The Role of Relatedness and Unrelatedness for the Geography of Technological Breakthroughs in Europe

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abstract

This article proposes a framework to study how the existing knowledge portfolio of regional economies affects the emergence and occurrence of breakthrough technologies. The study discusses the relevance of cognitive distance between the technology of a breakthrough invention and the existing technological base in their geographic vicinity. Theoretically, it introduces the idea that both relatedness and unrelatedness between the technologies in breakthrough inventions and the regional portfolio of technologies can positively influence the appearance of these breakthroughs, but especially relatedness. Empirically, it investigates a sample of 277 NUTS2 regions in Europe in the period 1981 to 2010 and reveals that, by far, most combinations breakthrough inventions make are between related technologies: almost no breakthrough patent combines unrelated technologies only. Regressions show that the occurrence of breakthrough patents in a technology in a region is positively affected by the local stock of technologies that are related to such technology, but such an effect for the local stock of unrelated technologies is not found. However, the region's ability to enter new breakthrough inventions in a technology relies on the combination of knowledge that is both related and unrelated to such technology.

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A wide body of literature in the field of economics of innovation has investigated the occurrence of technological breakthroughs (Schumpeter 1939; Schmookler 1966; Freeman, Clark, and Soete 1982; Scherer 1982; Kleinknecht 1987; Arts and Veugelers 2015). Breakthrough technologies attract a lot of attention, because they are considered to have a large impact on subsequent technological change and economic development (Boschma 1999; Carnabuci and Operti 2013; Arts and Veugelers 2015; World Intellectual Property Organization [WIPO] 2015; Verhoeven, Bakker, and Veugelers 2016).

Many studies have looked into the geography of such breakthrough technologies (O'hUallichain 1999; Varga 2000; Carlino, Chatterjee, and Hunt 2007; Kerr 2010; Balland and Rigby 2017; Castaldi and Los 2017; Li 2020; Berkes and Gaetani 2021; Coniglio et al. 2021; De Noni and Belussi 2021; Esposito 2021). This literature has been heavily influenced by the work of Jane Jacobs (1969) on the relationship between urban diversity and innovation, claiming that cities and regions with a diverse pool of knowledge trigger new ideas and atypical combinations that result in breakthrough inventions (Bettencourt, Lobo, and Strumsky 2007; Desrochers and Leppälä 2011; Mewes 2019; Abbasiharofteh, Kogler, and Lengyel 2020). Scholars have argued that unrelated variety in particular enhances the occurrence of technological breakthroughs (Saviotti and Frenken 2008; Castaldi, Frenken, and Los 2015; Martynovich and Taalbi 2020), because they make combinations across unrelated knowledge fields. As unrelated combinations involve low cognitive proximity between the combined technologies, geographic proximity favors the likelihood of such uncommon combinations (Phene, Fladmoe-Lindquist, and Marsh 2006; Kelley, Ali, and Zahra 2013; Li, Heimeriks, and Alkemade 2021).

Yet, combinations of related technologies can still be crucial for the development of breakthrough ideas. From a theoretical perspective, one could argue that the introduction and development of breakthroughs are accompanied by high risks and uncertainties due to their novel character. In order to dampen and accommodate those risks, successful breakthroughs will have to rely primarily on combinations made previously, rather than building on unrelated combinations. It will be relatively easier, and adjustment costs will be lower when diversifying into new technologies that can leverage relevant regional capabilities (Balland et al. 2019). Kaplan and Vakili (2015) argued that truly novel breakthrough patents are primarily engaged in local, not distant, search. Recombinations of distant knowledge may therefore be considered to be detrimental to breakthrough inventions (Weisberg 1999; Taylor and Greve 2006; Kaplan and Vakili 2015). If local search processes do indeed play a key role in the emergence of breakthrough technologies, we might expect that they have a greater likelihood to develop in a region where their technologies are more related to the local stock of technologies. Boschma (2017) argued that new activities in regions, even the more radical ones, combine related and unrelated capabilities. Yet, the role of relatedness on breakthrough technologies has been somewhat neglected by the literature, with few exceptions (De Noni and Belussi 2021).

Thus, we argue that relatedness and unrelatedness may simultaneously enhance the occurrence and emergence of breakthrough inventions in regions. This article takes up this topic, since studies have not yet looked into this question. Theoretically, we aim to understand the potential role of relatedness and unrelatedness between the technologies in breakthrough inventions and the regional technological portfolio on the development of these breakthroughs, and argue that both can positively influence their appearance. Empirically, we study the occurrence and emergence of breakthrough patents in 277 European regions in the period 1981 to 2010, and whether the ability of regions to produce such patents in a given technological field is conditioned by the stock of local technologies related and unrelated to that field. Our study deviates from previous articles (Castaldi, Frenken, and Los 2015; Miguélez and Moreno 2018) that aimed to measure these effects in terms of related and unrelated variety, because they did not investigate whether local technologies in the variety measures are actually related or unrelated to the technology of the breakthrough inventions. Inspired by the regional diversification literature (Boschma 2017), we use and develop instead measures of relatedness and unrelatedness density that capture how close and how distant, respectively, the technology of a breakthrough invention actually is to the existing portfolio of technologies in a region. Our study finds evidence for the effect of relatedness density on the occurrence of breakthrough inventions in regions but no effect of unrelatedness density. However, when the ability of regions to enter and develop breakthrough patents in technologies not yet present in the region is analyzed, we find that also unrelatedness matters.

The article is structured as follows. The following section discusses the theoretical background and develops hypotheses. Then we introduce the data and explain how we define and measure breakthrough patents, relatedness, and unrelatedness density. This is followed by a description of the type of combinations breakthrough inventions make, based on unit-record data of millions of European Patent Office (EPO) patents. Then, we present findings from region-technology–level estimations explaining the occurrence and emergence of breakthrough patents in Europe. A final section concludes and discusses the main findings.

