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Knowledge search and regional technological diversification

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ABSTRACT
This paper explores the role of knowledge search within processes of regional technological diversification. We consider two distinct dimensions of search: regional search breadth reflects the spectrum of knowledge domains combined in the development of new technologies; and regional search depth describes how intensively regions draw upon previously cumulated knowledge. Using a panel dataset of NUTS-2 regions across Europe for the period 1990–2014, we find that both regional search breadth and regional search depth, alongside relatedness in localised capabilities, exert a positive effect on regional diversification into new technology fields. However, both dimensions are found to be characterised by non-linear returns.

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1. Introduction

The evolutionary economic geography (EEG) literature has long discussed technological change as a spatially bounded phenomenon (Boschma & Martin, 2007), depending on the regional fabric of technological specialisations and processes of collective learning shaped by knowledge spillovers across cumulated capabilities (Balland & Boschma, 2022; Neffke et al., 2011). These contributions have laid the foundation for a significant strand of research focusing on the degree of cognitive relatedness between the knowledge space of regions and emerging technologies to explain regional technological diversification as a branching process emerging from established trajectories (Boschma, 2017; Kogler et al., 2016).

A growing number of studies has evidenced the relationship between relatedness and regional technological entry (Kogler et al., 2016; Neffke et al., 2011; Rigby, 2015). This has been extended to the context of inventor and collaboration networks (Kogler et al., 2023), migrant inventors (Miguelez & Morrison, 2023), green transition (Moreno & Ocampo-Corrales, 2022), key enabling technologies (Montresor & Quatraro, 2017), interregional linkages and Smart Specialisation Strategy (Balland & Boschma, 2021). This approach has similarly been applied to explore the geography of technological breakthroughs (Boschma et al., 2023; De Noni & Belussi, 2021).

As shown in this literature, the proximity framework has provided critical insights for understanding regional technological diversification through its emphasis on the structure of the regional knowledge space, suggesting that the set of knowledge components available in the region and their cognitive proximity to new trajectories broadly define the boundaries for and likelihood of future recombination opportunities. Yet, while the relatedness literature rests on the intuition that knowledge recombination occurs between localised activities connected by technological proximity, it does not explicitly examine the underlying mechanisms that define such recombination processes (Bathelt & Storper, 2023; Whittle & Kogler, 2020). Thus, despite the widespread acknowledgment of the importance of knowledge recombination for regional technological diversification, direct evidence and research on knowledge recombination processes remain unexplored in the relatedness literature (Bathelt & Storper, 2023; Content & Frenken, 2016). In particular, against a large literature focusing on the output side of regional technological activities, we still have

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limited insights and evidence on knowledge recombination occurring on the input side, capturing the search patterns and the specific composition of prior knowledge connected within regional innovation activities.

In contrast, the innovation literature has long explored the micro-foundations of knowledge recombination by focusing on the characteristics and patterns of the underlying search activities. Drawing on seminal insights on organisational learning (March, 1991) and a conceptualisation of invention as a process of recombinant search (Fleming & Sorenson, 2004; Weitzman, 1998), scholars and firm-level studies have discussed new technologies as the result of knowledge search occurring broadly along two dimensions, namely breadth and depth. Breadth is typically associated with the range of diverse technological domains being recombined to generate new inventions (Fleming et al., 2007), while depth reflects the extent of search activities drawing from and reusing prior knowledge (Katila & Ahuja, 2002; Wang & von Tunzelmann, 2000). Search across a greater variety of knowledge sources may widen combinative opportunities, though it may increase complexity within innovation processes (Ahuja & Morris Lampert, 2001). At the same time, drawing deeply from existing sources may reduce uncertainty within knowledge search, though it may also raise risks of lock-in effects (Kaplan & Vakili, 2015; Katila & Ahuja, 2002; Laursen & Salter, 2006).

In this paper, we aim to offer a novel perspective to debates on regional technological diversification by bringing to the fore the role of regional knowledge search. To this end, we integrate current approaches in EEG examining the relatedness of the regional knowledge space with emerging trajectories as a key determinant of regional technological diversification (Boschma et al., 2023; Boschma & Frenken, 2012; Kogler et al., 2016), with insights from the innovation literature on recombinant search that has explored dimensions of search breadth and search depth for innovation at the firm level (Fleming et al., 2007; Katila & Ahuja, 2002; Laursen & Salter, 2006). We contend that – alongside relatedness effects reflecting complementarities and cognitive proximity defined at the output side of regional technological activities – regional knowledge recombination is shaped by the specific qualities of localised search activities underpinning the input side of new knowledge creation. Specifically, we focus on the knowledge antecedents of regional technological output – as reflected in backward citations – to understand the role of regional search patterns in explaining how regions mobilise and recombine technological components, thereby defining processes of regional technological diversification. We look at two distinct dimensions of regional knowledge search, namely regional search breadth and regional search depth, and discuss how these may exert a significant role in the entry of new regional technological specialisations.

We complement this discussion with an empirical analysis based on a panel dataset comprising information on patenting activities across NUTS-2 regions of 30 countries in Europe for the period 1990–2014. Specifically, we introduce measures for regional search breadth and regional search depth using information on backward citations of patents as a proxy for knowledge linkages between inventions, as defined within prior research on recombinant search in innovation studies (Fleming, 2001; Fleming & Sorenson, 2004; Miguelez & Moreno, 2018). These measures are merged into the proximity framework to analyse regional technological diversification in line with established approaches focusing on the entry of new technological specialisations (Kogler et al., 2016; Miguelez & Morrison, 2023; Rigby, 2015) as well as more recent contributions looking at regional entry of breakthrough technologies (Boschma et al., 2023). Our findings provide novel evidence highlighting a significant role of both dimensions of regional knowledge search in technological entry, although these effects are characterised by non-linear returns and ultimately an inverted-'U' relationship.

2. Theoretical background

2.1. Knowledge relatedness and regional technological entry

In the literature, it is widely acknowledged that the economic and institutional configuration of a region carries the inherited legacy of its past activities, while also affecting its future development (Isaksen, 2015). By leveraging a thick industrial structure, specific support infrastructures and institutional arrangements through different forms of proximity, regions allow for knowledge to spill over and promote the recombination of novel ideas (Boschma, 2005; Storper, 2018; Whittle & Kogler, 2020), reflecting the role of proximity in reducing the complexity and uncertainty in innovation activities (Capello, 1999; Li et al.,

2021; Sorenson et al., 2006). These elements define cumulative learning mechanisms that, shaped by different structural configurations, contribute to knowledge creation and innovation within a local economy (Grillitsch et al., 2018; Hassink et al., 2019; Petralia et al., 2017).

