
Unrelated Variety		0.0804		0.207**
		(0.0690)		(0.0823)
ln(R&D per capita)	0.167***	0.174***	0.146*	0.161**
	(0.0540)	(0.0561)	(0.0773)	(0.0782)
HRST	0.0123*	0.0118*	0.0136	0.0134
	(0.00707)	(0.00671)	(0.00874)	(0.00846)
ShareInd	0.0442***	0.0457***	0.0661***	0.0661***
	(0.00925)	(0.00856)	(0.0114)	(0.0109)
Constant	2.377***	2.383***	2.513***	2.544***
	(0.283)	(0.291)	(0.371)	(0.374)
Observations	2,235	2,235	2,235	2,235
Number of regions	261	261	261	261
Region FE	yes	yes	yes	yes
Time FE	yes	yes	yes	yes
Overall-R2	0.557	0.587	0.385	0.421
F-stat	24.39	25.81	16.76	15.36
F-prob	0.000	0.000	0.000	0.000

Notes: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

In all the cases, the Hausman test rejects the null hypothesis that individual effects are uncorrelated with the independent variables, so the FE model is preferred to the expense of the random-effects – results provided upon request. In general, the KPF holds in the European regional case for the period under consideration. The elasticity of patents with respect to R&D expenditures presents significant values (0.10-0.20), which is in line with the value obtained in the literature (Jaffe, 1989; Bottazzi and Peri, 2003).

With respect to the variety index, results indicate that the variety in knowledge stocks of regions is indeed positively and significantly related to regions' innovation output. The same as for the case of employment and productivity (Boschma and Frenken, 2010), diversity of knowledge, rather than specialization, is more relevant for regional innovation, given that diversity and variety of knowledge in clusters eases the transfer of knowledge between local actors.

Interestingly, once variety is split into related and unrelated, only related variety is significant. This result seems to indicate that the higher the number of related technologies in a region, the larger the knowledge spillovers and, as a consequence, the more the learning opportunities across them (Frenken et al., 2007). That is, learning opportunities generated by a variety of technologies within the region are relevant when such technologies are related, which ultimately will generate more knowledge externalities across them. Meanwhile, if the knowledge flows across technologies far away from each other (unrelated variety), it will be more difficult to assemble them and produce new ideas and innovation.

Columns (iii) and (iv) of Table 2 slightly modify our dependent variable in order to weight the innovation output measure, patents, according to their impact. As largely argued in the related literature, the number of forward citations received presumably conveys information about the importance of patents, thus providing a way of assessing the enormous heterogeneity in the value of patents (Hall et al., 2005). This extreme is confirmed by several studies that have found strong correlations between the number of forward citations received and the economic value of patents (Trajtenberg, 1990; Harhoff et al., 1999; Lanjouw and Schankerman, 2004). We therefore use citations as an imperfect, but widely used, proxy for patent quality and weight the number of patents by the number of citations the patent has received in subsequent patent documents.

All our results and conclusions with respect to columns (i) and (ii) hold, except for the case of unrelated variety, that increases considerably its point estimate and becomes now highly significant. It seems therefore that the combination of unrelated technologies does not necessarily imply the creation of new average knowledge (as inferred from results in columns (i) and (ii)); but if such combination is achieved, the knowledge that is generated is presumably of high value and economic impact. Put differently, European regions seem to be capable of generating breakthrough innovations when the knowledge base in the region is composed of inventors sufficiently different from each other (for comparable results for the US context, see Castaldi et al., 2015).

5.2 Technological relatedness and external linkages

This section looks at the role of external-to-the-region inflows of knowledge. As it has been set forth above, it is critical for regions to maintain external connections bringing new knowledge into the region from a variety of sectors located elsewhere. We distinguish between incoming knowledge flows that remain within the same technology (SIMILARITY) from those transferred from different technologies (RELATEDNESS), using data on patent citations to build our variables.