Relatedness, Unrelatedness, and the Geography of Technological Breakthroughs

A large body of literature has focused attention on the geography of technological breakthroughs. Inspired by Schumpeter (1939), breakthroughs are considered to have a big impact on the economic fortunes of regions (Markusen, Hall, and Glasmeier 1986; Marshall 1987; Hall and Preston 1988), since they bring into existence new places of growth (Perez and Soete 1988; Scott 1988). Likewise, breakthroughs also have disruptive impacts on existing economic activities in regions such as automation (Autor 2015; Acemoglu and Restrepo 2019; Felten, Raj, and Seamans 2021).

This has led to a search for factors that affect the geography of breakthrough technologies. There is evidence that breakthrough inventions tend to concentrate in large cities, due to the presence of talent and high-skilled people, an advanced knowledge infrastructure, and high-complex knowledge (O'hUallichain 1999; Varga 2000; Carlino, Chatterjee, and Hunt 2007; Balland and Rigby 2017; Castaldi and Los 2017). This tendency of technological breakthroughs to concentrate in the largest cities has accelerated since the early twentieth century (Mewes 2019), although breakthroughs also occur outside large cities (Fritsch and Wyrwich 2021).

Jacobs (1969) argued that a diverse knowledge pool in large cities would trigger new ideas and innovations, because it provides opportunities to make new knowledge combinations (Bettencourt, Lobo, and Strumsky 2007; Desrochers and Leppälä 2011). Building on Frenken, van Oort, and Verburg (2007), Castaldi, Frenken, and Los (2015) argued that not variety per se, but rather related variety in a region would favor inventions, because related knowledge domains can be more easily and effectively combined (Tavassoli and Carbonara 2014; Aarstad, Kvitastein, and Jakobsen 2016; Miguélez and Moreno 2018; Martynovich and Taalbi 2020). When local agents search for new combinations, they focus on knowledge pieces in their immediate surroundings that they have prior experience in, and they look into combinations that have been combined before, to reduce uncertainty and to lower adjustment costs (Nelson and Winter 1982; Nooteboom 2000). In contrast, unrelated variety would slow down inventions in a region because the cognitive distance between technologies would be too large, and therefore, it would be too risky and too costly to combine those.

Contrarily, Saviotti and Frenken (2008) argued that unrelated variety instead would enhance the occurrence of radical inventions, since they tend to make combinations across unrelated knowledge fields. They build on recombinant search theory (Weitzman 1998) in which radical inventions are considered to make combinations across existing knowledge domains not combined before (Ahuja and Lampert 2001; Schoenmakers and Duysters 2010; Strumsky and Lobo 2015). Recombining knowledge from distant technology fields is perceived to result in more novel and valuable inventions (March 1991; Trajtenberg, Henderson, and Jaffe 1997; Fleming 2001; Dahlin and Behrens 2005). As unrelated combinations represent high cognitive distance between the knowledge fields involved, scholars have argued that geographic proximity enhances the likelihood of such uncommon combinations (Li, Heimeriks, and Alkemade 2021). While new technologies tend to draw on local knowledge sources (Jaffe, Trajtenberg, and Henderson 1993; O'hUallichain 1999; Acs, Anselin, and Varga 2002; Audretsch and Feldman 2004; Sonn and Storper 2008; Breschi and Lissoni 2009; Hervás-Oliver et al. 2018; Arant et al. 2019; Grashof, Hesse, and Fornahl 2019), this would be even more true for breakthroughs, since these would stem from combinations of unrelated knowledge domains. These combinations are more likely to occur and become successful when available in the same region (Phene, Fladmoe-Lindquist, and Marsh 2006; Kelley, Ali, and Zahra 2013). Castaldi, Frenken, and Los (2015) found indeed a positive correlation between unrelated variety and technological breakthroughs in US states but no correlation with related variety. Other studies also found a positive effect of related variety on the occurrence of breakthrough technologies in regions (Miguélez and Moreno 2018; Hesse and Fornahl 2020).[1]

Yet, it might be crucial to consider the role of relatedness, since the novel character of technological breakthroughs means their emergence and development might be accompanied by high risks and uncertainties (Perez and Soete 1988). In order to dampen and accommodate those risks, to lower adjustment costs, and to enhance their successful development, breakthroughs might have to rely primarily on combinations made previously, rather than building on unrelated combinations. Kaplan and Vakili (2015) claimed that breakthrough patents that represent novel topics are more likely to be engaged in local rather than distant search. Local search is needed to identify anomalies that require a deep understanding of a particular knowledge domain. According to this view, recombinations of distant (diverse) knowledge are regarded as detrimental to breakthrough inventions (Weisberg 1999; Taylor and Greve 2006; Kaplan and Vakili 2015).

This comes close to the claim of the regional diversification literature (Boschma 2017) that it will be relatively easier and adjustment costs will be lower for regions when diversifying into new technologies that can leverage relevant regional capabilities (Balland et al. 2019; Pinheiro et al. 2021). This principle of relatedness (Hidalgo et al. 2018) has been demonstrated for the regional entry of new technologies (Boschma, Balland, and Kogler 2015; Rigby 2015; Montresor and Quatraro 2017) and for specific technologies such as nano-technologies (Colombelli, Krafft, and Quatraro 2014), biotechnologies (Boschma, Heimeriks, and Balland 2014), fuel cell technologies (Tanner 2016), green technologies (Corradini 2019; Montresor and Quatraro 2019), and renewable energy technologies (Li 2020; Moreno and Ocampo-Corrales 2022). So far, these studies have focused on technologies, rather than breakthrough technologies. Few studies have looked into the question whether relatedness is actually a key factor enhancing the introduction and development of such inventions in regions (De Noni and Belussi 2021). As local search processes play a key role in the emergence of breakthrough technologies as well (Kaplan and Vakili 2015), we therefore expect that breakthrough inventions will have a greater likelihood to develop in a region where their technologies are more related to the local stock of technologies. Based on this theory, we formulate the two following hypotheses:

> **H_{1a}**: Breakthrough inventions are more likely to occur (be more abundant) in a region, the more related their technologies are to the local stock of technologies.
>
> **H_{1b}**: Breakthrough inventions are more likely to emerge (enter for the first time) in a region, the more related their technologies are to the local stock of technologies.