Building on these insights, research in evolutionary economics geography suggests that the emergence of new technological specialisations is fundamentally a place-based and path dependent phenomenon underpinned by the existing knowledge structure and learning processes within the region (Martin & Sunley, 2006). In particular, the presence of similarities and complementarities in localised capabilities is expected to generate more opportunities for learning, spillovers and ultimately novel knowledge recombination (Boschma, 2017; Frenken et al., 2007), contributing to further technological activity in that space (Castaldi et al., 2015). Accordingly, the emergence of new industries and technology fields is shaped by the region's cumulated technological capabilities, with new activities branching out of existing related activities (Neffke et al., 2011). This is rooted in the concept of technological relatedness, referring to the cognitive proximity between the region's existing technological configuration and the new technological class (Boschma & Frenken, 2012; Pintar & Scherngell, 2022; Whittle & Kogler, 2020). These ideas suggest that regions have a higher probability to diversify within bounded technology space, supporting a more effective recombination of extant knowledge, and thus to move into technology classes that are related to the set of technologies in which they are already specialised (Boschma, 2017).

A substantial number of empirical studies has emerged offering evidence of the role of relatedness in the entry of new technology classes in the region (Boschma, 2017; Kogler et al., 2016). For example, studies on the emergence of Industry 4.0 technologies in European regions find that technological entry is positively affected by the density of pre-existing technological knowledge being related to the new specialisation (Balland & Boschma, 2021; Corradini et al., 2021). Comparable findings have been offered for other areas, including green technological entry (Corradini, 2019; Moreno & Ocampo-Corrales, 2022), key enabling technologies (Montresor & Quatraro, 2017) and collaboration networks (Kogler et al., 2023), amongst others. This approach has similarly been applied to explore the geography of technological breakthroughs (Boschma et al., 2023; De Noni & Belussi, 2021).

As recently noted by Bathelt and Storper (2023), the relatedness literature convincingly builds on the assumption that technological proximity would increase the logical possibility that spillovers and knowledge recombination take place within regions. Still, evidence directly capturing recombination across technologies – as defined at the inventive stage – remains scant (Content & Frenken, 2016). Accordingly, scholars have called for a more nuanced and comprehensive understanding of knowledge recombination processes implied at the core this framework (Bathelt & Storper, 2023). While relatedness across technologies a region produces may increase the potential for absorptive capacity, interaction and synergies, some of these opportunities may not be exploited (Bathelt & Storper, 2023; Whittle & Kogler, 2020). More generally, there can still be other sources and drivers of variation in knowledge recombination processes across regions. In particular, we argue knowledge recombination underpinning regional technological entry is not solely a function of the knowledge space reflected in a region's innovation output and the level of relatedness between new and existing knowledge domains (Balland et al., 2015; Boschma, 2017; Hassink et al., 2019). It may also depend on other mechanisms defining regions' ability to identify, access and connect combinative opportunities. Specifically, we posit recombination is also inherently defined by search activities – occurring on the input side of technological invention – through which regions connect knowledge components and specific technology antecedents within their innovation efforts. In other words, it is possible to argue that regions with similar levels of relatedness vis-à-vis new technological trajectories, widely identified in the EEG literature as a key driver of regional diversification, may differ in the way they search for and recombine knowledge.

2.2. Breadth and depth of the regional knowledge search

Scholars in innovation studies have long presented invention as a process of recombinant search, in which technological change arises from new combinations of existing and/or new knowledge elements guided by cognitively bounded search efforts and routines (Dosi, 1982; Fleming, 2001; Nelson & Winter, 1982; Weitzman, 1998). Connecting to the foundational distinction between exploitation and exploration processes in organisational learning (March, 1991), this literature has emphasised the role of cognitive distance in search

processes (Martin & Mitchell, 1998) and the multidimensional nature of firms' knowledge search (Arthur, 1994; Dosi, 1982). Against this backdrop, scholars have developed more fine-grained conceptualisations of search behaviour, introducing complementary dimensions of search breadth and search depth to explain how organisations mobilise and recombine knowledge during inventive activities and the input side of innovation activities (Boh et al., 2014; Fleming et al., 2007; Katila & Ahuja, 2002; Laursen & Salter, 2006). Search efforts can arise from the recombination of a greater variety of knowledge components identified through a wider scope in search activities (Fleming, 2001), defining search breadth, just as they can occur within a familiar knowledge space for the inventor through the repeated usage of prior art (Katila & Ahuja, 2002), reflecting search depth.

Translating these considerations to the regional context, we examine the effects of different search patterns on regional technological entry. In line with the innovation literature outlined above, we consider search activities within regions along two distinct dimensions of regional search breadth and regional search depth.

Regional search breadth captures the number of knowledge bases that the region engages with to sustain its technological activity. This definition echoes the idea of breadth as 'the range of areas that have to be investigated to develop a particular subject' (Wang & von Tunzelmann, 2000, p. 806). By encompassing a variety of knowledge, skills, and experiences (Fleming et al., 2007), the degree of search breadth defines the set of distinctive variations and components being connected within the recombinant search space (Fleming & Sorenson, 2001; Katila & Ahuja, 2002). Broader search activities reflect the ability to recombine knowledge from a higher number of technological domains, providing a wider spectrum of solutions for technical problems and preventing cognitive and social exhaustion of combinatoric possibilities (Fleming & Sorenson, 2001; Wang et al., 2024). This translates into larger benefits for those regions characterised by knowledge search processes across multiple technological domains, as it expands the range of, and capabilities for, recombinant innovation (Rigby & Essletzbichler, 1997). In line with the seminal insights by Jacobs (1969), variety in search breadth accelerates technological activity through cross-fertilisation and the recombination of non-redundant knowledge (Castaldi et al., 2015; George et al., 2008; Saviotti & Frenken, 2008). In this scenario, the regional propensity to explore a greater variety of knowledge components may open new technological trajectories from the emerging combinations (Dosi, 1982), supporting the creation of new technological fields in the region (Beaudry & Schiffauerova, 2009; Harrison et al., 1996).

Nevertheless, there are also limitations arising from excessive regional search breadth. New combinations within a broader set of knowledge bases involve increasing knowledge integration costs and more uncertain outcomes due to the complexity of establishing relationships across more diverse technology components (Katila & Ahuja, 2002). Furthermore, excessive regional search breadth leading to a higher variety of knowledge involved in the innovation processes of the region might exacerbate cognitive distance across technological domains drawn into these processes, reducing the benefits of and opportunities for knowledge flows (Aarstad et al., 2016). These aspects would reflect a problem of 'over-search', which may be further aggravated by coordination issues and an inefficient allocation of searching capabilities (Laursen & Salter, 2006). Based on these considerations we develop the following hypothesis:

Hypothesis 1: Regional search breadth has an inverted 'U'-shaped effect on regional technological diversification.