Table 3 shows the results when the SIMILARITY and the RELATEDNESS indices are included to explicitly consider to what extent the knowledge that flows from other regions is related to the knowledge stock of the host region. As observed in column (i), the higher the SIMILARITY between the technological composition of the local knowledge and that of the cross-regional knowledge flows, the higher the impact on the regions' innovative output. In other words, if the knowledge that flows into a region comes from technologies in which the region already patents, there seems to be plenty of opportunities for absorbing such knowledge without having the problem of not adding much to the already existing local knowledge base. We interpret this result as evidence that the knowledge coming from other regions already convey a certain degree of novelty as compared to the local knowledge base, which is not embodied in the technological classification used in the present paper. Conversely, the non-significant parameter of the RELATEDNESS index implies that when only a certain degree of relatedness exists, it is not easy to create useful interconnections that can end up producing any significant innovation outcome; therefore, larger similarity is needed.

Table 3. Relatedness and external linkages

	(i) Patents pc	(ii) Quality-weighted patents pc	(iii) Patents pc	(iv) Quality-weighted patents pc
Variety	0.0863***	0.140***	0.0868***	0.141***
	(0.0282)	(0.0349)	(0.0282)	(0.0349)
Similarity	0.0724***	0.0757***		
	(0.0149)	(0.0180)		
Relatedness	0.441	0.862**		
	(0.346)	(0.430)		
Similarity int'l			0.0712***	0.0748***
			(0.0152)	(0.0185)
Relatedness int'l			0.504	0.877**
			(0.363)	(0.441)
ln(R&D per capita)	0.134**	0.113	0.134**	0.112
	(0.0521)	(0.0757)	(0.0520)	(0.0757)
HRST	0.00887	0.00989	0.00877	0.00984
	(0.00632)	(0.00794)	(0.00629)	(0.00790)
ShareInd	0.0394***	0.0609***	0.0395***	0.0610***
	(0.00861)	(0.0112)	(0.00864)	(0.0113)
Constant	2.107***	2.230***	2.122***	2.243***
	(0.254)	(0.339)	(0.252)	(0.337)
Observations	2,235	2,235	2,235	2,235
Number of regions	261	261	261	261
Region FE	yes	yes	yes	yes
Time FE	yes	yes	yes	yes
Overall-R2	0.720	0.554	0.712	0.546
F-stat	29.60	20.94	29.68	21.05
F-prob	0.000	0.000	0.000	0.000

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Interestingly again, when the patents are weighted by their quality (column ii), the coefficient accompanying the RELATEDNESS index increases considerably and becomes statistically significant, suggesting that an extra-regional knowledge that is complementary, but not similar, to the existing knowledge base in the region will particularly boost interactive learning that can bring out breakthrough innovations (Bunnell and Coe, 2001). We can conclude, therefore, that in order to develop a worthy interexchange of knowledge across regions, it is necessary to have a certain level of similarity so as to have the opportunity to learn across technologies. However, when the value of the innovations produced is taken into account, related, but not the same, incoming knowledge flows are also critical.

For robustness purposes, columns (iii) and (iv) of Table 3 mimic columns (i) and (ii) but using international incoming knowledge flows, that is to say, the indices of SIMILARITY and RELATEDNESS are computed using backward citations to other countries only. This modification allows us to be sure that the incoming knowledge really comes from external sources, and it is not the result of commuting or labour mobility within the same local labour markets. In general, results and conclusions with respect to columns (i) and (ii) are maintained.

5.3 Robustness analysis

In Table 4 we present alternative econometric specifications to test the robustness of our results. Specifically, we test the theoretical statements discussed earlier through the use of a more general dependent variable on regional economic performance, such as the annual growth rate of GDP per capita. Despite the fact that GDP growth does not reflect a direct measure of innovation, its use avoids potential criticisms derived from the use of patent data to build both the dependent and independent variables, as we did in previous sections. Data on regional GDP per capita is retrieved from Eurostat, and the dependent variable is computed as the log of the ratio between per capita GDP at time t_1 and per capita GDP at t_0. Moreover, regressions include the log of per capita GDP at t_0 as an additional control, as done in much of the growth literature.