[1]These studies did not investigate whether local technologies, as proxied by related and unrelated variety measures, were actually related or unrelated to the breakthrough technology. This requires measures of relatedness and unrelatedness that capture how close and how distant the technology of a breakthrough invention actually is to the portfolio of technologies in a region. To our knowledge, no study has yet examined that. Only De Noni and Belussi (2021) applied the relatedness framework to investigate the regional occurrence of a breakthrough, but they followed a different approach compared to the current article and looked at industries, not technologies.

While hypothesis 1 expects relatedness to drive the emergence and occurrence of breakthrough inventions in regions due to their novel and original character, we do not deny the relevance of unrelatedness, as largely discussed in the literature (Saviotti and Frenken 2008; Castaldi, Frenken, and Los 2015). In fact, these and other studies have contended that having related technologies within a region may not be as important as having unrelated technologies, especially at the early stages of the emergence of breakthrough inventions.

However, as Boschma (2017) argued, new activities are likely to combine related and unrelated capabilities. Therefore, both relatedness and unrelatedness might enhance the development of breakthrough inventions in regions. In other words, the two factors need not to be mutually exclusive (Castaldi, Frenken, and Los 2015). Studies have not yet looked into the question whether relatedness and unrelatedness simultaneously are factors enhancing breakthrough inventions in regions. Therefore, we formulate the following hypotheses:

> **H_{2a}**: Breakthrough inventions are more likely to occur (be more abundant) in a region, the more unrelated their technologies are to the local stock of technologies, regardless of the degree of related technologies already present in that region.
>
> **H_{2b}**: Breakthrough inventions are more likely to emerge (enter for the first time) in a region, the more unrelated their technologies are to the local stock of technologies, regardless of the degree of related technologies already present in that region.

Data, Variables, and Method

Data

We use EPO patents unit-record data from OECD REGPAT database (September 2015 edition; Maraut et al. 2008), as well as forward citations (EPO-to-EPO, including indirect links through patent families) from ICRIOS database (Coffano and Tarasconi 2014), to build almost all our variables. The analysis covers 621 technological classes in 277 NUTS2 European regions of 30 countries—EU-27, plus the UK, Norway, and Switzerland—for the period 1981 to 2010.

We use inventors' addresses to attribute patents to regions. When patents are produced by several inventors resident in different NUTS2 regions, they have been fully assigned to the different regions (full counting). That is, if a patent is produced by more than one inventor and they reside in different regions, the count of patents of each of these regions increases by one rather than a proportion of it—as it would be for fractional counts. Knowledge is arguably a nondivisible asset. If a given technology is in a location to allow the emergence of breakthroughs, that idea will exist there in full, regardless if it is produced in collaboration with inventors from other regions or not.

In order to smooth the yearly lumpiness of patent data, we create time windows of five years starting from 1981 and lasting until 2010, combining the data over nonoverlapping five-year periods (1981–85, 1986–90, 1991–95, 1996–2000, 2001–5, and 2006–10).[2] We now turn to the description of the variables used in the regression analysis.

[2]The consideration of data in five-year periods is common practice in empirical analyses using patent data (among many, see Montresor and Quatraro 2019, and Santoalha and Boschma 2021).

Dependent Variable: Occurrence and Emergence of Breakthrough Inventions

Most inventions are incremental in the sense that they improve and refine existing inventions, whereas a few are breakthroughs. Despite being a minority, breakthroughs are considered the foundational inventions that serve extensively as the basis for many subsequent technological inventions and that introduce new solutions (Ahuja and Lampert 2001; Fleming 2001). Following this simple idea, one of the most traditionally used definitions of breakthroughs considers their *ex post* impact and reutilization. Indeed, breakthrough inventions are viewed as introducing new paradigms on which many future inventions build (Dosi 1982; Fleming 2001). We thus define breakthrough inventions as those patents with more forward citations. This approach assumes that if a patent receives many citations, it means that it is being influential for the creation of new ideas (Jaffe and de Rassenfosse 2016). Moreover, studies have indeed shown that the number of forward citations received conveys information about the importance and economic value of patents (Trajtenberg 1990; Harhoff et al. 1999; Lanjouw and Schankerman 2004; Hall, Jaffe, and Trajtenberg 2005; Kogan et al. 2017).

We define a patent as a breakthrough when it is in the upper 5 percent of the distribution according to the number of forward citations it collects, for the technology and year it belongs to.[3] We do this to control for the fact that some technologies are more dynamic in patenting and citing (Schmoch 2008), and also that older patents have had higher chances to be cited.[4]

We use two proxies for the occurrence of breakthroughs and a proxy for their emergence. As for the occurrence, we consider the total number of breakthrough patents (*BP_Tot*) as well as the share of breakthroughs out of the total number of patents in such technology (*BP_Share*). As for the emergence, we consider an entry variable defined as a binary indicator switching to 1, if the region in a given period (time window) has at least one breakthrough patent in a specific technology while it was not the case in the previous period (*BP_Entry*).[5]

Measuring Relatedness and Unrelatedness

To determine the degree of (un)relatedness between technologies, we start by computing the co-occurrence of any two IPC classification codes (for a total of 621 four-digit

[3]We also make robustness analyses with different thresholds, that is, the upper 10 percent and the upper 1 percent of the distribution of collected forward citations.