Another dimension of search activities corresponds to regional search depth. This describes the intensity with which the region repeatedly mobilises previously explored knowledge components in the generation of new technology. Following a trajectory of path-dependent technological evolution, regions can accumulate knowledge of the technology and of the space of combinative opportunities surrounding it through learning-by-doing and specialisation (Arthur, 1994; Rigby & Essletzbichler, 1997). The acquired expertise is then used to create new combinations from a known set of technology components or to improve existing combinations (Fleming, 2001). Differently from search breadth capturing the variety of knowledge sources mobilised, the focus here is on the intensity with which previously accumulated knowledge is reused.

Extensive literature has long associated processes of search depth with changes along well-established technological trajectories. By exploiting and deepening prior knowledge (Levinthal & March, 1993;

March, 1991), searching within familiar components contributes to the sophistication and refinement of existing practices and routines (Katila & Ahuja, 2002; Wang & von Tunzelmann, 2000), while also facilitating coordination mechanisms (Laursen & Salter, 2006). Indeed, a deep knowledge of one specific domain enables a more detailed understanding of the knowledge gaps in the same field (Wang et al., 2024), as well as the identification of anomalies in new combinations (Kaplan & Vakili, 2015). These insights complement the EEG framework, suggesting that search depth may reinforce a region's expertise in specific domains and strengthen its potential to generate new technological combinations in related fields (Balland et al., 2019; Boschma et al., 2023).

However, excessive reliance on repeatedly mobilising the same knowledge elements may gradually exhaust available recombination opportunities and the likelihood of developing new technological trajectories (Dosi, 1982), leading to decreasing returns from searching within an established knowledge space (Katila & Ahuja, 2002). Furthermore, building on the same knowledge can lead to myopic search behaviour and rigidity (Levinthal & March, 1993), increasing the risk for new technological activity in the region to be locked into the current technological trajectory (Cimoli & Dosi, 1995; Martin & Sunley, 2006). Hence, we hypothesise:

Hypothesis 2: Regional search depth has an inverted 'U'-shaped effect on regional technological entry

3. Data and methods

3.1. Data

Our analysis builds on a panel dataset obtained merging information on patents from the ICRIOS database.[1] As noted in the strand of literature on regional technological diversification (Corradini et al., 2021; Kogler et al., 2016), we approach patent data acknowledging their role as a measure of invention to track technological change dynamics rather than overall innovation activities (Griliches, 1990). In this context, patents are widely used as they ensure the presence of a significant inventive step whilst offering fine-grained information on geographical location of inventors and disaggregated technological fields related to the invention, providing essential information for studies on recombinant knowledge processes and technological relatedness (Breschi et al., 2003). Furthermore, information from patent citations can be used to account for heterogeneity in patent quality and provide insights on breakthrough technologies (Boschma et al., 2023; Hall et al., 2001; Kaplan & Vakili, 2015). In our case, they are also essential for capturing different dimensions of search processes across prior art (Jaffe & De Rassenfosse, 2019).

The analysis covers 633 four-digit International Patent Classification (IPC) technological classes across NUTS-2 regions of 30 countries in Europe, specifically EU-27 countries plus the UK, Norway, and Switzerland. As customary in prior research on regional diversification (e.g., Boschma et al., 2023; Kogler et al., 2016, 2023; Moreno & Ocampo-Corrales, 2022), we combine patents' information over non-overlapping five-year time windows to smooth out volatile year-to-year variation in patenting activity, for a total of five periods starting from 1990 to 2014.

In our analysis, patents are allocated to NUTS-2 regions based on inventors' addresses. For patents with multiple inventors listed in the application, we apply fractional counts to allocate a proportion of each patent across the regions where co-inventors are located (Kogler et al., 2016, 2023). We then follow a similar approach with respect to the allocation of four-digit IPC technological classes. Most patent documents list more than one IPC class, with each assigned to different regions applying a fractional count reflecting the four-digit IPC proportion by inventor and region.

The resulting dataset was merged to information on key socio-economic indicators, introduced as control variables, obtained from the AREDCO database and other Eurostat sources.

3.2. Estimation methodology

In order to analyse the effect of regional search processes on the diversification of regions into new technologies, we estimate a panel linear probability model with IPC four-digit class, regional and time fixed-

effects.[2] Accordingly, we define the following specification:

$$\begin{aligned} Y_{irt} &= \beta_0 + \beta_1 RELDENS_{irt} + \beta_2 BREADTH_{irt} \\ &\quad + \beta_3 BREADTH^2_{irt} + \beta_4 DEPTH_{irt} + \beta_5 DEPTH^2_{irt} \\ &\quad + X_{irt} + \lambda_{rt} + \varphi_i + \omega_r + \alpha_t + \varepsilon_{irt} \end{aligned} \tag{1}$$

where Y_{irt} represents our main dependent variable measuring regional technological entry for (IPC four-digit) technology class i, (NUTS-2) region r and five-year time window t level. The main explanatory variables in the model represent regional technological relatedness (*RELDENS*), capturing the technological proximity between patents developed in the region and the technological class of interest i where entry may occur, and novel indicators of *REG_BREADTH* and *REG_DEPTH* of knowledge search processes based on regional patents' backward citations. For *REG_BREADTH* and *REG_DEPTH*, a quadratic term is added to model non-linear returns on both search dimensions and test the presence of a 'U'-shaped effect on regional technological entry. Finally, we add a vector X_{irt} of time-variant region–technology controls and vector λ_{rt} for region-specific socio-economic characteristics. The regression models include IPC four-digit technology class, region and time fixed effects, noted respectively as φ_i, ω_r, and α_t, to control for time-invariant unobserved heterogeneity[3] across all three dimensions. Estimates are obtained applying heteroskedasticity-robust standard errors clustered on IPC four-digit class and regional pairs.