Results reported in columns (i) and (ii) concerning related and unrelated variety are in line with much of the related literature for specific countries (Frenken et al., 2007, for the Netherlands; Boschma and Iammarino, 2009, for Italy; Bishop and Gripaios, 2010, for Great Britain; Quatraro, 2010, for Italy; Hartog et al., 2012, for Finland and Boschma et al., 2012, for Spain) even if in our regressions, variety indicators are computed using technology fields from patent applications, instead of employment by economic activities. The results reported show the significant impact of variety, both in related and unrelated technologies. This evidence supports the hypothesis that economic growth benefits from diversification in technologies too. Note that in previous tables we found that unrelated variety only impacts innovation if weighted by their value using forward citations – breakthrough innovations. Interestingly, both related and unrelated variety strongly influence regional economic growth, which we attribute to the strong link between economic growth and breakthrough innovations, as witnessed by the recent report of the World Intellectual Property Organization (Wipo, 2015). Results concerning incoming knowledge flows and regional economic growth (columns (iii) and (iv)) are also consistent with the previous results presented in Table 3.

Reassuringly, we have shown that our results are not driven by mechanical correlation between dependent and independent variables, given that the use of an alternative measure not directly retrieved from patent documents, such as per capita GDP growth, does support our key findings.

Table 4. Robustness analysis: technological variety and economic growth

	(1)	(2)	(3)	(4)
Ln GDP	-0.129***	-0.120***	-0.137***	-0.137***
	(0.0278)	(0.0267)	(0.0275)	(0.0275)
Variety	0.0104***		0.00935***	0.00943***
	(0.00222)		(0.00225)	(0.00224)
Related Variety		0.0117**		
		(0.00574)		
Unrelated Variety		0.0116***		
		(0.00432)		
Similarity			0.00424***	
			(0.00132)	
Relatedness			-0.0454	
			(0.0337)	
Similarity int'l				0.00413***
				(0.00131)
Relatedness int'l				-0.0506
				(0.0337)
ln(R&D per capita)	0.00171***	0.00176***	0.00154**	0.00154**
	(0.000628)	(0.000606)	(0.000615)	(0.000615)
HRST	0.00476***	0.00501***	0.00452***	0.00452***
	(0.00136)	(0.00137)	(0.00137)	(0.00137)
Constant	1.125***	1.043***	1.192***	1.192***
	(0.264)	(0.255)	(0.261)	(0.261)
Observations	1,835	1,835	1,835	1,835
Number of regions	238	238	238	238
Region FE	yes	yes	yes	yes
Time FE	yes	yes	yes	yes
Overall-R2	0.176	0.176	0.176	0.176
F-stat	86.20	86.20	86.20	86.20
F-prob	0	0	0	0

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Dependent variable: annual growth rate of GDP per capita.

6. CONCLUSION

Previous studies have looked at the impact of related and unrelated variety on regional economic performance, under the assumption that the relationship between them goes via the generation of knowledge spillovers and innovation – yet, without directly testing this relationship. In this paper, we focus explicitly on the impact of technological variety within the region for the generation of innovation and we assess which diversified technological structure (related vs. unrelated variety) generates more knowledge spillovers which will ultimately enhance the innovation output. In addition, since knowledge can also be brought into a region from "outside", we assess whether the degree of relatedness between incoming knowledge that flows into a region and the local knowledge base influences regional innovation performance. As it is usually done in the related literature, knowledge flows are proxied through the use of backward patent citations, which is more related to our scope of analysis that the use of trade or labour mobility as conduits of knowledge flows (e.g. Boschma and Iammarino, 2009; Tavassoli and Carbonara, 2014; Boschma et al., 2009).