[4]In a recent article, Kuhn, Younge, and Marco (2020) showed that the changes in the data generation process for patent citations present several problems for applied economists. Although not exclusively, the main issue refers to the increase in the number of citations in the last decades, which may be problematic when citations are used to compare patents between cohorts. However, in our article we use the number of forward citations to weight the patents within a given period, and we do it for each technology separately, which should lessen the problem. In addition, as Kuhn, Younge, and Marco (2020, 110) concluded in their article "correcting citation counts to return to the original goal of devising a measure of innovation activity that is broadly comparable across contexts, however, is problematic due to endogeneity in the pendency, citation lags, and filing years of a given sample." In any case, as it will be shown later in our article, we check the robustness of our results with a different definition of breakthroughs according to which a patent is considered to be a breakthrough, if it combines two technologies for the first time.

[5]We restrict to only one jump in a region for a technology and forcing missing values in case the region already had breakthroughs in the first period of the analysis.

technology classes) in the same patent document.[6] We do so by counting the times any two technologies appear together in a patent (Breschi, Lissoni, and Malerba 2003). To control for the fact that this co-occurrence can be random and caused by chance, we normalize it using the association probability measure presented in van Eck and Waltman (2009). All in all, we consider a probabilistic measure resulting in a co-occurrence measure between any two technologies i and j (ϕ_{ij}) as

$$\phi_{ij} = \frac{mc_{ij}}{s_i s_j} \tag{1}$$

where c_{ij} denotes the number of times technologies i and j occur together in the same patent, s_i and s_j are the total number of times technologies i and j appear, and m is the total number of patents.[7] We compute a co-occurrence matrix for each of the time periods under consideration—see below.

For unrelatedness, we consider values of $\phi_{ij} \leq 1$ to indicate that technologies i and j are observed together as often as if they would co-occur by chance. In this case, they are considered to be unrelated. We obtain a matrix of dimension 621 × 621 of unrelatedness for each time period, where each element ψ_{ij}=1 if $\phi_{ij} \leq 1$, and zero otherwise. As per relatedness, since those values of $\phi_{ij} > 1$ indicate that technologies i and j are observed together more frequently than would be expected by chance, we consider them to be related. We construct a matrix of dimension 621 × 621 for each time period, where each element $\eta_{ij} = 1$ if $\phi_{ij} > 1$, and zero otherwise.

To build our density measures, we need to construct variables for each set region-technology indicating how close a technology is to the existing technological base of a region, with the purpose of studying to what extent this closeness favors the emergence and the occurrence of breakthroughs. The technological base consists of those technologies in which a region has developed a relative specialization, measured as the revealed technological advantage (RTA) (Soete 1987). Specifically, region r has the RTA in technology i if the share of patents in technology i in its technological portfolio is higher than the share of technology i in the portfolio of all European regions

$$RTA_{ir} = 1 \ if \ \frac{\frac{patents_{ir}}{\sum_i patents_{ir}}}{\frac{\sum_r patents_{ir}}{\sum_r \sum_i patents_{ir}}} > 1 \ and \ 0 \ otherwise. \tag{2}$$

[6]IPC stands for International Patent Classification. Taking the four-digit disaggregation of IPC classification codes, our data set contains 640 technologies, but the 621 included in the analyses are those that are present for the whole period under consideration.

[7]Following van Eck and Waltman (2009), the use of a probabilistic similarity measure at the patent level is superior to other types of similarity measures based on co-occurrence. The co-occurrence of two objects can be driven by two independent effects: the similarity effect and the size effect. The similarity effect is the one in which two objects co-occur because they are related to each other. The size effect is the one in which a high frequency of co-occurrence of two objects can be due to the fact that one of them occurs a lot. van Eck and Waltman (2009) offered a detailed discussion of why our similarity measure remains unchanged when the occurrence of an object doubles, as well as the co-occurrences. This is not the case in other measures that fail to capture the size effect in co-occurrence. This indicator has been used before by Boschma et al. (2014) and Balland et al. (2019), among others.

where $patents_{ir}$ represents the total number of patents in technology i in region r. Thus, having the RTA in technology i would imply that the region is more specialized in technology i than the EU average. We then combine the RTA measures with the co-occurrence matrix to derive a density indicator, as in Boschma, Heimeriks, and Balland (2014):

$$UnrelD_{ir} = \frac{\sum_{i \epsilon r} \psi_{ij} RTA_{ir}}{\sum_i \psi_{ij}} \tag{3}$$

$$RelD_{ir} = \frac{\sum_{i \epsilon r} \eta_{ij} RTA_{ir}}{\sum_i \eta_{ij}} \tag{4}$$

The unrelatedness density indicator ($UnrelD_{ir}$) determines how close the set of technologies unrelated to technology i is to the technologies in which region r has an RTA. This is computed as the sum of all technologies j that are unrelated to technology i (ψ_{ij}=1) in which region r has an RTA, divided by the sum of unrelatedness of technology i to all other technologies j in all regions. A similar reasoning applies for the relatedness density indicator ($RelD_{ir}$). The values of both lie between 0 percent and 100 percent. A relatedness density of 60 percent would imply that region r has an RTA in 60 percent of the technologies that are related to technology i. An unrelatedness density of 20 percent would imply that region r has an RTA in 20 percent of the technologies that are unrelated to technology i.[8] These two density measures are our main variables of interest to explain the emergence and occurrence of truly radical and novel inventions.

Recall that these two density measures are different from the entropy measures capturing related and unrelated variety that are commonly used in this literature (e.g., Castaldi, Frenken, and Los 2015; Miguélez and Moreno 2018; Martynovich and Taalbi 2020). The latter measures are not fully satisfactory in our framework, since they do not make specific whether the local technologies in the variety measures are actually related or unrelated to the technological field of the breakthrough inventions. Inspired by the regional diversification literature (Boschma 2017; Balland et al. 2019), our indicators of relatedness and unrelatedness density capture how close and how distant, respectively, the technology of a breakthrough invention actually is to the existing portfolio of technologies in a region. These density measures will be used to analyze whether the ability of regions to produce breakthrough patents in a technology is conditioned on the local stock of technologies related or unrelated to that technology, or a combination of both.