3.3. Dependent variable

Following an established approach in the literature on regional technological diversification (Kogler et al., 2016; Miguelez & Morrison, 2023; Rigby, 2015), we model the probability of a region diversifying into a new technological domain by setting a dichotomous variable capturing the emergence of a new revealed technological advantage (RTA) in a given technology. The presence of an RTA is defined applying the Balassa (1965) approach to capture revealed comparative advantages, as follows:

$$RTA_{irt} = 1 \text{ if } \frac{P_{irt} \,/\, \sum_i P_{rt}}{\sum_{ir} P_t \,/\, \sum_{irt} P} > 1, \text{ and 0 otherwise} \tag{2}$$

where $P_{irt} \,/\, \sum_i P_{rt}$ represent the share of patents in technology i for region r at time t, whilst the denominator represents the share of patents in technology i at time t across the portfolio of all European regions. Based on this, we then define our main dependent variable *REG_ENTRY* as a dichotomous variable equal to 1 if a region first develops an RTA.[4] Specifically, we define:

$$REG_ENTRY_{irt} = \left\{ \begin{array}{l} 1 \text{ if } (RTA_{irt} >= 1 \text{ and } 0 < RTA_{irt} - 1 < 1) \\ 0 \text{ otherwise} \end{array} \right\} \tag{3}$$

As a robustness test, we also consider a complementary perspective on the development of a new RTA as explored in recent contributions (Boschma et al., 2023), focusing specifically on the first emergence of a breakthrough patent in a specific technology across regions. Following Boschma et al. (2023) and the seminal work by Hall et al. (2001) on forward citations as a proxy for patents' impact, we define breakthrough patents as those that are in the top 5% of the distribution of forward citations received with respect to all patents in the same technology and year to account for time and technology specific heterogeneity in patenting and citing (Schmoch, 2008). Then, we set the variable *BT_ENTRY* as a dichotomous variable set equal to 1 if a region develops a breakthrough patent in a specific technology while it was not the case in the previous period.[5]

As noted in equation (1), our main model specification does not feature lagged explanatory variables. We follow this approach to retain the direct connection between patents that define regional entry and their own specific underlying search patterns. In this setting, temporal precedence addressing potential simultaneity bias is set by the relationship between search processes captured by backward citations and patent output, where the former is inherently antecedent but also directly shapes the latter. At the same time, in the following Robustness section we also present results based on an alternative specification where all explanatory variables all lagged. This further reduces reverse causality issues. It also offers complementary evidence, shifting the focus of the analysis from search characteristics of patents associated with entry to the effect of pre-existing search patterns on the likelihood of subsequent entry.

3.4. Independent variables

The main novel independent variables in our analysis aim to capture breadth and depth of technological search processes. To build these indicators, we focus on backward citations of patents, which are widely used in the literature to capture knowledge flows in the form of technological antecedents of an invention (Jaffe & De Rassenfosse, 2019; Katila & Ahuja, 2002). Thus, in line with the literature on knowledge search, we examine knowledge recombination through the use of patent citations as a proxy for knowledge linkages between inventions. In doing so, we do not claim that inventors operate by directly recombining patents' technological classes; rather, these allow us to indirectly capture recombinant search processes (Fleming, 2001; Miguelez & Moreno, 2018). Given the granularity of our data structure, not all observations include backward citation. Thus, we take a conservative approach removing from the analysis observations with zero backward citations. In the Robustness section, we present results including patents with no backward citations, which yield fully consistent results.

Our concept of search breadth aims to reflect regional capabilities to monitor and absorb knowledge from a diverse set of technological fields within their search processes. To capture this, we follow prior research on technological diversification (Beaudry & Schiffauerova, 2009; Corradini et al., 2021; Hall et al., 2001) and define regional search breadth as an inverse Herfindahl index of concentration measuring the heterogeneity of technological classes cited within regional patenting activities as follows:

$$REG_BREADTH_{irt} = 1 - \sum_{j=1}^{J}\left(\frac{N_{jirt}}{N_{irt}}\right)^2 \tag{4}$$

where the numerator is the number of backward citations to IPC class j by patents in IPC class i at time t in region r; and the denominator is the total number of backward citations in the region by patents in IPC class i at time t.

Regional search depth refers to the accumulation of search experience with knowledge already acquired within previous invention activities. Building on the idea of backward citations as an indicator of the extent of reliance on previous technology (Jaffe & De Rassenfosse, 2019), we define the variable *REG_DEPTH* as the share of backward citations in period t to patents already cited in the previous five-year time period within each IPC four-region pair. Specifically, we define this variable as follows:

$$REG_DEPTH_{irt} = \frac{RBC_{irt}}{TBC_{irt}} \tag{5}$$

where RBC represents the number of repeated backward citations at time t from time $t-1$, while TBC represents the total number of backward citations in region r by patents in IPC class i at time t.

Considering that these regional search processes can have different effects on regional technological diversification depending on the cognitive distance across technological domains drawn into these processes (Aarstad et al., 2016; Fleming, 2001; Plunket & Starosta de Waldemar, 2023), we investigate search breadth and search depth by taking into account also the cognitive relatedness across technological classes, rather than relying solely on the formal structure of the IPC patent classification. To this end, we first calculate a measure of relatedness φ_{ijt} between technologies i and j for each of the five t time periods considered using a cosine index of similarity (Breschi et al., 2003).[6] Then, we define *REG_BREADTH_W* as the inverse of the average cosine similarity across IPC classes of backward citations weighted by their relative fractional patent counts. We apply the same approach for *REG_DEPTH_W*, focusing on the weighted average of cosine similarity between IPC classes of backward citations at time t and those at time $t-1$.

To capture the effect of knowledge relatedness on regional technological entry, as extensively explored in EEG literature (e.g., Kogler et al., 2016; Miguelez & Morrison, 2023; Moreno & Ocampo-Corrales, 2022), we define the variable *RELDENS* as the density of knowledge production in the proximity of each technology class i where regions exhibit an RTA as measured in equation (2). Using the cosine index φ_{ijt} introduced above measure similarity across IPC classes, we then construct *RELDENS* combining the relatedness index for each technology i in which region r presents a RTA in time t, divided by the sum of technological relatedness of technology i to all the other technologies. Accordingly, we specify the following density index

(Boschma et al., 2014):

$$RELDENS_{irt} = \frac{\sum_{j \in r,\, j \neq i} x_j \varphi_{ij,t}}{\sum_{j \neq i} \varphi_{ij,t}} * 100 \quad (6)$$

where $x_j = 1$ if $RTA_{jrt} > 1$.