According to our results, diversity of knowledge, or variety, is more relevant for regional innovation than specialization. However, only knowledge flowing from different but similar technologies (related variety) will generate new knowledge that incrementally constructs on established cognitive structures across related technologies. Notwithstanding these results, an interesting conclusion arises when the patenting activity is weighted by the quality of such patents through the forward citations received – which is used as an attempt to give more importance to breakthrough innovations: in this particular case, the more diversified across unrelated technologies is a region, the higher is the output in terms of breakthrough innovations. Thus, evidence supports the hypothesis that innovation in general benefits from diversification in related technologies whereas more radical innovation also benefits from variety in unrelated technologies.

Our study also shows that not only being connected to the outside world is important, as signalled in previous studies (Bathelt et al., 2004; Camagni, 1991; Grabher, 1993), but that extra-regional incoming knowledge flows have a higher impact, the higher the similarity between these knowledge flows and the extant local knowledge base. While this is true for the generation of average innovations, again differences emerge when accounting for the impact of the innovations produced: for the generation of breakthrough innovations, the technological contents of the extra-regional linkages do not necessarily need to be very similar to the local technological base, but a certain degree of relatedness seems to be sufficient. This degree of relatedness assures certain cognitive proximity between agents located at a geographical distance, while at the same time brings in the necessary variety to offer the building blocks for technological revolutions.

From our results we can conclude that there is a need for a regional system to have certain degree of variety but at the same time certain cognitive proximity in its industries, so as to promote innovation in the region. This entails that regional governments may establish policies targeted to develop a collection of complementary technologies in the region, possibly taking away the bottlenecks that may impede some sectors to enter.

Future research should thoroughly look at the effect of regional unrelated variety on breakthrough innovations. On the one hand, it could be interesting to analyse if breakthrough innovations – i.e., those at the upper-tail of the citations distribution - in a region actually combine technology classes that are unrelated, defined through co-occurrence analysis (see Boschma et al., 2015, as an example of this type of analysis), but present in the region concerned. On the other hand, it is plausible to think that the impact of technological unrelated variety on the generation of breakthrough innovations can be stronger in the long run since the combination and recombination of previously unrelated technologies may imply some time to be fulfilled. Thus, it would be interesting to analyse the time profile of the impact of related and unrelated variety on the probability to produce breakthroughs.

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APPENDIX

Table A1: Technology fields based on IPC codes

Broad field	Technology field
Electrical engineering	Electrical machinery, energy
Electrical engineering	Audio-visual technology
Electrical engineering	Telecommunications
Electrical engineering	Digital communication
Electrical engineering	Basic communication processes
Electrical engineering	Computer technology
Electrical engineering	IT methods for management
Electrical engineering	Semiconductors
Instruments	Optics
Instruments	Measurement
Instruments	Analysis of bio materials
Instruments	Control apparatus
Instruments	Medical technology
Chemistry	Organic fine chemistry
Chemistry	Biotechnology
Chemistry	Pharmaceuticals
Chemistry	Macromolecular chemistry, polymers
Chemistry	Food chemistry
Chemistry	Basic materials chemistry
Chemistry	Materials metallurgy
Chemistry	Surface tech coating
Chemistry	Micro-structure and nano-technology
Chemistry	Chemical engineering
Chemistry	Environmental technology
Mechanical engineering	Handling
Mechanical engineering	Machine tools
Mechanical engineering	Engines, pumps, turbines
Mechanical engineering	Textile and paper
Mechanical engineering	Other spec machines
Mechanical engineering	Thermal processes and apparatus
Mechanical engineering	Mechanical elements
Mechanical engineering	Transport
Other	Furniture, games
Other	Other cons goods
Other	Civil engineering
Other	Other

Source: Schmoch (2008)**.**

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[i] For an application to the US using USPTO data, see Castaldi et al., 2015.
[ii] Subclasses are further divided into groups and subgroups, so each IPC code can contain up to 10 digits.
[iii] See the Appendix for the list of the 35 fields and the 5 broad fields.

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