Control Variables

For our regressions, we also build a number of control variables. Following Balland et al. (2019), we control for the technological intensity of both regions and technologies.

[8]While at the level of the co-occurrence matrices, being unrelated and related are opposite (either any two technologies are related or otherwise they are unrelated), once we transfer this to the regional level and consider only technologies in which the region has RTA, they are no longer opposite. Indeed, the relatedness and unrelatedness density indicators are positively correlated.

That is, we include the technological stock (*Tech Stock*), measured as the sum of technological claims in a region, to proxy for the regional invention capacity and the number of ideas that could potentially be combined in such a region. We include technological size (*Tech Size*), measured as the sum of technological claims per technology, to proxy for the inventive capacity of the technological field.

We also control for other drivers of innovation performance at the regional level. First, we include gross domestic product (GDP) per million inhabitants (*GDPpc*) to control for the economic wealth in the region, which is an important driver of innovation in general, and breakthroughs in particular, as well as a proxy for the availability of resources, and the chance of a region to support innovation (De Noni and Belussi 2021)—data from Eurostat. We also include population density (*Pop Dens*) as a proxy for agglomeration and urbanization economies (Boschma, Balland, and Kogler 2015), and its square term to pick up nonlinearities (*Pop Dens Sq*) (source: Eurostat). Finally, when the dependent variable refers to the total number of breakthrough patents as well as for the entry model (*BP_Tot* and *BP_Entry*, respectively), we include a measure of the overall patents produced in a region-technology in a given time window (*TotPat*), to proxy for the overall innovativeness capacity of a region in general terms. Given our geographic sample and time span, other control variables are impossible to obtain. The description of the dependent and explanatory variables as well as the correlation matrix of the explanatory variables are presented in Appendix A in the online material.

Empirical Methods

The empirical evidence of the article is provided in two different sections: first, a descriptive analysis at the patent level; second, a regression approach at the region-technology pair level.

The patent-level analysis provides descriptive evidence to understand to what extent the knowledge used and combined to generate a breakthrough invention is different from the knowledge used and combined in an average patent. More specifically, we analyze to what extent breakthrough inventions rely on combinations of related and unrelated technologies.

The region-technology–level approach is based on regression analysis. In our estimations, the dependent variable is a measure of the occurrence or emergence of breakthrough patents in technology i in region r. This is regressed on the key measures of the degree of relatedness and unrelatedness that such technology i maintains with the technological portfolio of region r, while controlling for regional and technological characteristics, for different time windows, using the following specification

$$BP_{ir,t} = \beta_0 + \beta_1 RelD_{ir,t-1} + \beta_2 UnrelD_{ir,t-1} + X_{ir,\,t-1}\,\gamma + \omega_r + \varphi_i + \alpha_t + \varepsilon_{irt} \quad (5)$$

where r refers to region, i to technology, and t to time period. *BP* is a measure of breakthrough patents (either *BP_Tot, BP_Share,* or *BP_Entry*), *RelD* and *UnrelD* stand for relatedness and unrelatedness density, respectively, and X is a set of controls, as discussed above. All the independent variables are computed for five-year, nonoverlapping time windows (five-year averages for GDP and population density) and are introduced with a time lag of one time window (t-1) with respect to the dependent variables in order to reduce potential endogeneity issues due to reverse causality (Boschma, Heimeriks, and Balland 2014; Balland et al. 2019).[9] All the estimations include region, technology, and time fixed effects (ω_r, φ_i, and α_t, respectively), to control for unobserved heterogeneity at these three dimensions. To consider deviations from the theory, a well-behaved error term is introduced, ε_{irt}. All variables are z-standardized, so that the coefficients can be compared within the estimation.

Given the high number of fixed effects included in the estimations, our primary method of estimation will be the fixed effects linear model with heteroskedasticity-robust standard errors and clustered at the regional level. However, in the case of the occurrence of breakthroughs proxied with the count variable (*BP_Tot*), we also estimate the model using Poisson Pseudo-Maximum Likelihood (PPML)—see Appendix D, Table D1 in the online material. On the other hand, in the case of the emergence of breakthroughs, given the binary nature of our dependent variable, the method of estimation is not so evident. Besides a linear probability model, a logit or probit specification can be used for a binary outcome regression. Although the logit model is more consistent with the binary nature of the dependent variable, the fact of introducing dummies to control for fixed effects in such a nonlinear model can generate an incidental parameter problem, potentially delivering biased and inconsistent results (Greene 2012; Gomila 2021). This is why we prefer to stick to the linear probability model.

Findings from the Descriptive, Patent-Level Analysis

In this section we present some descriptive analysis based on the information provided at the patent level. The objective is to analyze the extent to which breakthrough inventions (patents) rely on unrelated and related combinations. In each table below, different shares are computed separately for breakthrough and for all patents, with the idea to compare to what extent the pattern observed for breakthroughs differ from the one followed by the bulk of patents.[10,11]

Table 1 shows the share of patents that combine different types of technological classes. After presenting the share of patents that only present one technology (columns 1 and 2), we show the share of patents that only combine related technologies (columns 3 and 4), the share of patents that combine unrelated technologies irrespectively of whether they also have related technologies at the same time (columns 5 and 6), and the share of patents that only combine unrelated technologies (columns 7 and 8).

[9]Since we are considering windows of five years for all the variables in the regressions, a time lag of one period (t-1) refers to the previous window of five years. This can contribute to reduce endogeneity due to reverse causality, as the future cannot predict the past. We are aware that many sources of endogeneity are still present. With the same aim, our set of fixed effects aims to account for a number of unobservables. Although again, this does not fully eliminate all endogeneity concerns.

[10]In this descriptive analysis, when a patent is breakthrough in one technology, it is considered as breakthrough in all the technologies in which it appears (even if in these other technologies it is not strictly classified as breakthrough).