3.5. Control variables

We include in our model controls for both patents' characteristics as well as key regional socio-economic indicators. With respect to patents, we first include the total number of patents applied for in the region (*NPAT*) as a general proxy of its invention capacity (De Noni & Belussi, 2021). We account for the inventive capacity of the technological field by introducing the variable *TECH_CLAIMS*,[7] defined as the average number of technological claims of each region–IPC class pair (Boschma et al., 2023). We control for core socio-economic characteristics of regions including a measure of per capita gross domestic product (GDP) in constant prices to capture the level of resources available and overall development in the area. To control for potential non-linear effects of regional economic development on entry, we also include a quadratic term for GDP. We also add controls for GDP percentage growth[8] as well as total employment (*EMPL*) in thousands. Finally, we include a measure of population density (*POP_DENS*), expressed as people/km^2, to account for potential agglomeration effects in the local economy.

Descriptive statistics for all variables are reported in Table 1. Figure 1 shows maps for regional search breadth and search depth across five quantiles of distribution. A correlation matrix[9] is reported in Table A1 in Appendix A in the supplemental data online. Notably, we confirm meaningful correlations between unweighted and weighted versions of our breadth and depth measures, 0.47 and 0.39 respectively, supporting their use as alternative specification for regional search characteristics. Importantly, both search breadth and search depth, whether weighted or unweighted, display very low correlations with the relatedness measure (ranging between 0.01 and 0.03). This suggests that our search variables capture a dimension of regional innovation dynamics that is largely orthogonal to the structure of the regional knowledge base. The lack of correlation between these measures provides initial empirical support for treating search as a distinct mechanism, consistent with the innovation literature that conceptualises search behaviours as separate from the underlying knowledge structure.

4. Results

4.1. Regional search depth, regional search breadth and new technological entry

We start presenting the results of our analysis by looking at the effect of regional search breadth and regional search depth on our first dependent variable, *REG_ENTRY*, reflecting the emergence of new technological specialisations across NUTS-2 regions. Estimates are reported in Table 2. The models presented in columns 1–3 provide estimates based on *REG_BREADTH* and *REG_DEPTH*, while in columns 4–6 we

Table 1. Descriptive statistics.

	Mean	SD	Median	Maximum	Minimum
reg_entry	0.304	0.460	0	1	0
bp_entry	0.089	0.284	0	1	0
reldens	30.413	17.814	27.460	100	0
Reg_breadth	0.693	0.303	0.795	1	0
Reg_depth	0.245	0.297	0.143	1	0
Reg_breadth_w	0.901	0.181	0.968	1	0
Reg_depth_w	0.081	0.164	0.007	1	0
npat	4.057	14.962	1	1230.581	0.002
tech_claims	7.628	9.373	5	139	1
log(*GDP*)	10.874	0.815	10.861	13.380	6.684
gdp_growth	9.953	7.681	9.331	82.590	−29.432
empl	1092.918	900.779	840.712	6142.538	15.116
log(*popdens*)	6.149	0.709	6.087	8.007	1.832

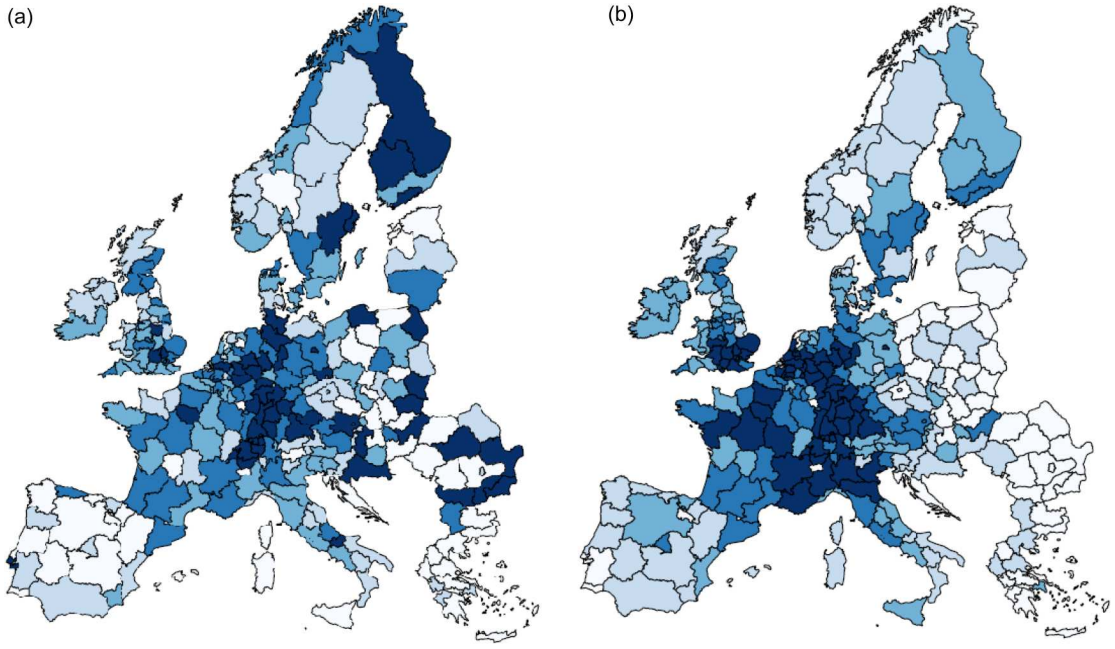


Figure 1. Regional search breadth (a) and depth (b) across five quintiles, NUTS-2 regions.

Table 2. Effects of regional search breadth and depth on regional technological entry.

	(1)	(2)	(3)	(4)	(5)	(6)
reldens	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Reg_breadth	0.385***		0.345***			
	(0.021)		(0.021)			
Reg_breadth^2	−0.430***		−0.396***			
	(0.021)		(0.021)			
Reg_depth		0.225***	0.189***			
		(0.018)	(0.018)			
Reg_depth^2		−0.227***	−0.189***			
		(0.019)	(0.020)			
Reg_breadth_w				0.649***		0.624***
				(0.034)		(0.034)
Reg_breadth_w^2				−0.859***		−0.832***
				(0.029)		(0.029)
Reg_depth_w					0.353***	0.271***
					(0.027)	(0.027)
Reg_depth_w^2					−0.282***	−0.221***
					(0.039)	(0.039)
npat	0.008***	0.009***	0.008***	0.007***	0.009***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
tech_claims	0.003***	0.003***	0.002***	0.007***	0.003***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(*GDP*)	1.011***	0.935***	0.983***	0.703***	0.916***	0.674***
	(0.183)	(0.183)	(0.183)	(0.181)	(0.183)	(0.181)
log(*GDP*)^2	−0.055***	−0.052***	−0.054***	−0.041***	−0.051***	−0.040***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
GDP growth	0.022	0.024	0.021	0.028	0.025	0.029
	(0.035)	(0.035)	(0.035)	(0.034)	(0.035)	(0.034)
empl	0.077***	0.074***	0.077***	0.067***	0.075***	0.068***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
log(*popdens*)	0.041	0.034	0.040	0.055	0.036	0.056
	(0.066)	(0.067)	(0.066)	(0.065)	(0.067)	(0.065)
_cons	−4.644***	−4.223***	−4.483***	−2.912***	−4.128***	−2.757***
	(1.023)	(1.022)	(1.023)	(1.005)	(1.022)	(1.006)
N	63,198	63,198	63,198	63,179	63,183	63,179
R^2	0.388	0.385	0.389	0.407	0.386	0.409
F	379.412	323.589	339.193	564.423	329.390	499.705

Note: NUTS-2 region–IPC four-digit class clustered standard errors. All regressions include NUTS-2 region, IPC four-digit class and time fixed-effects.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

show the results for the measures of breadth and depth weighted to account for technological relatedness across IPC classes. All models include region, time and IPC class fixed-effects.