[11]For each of the six time periods, we compute the shares of pairs of technologies that are related (observed together in the same patent document more frequently than expected by chance) and unrelated (observed together as rarely, as if they would co-occur by chance). It is much more common that two technologies are unrelated: around 90% of all pairs of technologies are unrelated, and around 10% related (see Table A3 in Appendix A in the online material.).

Table 1

Share of Patents According to the Number of Technological Classes Combined at the Patent Level

	Monotechnological Patents		Combining Only Related Tech.		Combining Unrelated Techs.		Combining Only Unrelated Techs.	
	P	BP	P	BP	P	BP	P	BP
1981–85	49.7%	49.4%	40.5%	39.8%	9.8%	10.8%	2.3%	1.5%
1986–90	47.7%	47.5%	42.2%	42.7%	10.1%	9.8%	2.1%	1.6%
1991–95	46.1%	46.8%	43.4%	42.4%	10.6%	10.8%	2.0%	1.3%
1996–2000	46.5%	44.9%	43.5%	44.7%	9.9%	10.4%	1.9%	1.2%
2001–5	50.4%	50.8%	40.3%	40.7%	9.3%	8.5%	2.1%	1.3%
2006–10	58.6%	62.3%	35.9%	33.8%	5.5%	3.9%	1.7%	1.1%

Note: BP refers to breakthrough patents and P refers to all patents. The information is obtained at the patent level and then aggregated to compute the share. *Monotechnological Patents* refers to the share of patents that only present one technology (columns 1 and 2). *Combining Only Related Technologies* refers to the share of patents that only combine related technologies (columns 3 and 4). *Combining Unrelated Technologies* refers to the share of patents that combine unrelated technologies irrespective of whether they also combine related technologies at the same time (columns 5 and 6). *Combining Only Unrelated Technologies* refers to the share of patents that only combine unrelated technologies (columns 7 and 8).

Again, for each case, the share is obtained both for breakthrough patents (BP) and all patents (P). Around 47 percent of all breakthrough patents belong to one technological class only, similarly to all patents. Interestingly, slightly more than 40 percent of all breakthroughs combine only related technologies, whereas only around 10 percent of all breakthroughs make unrelated combinations, and only 1.5 percent concerns combinations across unrelated technologies only. So, it is very rare that breakthrough patents make unrelated combinations, and when they do, they combine both related and unrelated combinations.

Table 2 shows the average ratio of the number of pairwise combinations of unrelated technologies within a patent document, over its total pairwise technological combinations. The idea is to measure the share of unrelated combinations made in a patent out of the total number of combinations. The share of unrelated combinations used by breakthrough patents is low, with an average of less than 8 percent in all periods, not being statistically different from patents in general.

All in all, this descriptive analysis at the patent level has shown that breakthrough inventions tend to rely primarily on related combinations. Indeed, breakthroughs mainly combine related technologies while the combination of unrelated technologies exclusively is the exception. We turn now to the regression analysis and dig deeper in these arguments.

Findings from Regression, Region-Technology–Level Analysis

Main Results Table 3 presents the fixed effects (FE) estimations for the occurrence of breakthrough patents. Column 1 presents our model to explain the number of patents,

Table 2

Number of Pairwise Combinations of Unrelated Technologies over Total Number of Pairwise Technologies within a Patent. Average Ratio

	P	BP	Diff
1981–85	0.098	0.074	
1986–90	0.094	0.065	
1991–95	0.091	0.064	
1996–2000	0.086	0.060	
2001–5	0.095	0.065	**
2006–10	0.075	0.050	***

Note: BP refers to breakthrough patents and P refers to all patents. The information is obtained at the patent level and then aggregated to compute the average ratio. *Diff* refers to the *t*-test of equality of means between P and BP. * denotes significant at 10%, ** 5% and ***1%

Table 3

Occurrence of Breakthroughs

	(1) BP_Tot	(2) BP_Tot	(3) BP_Tot	(4) BP_Tot	(5) BP_Share
TotPat	0.667***	0.663***	0.667***	0.663***	
	(0.070)	(0.070)	(0.070)	(0.070)	
Tech Stock	-0.056***	-0.055***	-0.057***	-0.055***	0.001***
	(0.013)	(0.014)	(0.013)	(0.013)	(0.000)
Tech Size	-0.082***	-0.081***	-0.082***	-0.081***	-0.000
	(0.014)	(0.014)	(0.014)	(0.014)	(0.000)
GDPpc	0.014	0.022	0.017	0.022	0.002**
	(0.012)	(0.013)	(0.013)	(0.014)	(0.001)
Pop Dens	0.196	0.307*	0.242	0.301*	-0.003
	(0.162)	(0.161)	(0.156)	(0.158)	(0.014)
Sq Pop Dens	-0.086	-0.133**	-0.105*	-0.131**	0.002
	(0.061)	(0.061)	(0.059)	(0.060)	(0.006)
RelD		0.041***		0.041***	0.005***
		(0.009)		(0.009)	(0.000)
UnrelD			0.015*	-0.003	0.000
			(0.009)	(0.010)	(0.001)
Constant	-0.001***	-0.002***	-0.001***	-0.002***	0.017***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Adjusted R^2	0.49	0.49	0.49	0.49	0.04
N	666,333	666,333	666,333	666,333	666,333
Technology FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Region-clustered standard errors. Explanatory variables are standardized.

without focal variables, which are introduced in a cascade way in columns 2 (relatedness density) and 3 (unrelatedness density), and both jointly in column 4. Results indicate that it is mainly relatedness density (RelD) that is positively and significantly related to both the absolute number (columns 2 and 4) as well as the share of breakthrough patents in a region (column 5). This confirms hypothesis 1a. In contrast, our hypothesis 2a is rejected, as unrelatedness density (UnrelD) is not significant—significant at the 10 percent level only when introduced alone, in column 3. This indicates that a region has a higher number and a higher share of breakthrough inventions in a given technology if the overall technological portfolio of the region is related to such given technology. That is, the occurrence of breakthrough patents in a region is enhanced by the local presence of related technologies, but not by the local presence of unrelated technologies. This would confirm the argument that breakthrough inventions might have to rely primarily on combinations of related technologies made previously, rather than building on unrelated combinations, in order to lessen the high risks and uncertainties associated to breakthrough inventions. Our findings thus show that local search processes play a key role in the development of breakthrough inventions, since they are more likely to occur in a region, the more related their technology is to the regional stock of technologies.