Looking at the role of technological relatedness between the new technological specialisation developed in the region and existing technologies, we confirm the benefits of a greater variety of related technological classes in the region to generate knowledge spillovers and form new or improved technological combinations, as postulated and extensively evidenced in the diversification literature (Boschma, 2017; Kogler et al., 2016; Neffke et al., 2011; Rigby, 2015).[10] Considering *REG_BREADTH* and *REG_DEPTH*, we find positive and statistically significant coefficients for both. This finding confirms the important role of both search dimensions for regional technological entry, alongside established determinants such as relatedness. Broder regional search breadth reflects regions that engage with a wider set of technological domains, thereby expanding the range of potential recombinant innovation (Rigby & Essletzbichler, 1997) and increasing the propensity to enter new technological fields (Beaudry & Schiffauerova, 2009; Harrison et al., 1996). On the other hand, regional search depth increases the space of recombinatory opportunities through learning-by-doing and specialisation, allowing regions to refine and extend existing knowledge combinations with lower uncertainty (Arthur, 1994; Fleming, 2001; Kaplan & Vakili, 2015; Rigby & Essletzbichler, 1997; Wang et al., 2024) and strengthening trajectories in related fields (Balland et al., 2019; Boschma et al., 2023).

In line with our hypotheses, the estimates of the quadratic term for both variables are also statistically significant. While increasing levels of breadth and depth enhance recombination opportunities, excessive levels may introduce frictions that reduce the effectiveness of search processes. In the case of search breadth, expanding across different technological domains raises knowledge integration costs, coordination complexity, and cognitive distance, ultimately limiting the ability of regional actors to effectively recombine heterogeneous knowledge (Katila & Ahuja, 2002; Laursen & Salter, 2006). Similarly, excessive search depth may lead to overreliance on a narrow set of previously explored knowledge components, resulting in diminishing returns and ultimately an inverted-'U' relationship due to cognitive lock-in, reduced novelty, and exhaustion of recombinatory opportunities (Katila & Ahuja, 2002).

To explore in more detail the non-linear nature of these effects, Figure 2 plots the predicted probabilities for *REG_ENTRY* across different levels of *REG_BREADTH* and *REG_DEPTH*, holding other variables at mean values. In line with our hypothesis and previous studies at the firm level (Katila & Ahuja, 2002; Laursen & Salter, 2006), we observe an inverted 'U'-shape for both dimensions of regional technological search.

We find similar results when looking at the results for models using *REG_BREADTH_W* and *REG_DEPTH_W*, in columns 4–6, measuring regional search breadth and regional search depth weighted by technological relatedness. This indicates that our findings are robust to incorporating the cognitive

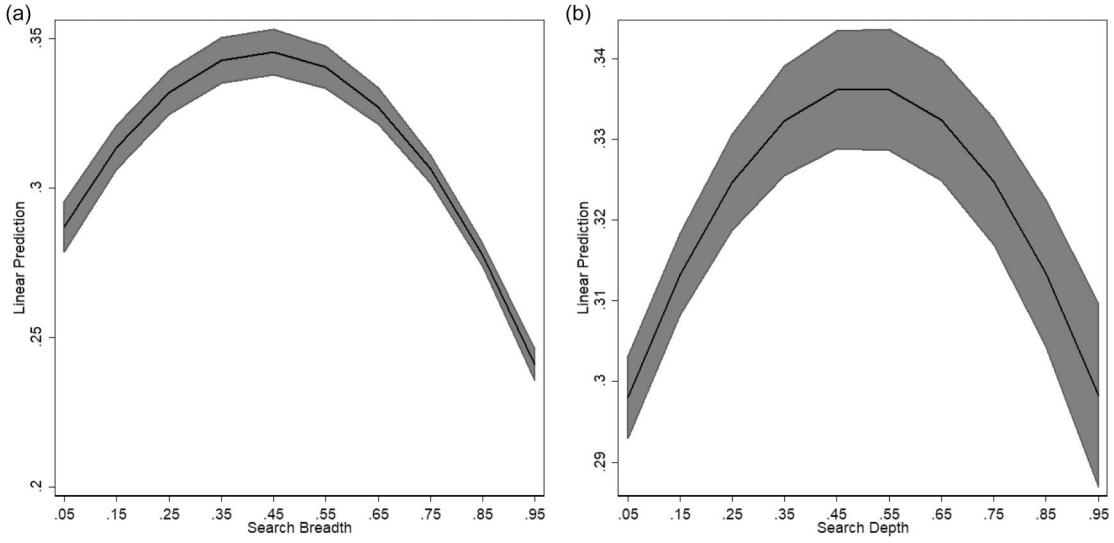


Figure 2. Predicted probabilities for search breadth (a) and depth (b) on regional technology entry.

proximity of the knowledge inputs involved in the regional search patterns, providing further evidence on the non-linear effects of search breadth and depth also when considering their relatedness structure.

Our findings point to the benefits of acquiring a deeper understanding of the technology through search depth to overcome the initial uncertainty surrounding any new technological combinations (Fleming & Sorenson, 2004; Wang et al., 2024; Wang & von Tunzelmann, 2000). Nevertheless, this approach may lead to myopic search behaviour (Levinthal & March, 1993), precluding the inventor from searching more broadly across technology fields and thus from renewing the set of useful combinations (Fusillo, 2023; Katila & Ahuja, 2002). Furthermore, these results support general insights from the literature on knowledge search and organisational learning that describe search processes as increasingly uncertain and costly when they involve a higher number of technological domains. Therefore, whilst necessary to promote cross-fertilisation and the recombination of non-redundant knowledge (George et al., 2008), excessive regional search breadth may also be detrimental to new technological entry due to growing knowledge integration costs (Katila & Ahuja, 2002).

With respect to our control variables, we find a positive and significant effect for both number of patents and technology claims, underlining the link between overall regional technological capabilities and the entry of new RTAs. Reflecting the complex effect of regional economic development on technological entry (Pinheiro et al., 2025), we find evidence of non-linear effects from higher GDP levels. Higher employment is also positively associated with entry.

We complement our analysis of the role of search breadth and search depth in regional technological diversification by looking at the first emergence of breakthrough technologies across regions. Estimates for the impact on *BP_ENTRY* are reported in Table 3.[11] Overall, our findings are similar to those observed

Table 3. Effects of regional search breadth and depth on breakthrough entry.

	(1)	(2)	(3)	(4)	(5)	(6)
reldens	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Reg_breadth	0.239***		0.223***			
	(0.016)		(0.017)			
Reg_breadth^2	−0.267***		−0.254***			
	(0.017)		(0.017)			
Reg_depth		0.106***	0.088***			
		(0.015)	(0.015)			
Reg_depth^2		−0.096***	−0.078***			
		(0.016)	(0.017)			
Reg_breadth_w				0.393***		0.383***
				(0.024)		(0.024)
Reg_breadth_w^2				−0.411***		−0.398***
				(0.022)		(0.022)
Reg_depth_w					0.165***	0.117***
					(0.024)	(0.024)
Reg_depth_w^2					−0.126***	−0.078**
					(0.033)	(0.033)
npat	0.021***	0.022***	0.021***	0.020***	0.022***	0.019***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
tech_claims	0.008***	0.008***	0.008***	0.011***	0.008***	0.010***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
log(*GDP*)	−0.424***	−0.481***	−0.437***	−0.478***	−0.470***	−0.478***
	(0.132)	(0.132)	(0.132)	(0.132)	(0.132)	(0.132)
log(*GDP*)^2	0.021***	0.024***	0.022***	0.024***	0.023***	0.023***
	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)
GDP growth	−0.005	−0.002	−0.004	−0.002	−0.001	−0.002
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
empl	−0.026	−0.029	−0.026	−0.024	−0.028	−0.023
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
log(*popdens*)	−0.039	−0.042	−0.036	−0.043	−0.043	−0.041
	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)
_cons	2.414***	2.724***	2.473***	2.725***	2.675***	2.717***
	(0.698)	(0.699)	(0.699)	(0.697)	(0.700)	(0.697)
N	84,860	84,860	84,860	84,826	84,834	84,826
R^2	0.175	0.173	0.175	0.177	0.173	0.178
F	326.637	275.687	289.708	369.991	274.341	325.406

Note: NUTS-2 region–IPC four-digit class clustered standard errors. All regressions include NUTS-2 region, IPC four-digit class and time fixed-effects.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

for *REG_ENTRY*. In particular, we find a positive and statistically significant effect of *RELATEDNESS*, confirming previous studies on the occurrence of breakthrough inventions (De Noni & Belussi, 2021) as well as the entry of a breakthrough patent in a region (Boschma et al., 2023). Both *REG_BREADTH* and *REG_DEPTH* report a positive and significant direct effect, as well as a negative quadratic effect.

In line with research on breakthrough technologies (Hall et al., 2001; Kaplan & Vakili, 2015), these results suggest that regions that are able to search widely may have advantages in their first development of highly cited patents. Results for regional search depth similarly complement prior research at the firm and technology level suggesting that familiarity and expertise with the components underpinning novel inventions may also be conducive to breakthrough innovation (Fleming, 2001). At the same time, we find evidence in support of an inverted-'U' relationship across both dimensions of knowledge search. Our findings are also confirmed when looking at predicted probabilities on *BP_ENTRY* across the distribution of *REG_BREADTH* and *REG_DEPTH*, which are consistent with the results shown in Figure 1.[12] These results are robust to measures of regional search breadth and regional search depth weighted by technological relatedness, reported in columns 4–6 of Table 3, confirming a statistically significant positive effect as well as the presence of decreasing returns ultimately defining an inverted-'U' relationship for both indicators also in the context of breakthrough entry in the region. Interestingly, we find similar non-linear effects with respect to GDP levels, possibly pointing to regions with average GDP levels being more focused on adopting and adapting existing technologies. This, once again, points to a complex relationship between regional economic development on technological entry (Pinheiro et al., 2025).

4.2. Robustness and heterogeneity analysis

As a robustness check, we also estimate our models including region–time and ICP class–time fixed effects in order to account for any unobserved region-variant and technology-variant heterogeneity, including technology-specific shocks or any other change in the regional economy. Accordingly, all socio-economic variables for the region are dropped from the model.[13] We report the results for both *REG_ENTRY* and

Table 4. Estimates for regional search breadth and depth including region–time and ICP class–time fixed effects.

	Entry		Breakthrough entry	
	(1)	(2)	(3)	(4)
reldens	0.004***	0.004***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Reg_breadth	0.363***		0.226***	
	(0.019)		(0.015)	
Reg_breadth^2	−0.407***		−0.258***	
	(0.019)		(0.015)	
Reg_depth	0.222***		0.068***	
	(0.016)		(0.014)	
Reg_depth^2	−0.216***		−0.053***	
	(0.018)		(0.015)	
Reg_breadth_w		0.618***		0.392***
		(0.032)		(0.022)
Reg_breadth_w^2		−0.805***		−0.413***
		(0.028)		(0.020)
Reg_depth_w		0.295***		0.103***
		(0.025)		(0.022)
Reg_depth_w^2		−0.245***		−0.059**
		(0.035)		(0.029)
npat	0.010***	0.006***	0.020***	0.018***
	(0.001)	(0.001)	(0.001)	(0.001)
tech_claims	0.002***	0.006***	0.008***	0.011***
	(0.000)	(0.000)	(0.000)	(0.001)
_cons	0.088***	0.213***	0.044***	0.034***
	(0.004)	(0.009)	(0.003)	(0.006)
IPC*Time fixed effects	Yes	Yes	Yes	Yes
NUTS*Time fixed effects	Yes	Yes	Yes	Yes
N	77,925	77,904	105,852	105,813
R^2	0.442	0.457	0.211	0.213
F	645.19	899.71	570.59	668.28

Note: NUTS-2 region–IPC four-digit class clustered standard errors. NUTS-2 regions for the UK and Switzerland also included. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

BP_ENTRY in Table 4. Overall, we find consistent results with those presented in the previous tables, confirming a positive effect as well as the presence of diminishing returns and ultimately an inverted-'U' relationship for both regional search breadth and regional search depth. Once again, these findings hold when using alternative measures accounting for relatedness across technological classes for both knowledge search dimensions.