We turn now to the analysis of the emergence of breakthrough inventions in a region in Table 4. We consider the entry of a breakthrough patent in a region and technology for the first time in one of the periods under consideration (*BP_Entry*)—again, our focal variables enter regressions first separately, and then jointly. What we observe again is that related density (RelD) always shows a positive and significant coefficient: the local presence of related technologies enhances the emergence of breakthrough inventions in European regions. Additionally, Tables 4 also shows that unrelated density (UnrelD) now has a significant, positive impact on the emergence of breakthrough inventions in regions. Yet, the magnitude of the effect of the local presence of related technologies is higher than for unrelated technologies. These findings lead us to conclude that unrelatedness also matters for the emergence of breakthrough inventions: relatedness and unrelatedness are not mutually exclusive, since both seem to enhance the entry of breakthroughs.

To summarize our findings above, the role of relatedness and unrelatedness is different for the emergence of breakthrough inventions compared to their occurrence/development. Whereas breakthroughs are more likely to occur in a region, the more related their technology is to the local stock of technological knowledge, breakthroughs are more likely to emerge for the first time, not only when the presence of related technologies in the region is abundant but also when unrelated technologies are present. Thus, we observe that both relatedness and unrelatedness simultaneously enhance the emergence of breakthrough inventions in regions. This result confirms our hypotheses 1b and 2b. Thus, the early emergence of a breakthrough technology requires some breaking from the past, bringing to the fore the role of unrelatedness. Whereas once a region has acquired the knowledge and capabilities needed to break from the past in order to generate new and radical knowledge, regions become more path dependent, and relatedness is highly relevant but unrelatedness is not.

Robustness Analysis. To check the robustness of our findings, we run a set of complementary analyses. First, we reproduce our results for different definitions of breakthrough patents. Following the recombinant search approach (Fleming 2001; Fleming, Mingo, and Chen 2007), we define breakthrough patents based on the *ex ante* characteristics of inventions, namely, a patent is considered a breakthrough when it combines two technological classes for the first time. The idea behind this measure is to account for the invention's degree of novelty (break from the past) as a signal of being a breakthrough,

Table 4

Emergence of Breakthroughs

	(1) BP_Entry	(2) BP_Entry	(3) BP_Entry
TotPat	0.119***	0.146***	0.118***
	(0.011)	(0.013)	(0.011)
Tech Stock	-0.011**	-0.020***	-0.015***
	(0.005)	(0.004)	(0.005)
Tech Size	-0.007**	-0.011***	-0.008**
	(0.003)	(0.003)	(0.003)
GDPpc	0.024	0.024	0.033*
	(0.017)	(0.017)	(0.018)
Pop Dens	0.022	0.027	0.104
	(0.242)	(0.224)	(0.242)
Sq Pop Dens	-0.034	-0.043	-0.079
	(0.100)	(0.092)	(0.100)
RelD	0.057***		0.049***
	(0.003)		(0.004)
UnrelD		0.052***	0.027***
		(0.006)	(0.007)
Constant	0.324***	0.324***	0.310***
	(0.022)	(0.021)	(0.023)
Adjusted R^2	0.24	0.24	0.24
N	66,885	66,885	66,885
Technology FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Region-clustered standard errors. Explanatory variables are standardized.

that is to say, patents that incorporate technologies that move away from existing practices (Carlo, Lyytinen, and Rose 2012). Indeed, Kaplan and Vakili (2015) showed that combining knowledge in an exploratory search (Gavetti and Levinthal 2000) tends to produce inventions that break from preexisting technological modes and eventually become highly cited (Phene, Fladmoe-Lindquist, and Marsh 2006). Novelty is associated with the emergence of key enabling technologies, too (Montresor, Orsatti, and Quatraro 2022). This way, the impact of an exploratory search on value occurs through the mechanism of novelty (Kaplan and Vakili 2015). We do not expect our findings to differ between the two definitions, because studies have shown that the more a patent combines formerly unconnected technologies, the higher its impact in terms of forward citations (Arts and Veugelers 2015). The results obtained confirm, to a greater extent, the main findings in this article (Appendix B, Tables B1 to B4 in the online material).

In addition, we use the same definition as in the main text of the article, based on the citations received, but with different breakthrough thresholds. This way, we define a patent as a breakthrough when it is in the upper 10 percent and 1 percent of the distribution according to the number of forward citations for the technology and year it belongs to. The main conclusions of the article remain (Appendix C, Tables C1 to C7 in the online material).

Second, we assess the sensitivity of the results to the use of different methods of estimation. In particular, we use the PPML estimator, which deals with the count nature of our dependent variable, the large share of zeros, and the nonnegative values. The main conclusions obtained, following the results in Appendix D, Table D1 in the online material, remain unchanged.

Concluding Remarks

Our study on the emergence and occurrence of breakthrough patents in European regions produced a number of novel and interesting findings. First, we found that, by far, most combinations breakthrough patents make are between related technologies: almost no breakthrough patent makes combinations between unrelated combinations only. Second, we found that the relatedness density between a given technology and the overall technological portfolio of a region enhances both the occurrence and emergence of breakthrough inventions in a region, whereas unrelatedness density (that is, a local stock of technologies unrelated to the technology of a breakthrough patent) has a positive impact only on the emergence of breakthroughs.

These results tend to challenge somewhat the tendency of the literature to overemphasize the disruptive nature of technological breakthroughs and the importance of unrelatedness for breakthrough patents. Our study shows that relatedness matters for the occurrence of breakthrough inventions in regions, not unrelatedness: breakthroughs are more likely to occur in a region, the more related their technology is to the local stock of technological knowledge. This is in line with theories claiming that processes of local search in its cognitive meaning are important in the context of technological breakthroughs (Nelson and Winter 1982; Kaplan and Vakili 2015), and that it might be crucial to rely on relatedness for breakthroughs to survive and be successful given the high uncertainties and adjustment costs (Perez and Soete 1988). This is confirmed by our patent-level finding that breakthrough inventions tend to rely primarily on related combinations: it is very uncommon that breakthrough patents make unrelated combinations, and when they do, they combine both related and unrelated combinations. These findings suggest that breakthroughs inventions rely, to a considerable degree, on preexisting and well-known local knowledge sources that have been used and combined before. This might be even considered essential for breakthroughs to survive, because relying on unrelated combinations only would be too risky. Relatedness also mattered for the emergence of breakthrough inventions in regions. These results have important implications for regional development, since breakthrough patents often have a large impact on subsequent technological change and economic development in countries and regions, as has been argued in a large body of literature in the field of innovation studies (Arts and Veugelers 2015; WIPO 2015; Verhoeven, Bakker, and Veugelers 2016) and economic geography (Markusen, Hall, and Glasmeier 1986; Marshall 1987; Hall and Preston 1988; Boschma 1999; Mewes 2019).[12]

Another important finding of our study is that local stocks of both related and unrelated technologies mattered for the emergence of technological breakthroughs for the

[12]Rigby et al. (2022) did not look at breakthrough patents explicitly, but their study found that regions that diversified into related technologies that also made their local economy more complex showed higher economic growth rates in terms of GDP and employment growth.

first time in regions. Although the magnitude of the effect of the local supply of related technologies is higher than the one of unrelated technologies, unrelatedness also mattered for the entry of breakthrough inventions. This is in line with the theoretical argument on the importance of unrelatedness for breakthrough inventions in regions proposed by Saviotti and Frenken (2008) and Castaldi, Frenken, and Los (2015), which our novel measure of unrelatedness density was able to take up. This finding also shows that relatedness and unrelatedness are not mutually exclusive, but they simultaneously enhance the early entry of breakthrough technologies in regions. This builds on Boschma (2017) who claimed it is unlikely that breakthroughs in regions rely completely on local unrelated technologies because of the high uncertainty involved, and therefore are more likely to combine both related and unrelated capabilities.

This article has also raised issues that call for further research. First, the study has revealed the importance of a local stock of related technologies for the occurrence and the emergence of breakthrough inventions in regions. What still needs to be determined in future research is which technological breakthroughs are the most successful ones. The study suggests that making related combinations might be a necessary condition for breakthroughs to survive (the more so when they make unrelated combinations), but this needs to be explored more closely. Second, the study found there are a few breakthrough inventions that make only unrelated combinations. It would be very interesting to explore in detail how these emerge in regions, seemingly against all odds. Third, the study has focused on cognitive distance (degree of relatedness), but other dimensions, like social proximity, might favor the development of breakthrough inventions in regions as well (Fleming, Mingo, and Chen 2007; Crespo, Suire, and Vicente 2014). It would be interesting to investigate whether breakthrough inventions are more likely to make combinations that involve technologies with low or high social proximity. Fourth, we did not explore the role of interregional linkages for breakthrough patents (Balland and Boschma 2021). Miguélez and Moreno (2018) showed that extraregional knowledge linkages promote radical breakthroughs when the external knowledge is related (but not similar) to the knowledge base of the region. Hesse and Fornahl (2020) found that interregional linkages mattered at the dyadic level of unrelated combinations. This also begs the question whether technological breakthroughs depend on local combinations, and to what extent the related and unrelated combinations breakthrough patents make concern combinations of technologies inside the region. A next step is to research whether a technological breakthrough relies on interregional linkages with respect to the related combinations it makes, or to its unrelated combinations (Balland and Boschma 2021). Related to this, the relevant issue of spatial dependence may also arise in the distribution of our data. Although imperfect, our set of fixed effects can account for spatial interactions that are time invariant, though we still miss the time-variant ones. It could be interesting to assess the presence of spatial autocorrelation in our sample, although this is not straightforward given the high dimensionality of our empirical approach (time and space, but also technology). Future research must explore developments in spatial econometrics dealing with tests or estimators when regressions include more than two dimensions. Fifth, we did not investigate the role of regional institutions (and policy) that might be crucial for the development of technological breakthroughs (Boschma and Capone 2015). We envisage that bridging institutions favor the recombinant search process, since they enhance interactions and collective action (Cortinovis et al. 2017). These may be even more important for unrelated combinations that are harder and riskier to combine, and thus might require institutions (and institutional change) to bridge the cognitive distance between the combined technologies. This still needs to be investigated. And last, we did not look at the role of public policy at various spatial scales (European, national, regional) that might be crucial in developing technological breakthroughs. The roles of the public sector are multifold and complex, since it impacts the research infrastructure (like universities), the educational system (training), public procurement, patent laws and regulations, industrial and regional policy, among other domains. Our findings tend to suggest that policies that aim to develop new breakthrough technologies, such as artificial intelligence, should not build those from scratch. Instead, one could support initiatives that account for the local presence of relevant (related) capabilities in the region concerned and that aim to bring together and combine related and unrelated technologies (as can be done, for instance, in research collaboration programs), because that could enhance the probability of developing breakthrough technologies successfully in regions (Verspagen and Duysters 2004; Gilsing et al. 2008; Vicente, Balland, and Brossard 2011; Balland et al. 2019).

Supplementary Material

Supplemental data for this article can be accessed here https://doi.org/10.1080/00130095.2022.2134005.

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