While the focus of our analysis is on the direct link between patents defining regional technological entry and their underlying search characteristics, with temporal precedence being set by the backward citation search (input side) to granted patent (output side) relationship, we also present estimates where all explanatory variables are lagged to further address any potential reverse causality bias. These are reported in Table 5, columns 1 and 2 respectively for entry and breakthrough entry. Here, the interpretation is slightly different, as the focus of the analysis shifts from search characteristics specific to the patents associated with entry to the effect of pre-existing regional search patterns on the likelihood of subsequent entry. We find results fully consistent with our main findings of non-linear effects for both search breadth and depth on entry. However, coefficients for breakthrough entry are significant only at the 0.10 level, likely due to the reduction in available observations. These findings suggest the presence of a structural and path-dependent dimension in regional search, reflecting persistence dynamics in regional technological trajectories often discussed in the EEG literature.

As noted in our methodology section, our main results are based on a conservative approach excluding cells with no backward citations which allows us to avoid imputing values for undefined cases and prevents conflating a true absence of backward citations with genuinely narrow search breadth or depth. At the same time, we also present results including observations set equal to zero in the absence of backward citations at the region–technology–period level as robustness check against any potential bias due to such observations not representing a random subsample. Estimates reported in Table 5, columns 3 and 4, are fully consistent with our main results.[14]

Following previous literature, we also run several robustness checks to account for potential bias in the identification of RTAs due to a small number of patents. They are reported in Table A3 in Appendix A in the supplemental data online. In line with Grashof and Basilico (2025) and Pinheiro et al. (2025), we apply a minimum threshold of at least 10 patents in a given IPC class as further requirement to identify the presence of an RTA (columns 1–2). Similarly to Santoalha and Boschma (2021), we also test for RTAs additionally requiring absolute growth in the number of patents and remain specialised in a given IPC class in the following time period (columns 3–4). Results are fully robust to these alternative specifications.

To conclude, we run heterogeneity tests estimating our models separately for regions below and above average numbers of patents, as well as below and above the average number of technological claims of IPC classes to consider possible differences between the level of regional technological development and inventive capacity of the technological field. The results, reported in Table A4 in Appendix A in the supplemental data online, are fully consistent with our main findings[15] with the exception of coefficients for search depth

Table 5. Effects for regional entry breakthrough entry with lagged specification and inclusion of zero backward citations.

	Lagged specification		Zero backward citations	
	Entry (1)	Breakthrough entry (2)	Entry (3)	Breakthrough entry (4)
reldens	0.003***	0.001***	0.003***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
breadth	0.076**	0.046*	0.529***	0.312***
	(−0.035)	(−0.027)	(−0.019)	(−0.016)
breadth^2	−0.088**	−0.047*	−0.510***	−0.308***
	(−0.035)	(−0.028)	(−0.021)	(−0.017)
depth	0.126***	0.082***	0.202***	0.069***
	(−0.028)	(−0.029)	(−0.018)	(−0.015)
depth^2	−0.097***	−0.053*	−0.164***	−0.041**
	(−0.031)	(−0.031)	(−0.02)	(−0.016)
N	21,759	28,102	112,834	160,212
R^2	0.132	0.106	0.430	0.178
F	38.047	20.628	624.625	703.988

Note: NUTS-2 region–IPC four-digit class clustered standard errors. All regressions include controls on *npat*, *tech_claims*, log(*GDP*), *GDP growth*, *empl*, log(*popdens*) and *NUTS-2 region*, IPC four-digit class and time fixed-effects. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

in the case of regions below the average number of patents, which are no longer statistically significant. We interpret this as reflecting increasingly unclear and possibly weaker effects of learning from prior knowledge in places characterised by a narrower set of technological capabilities. We also confirm our results on regional search breadth and depth remain consistent across different relatedness levels. Predicted probabilities at the first, fifth and ninth decile of the relatedness distribution are reported in Figure A2 in Appendix A in the supplemental data online. Finally, we have looked at predicted probabilities at different combinations of regional search breadth and depth. These are reported in Figure A3 online. We find that the effect of search breadth does not significantly differ across different levels of search depth. In contrast, the effect of search depth tends to be slightly more pronounced at lower levels of search breadth. Considering these effects jointly, we observe higher entry probabilities for regions in the middle of the distribution of both regional search breadth and search depth.

5. Discussion and conclusions

This paper explores the role of specific dimensions of knowledge search within processes of regional technological diversification that shape the emergence of new technological specialisations (Boschma, 2017; Boschma & Frenken, 2012; Hassink et al., 2019; Neffke et al., 2011). In particular, we connect the proximity framework (Balland et al., 2015; Boschma, 2017; Grillitsch et al., 2018) with insights from the literature on knowledge search (Fleming & Sorenson, 2004; Katila & Ahuja, 2002), bringing to the fore the effects of the specific patterns and characteristics of regional search activities on technological recombination. Our approach complements current EEG perspectives centred on the structural configuration of the regional knowledge base, shifting the attention to the patterns through which regions search across and within knowledge domains, and if these patterns have a role in shaping technological trajectories. We focus on two distinct dimensions of search: regional search breadth reflecting the spectrum of knowledge domains explored for the development of new technologies; and regional search depth capturing how intensively regions draw upon and exploit previously utilised knowledge within their innovation processes.

Using a panel dataset for NUTS-2 regions and four-digit ICP technological class pairs across the period 1990–2014, we provide novel evidence indicating the presence of a significant role of different knowledge search dimensions, alongside relatedness between localised capabilities, as important drivers of regional technological diversification. We show both regional search breadth and regional search depth exert a positive and significant effect on the ability of regions to diversify into new technologies. Both dimensions are found to be defined by decreasing returns. These findings suggest that knowledge search is a relevant mechanism, but also one characterised by systematic trade-offs: while broader and deeper search expand recombination opportunities, excessive levels lead to coordination costs, cognitive distance, and lock-in effects that limit diversification. These results similarly apply to the analysis of regional entry of breakthrough technologies.

From a theoretical perspective, our findings extend perspectives centred on the structure of the knowledge base to the search processes through which knowledge is recombined; while the relatedness literature has discussed processes of new knowledge recombination by focusing on the degree of relatedness between regional knowledge capabilities (Boschma, 2005; Boschma et al., 2023; Castaldi et al., 2015), our results indicate that this is only part of the story. Following recent calls for more evidence on the underlying mechanisms that define such recombination activities (Bathelt & Storper, 2023; Content & Frenken, 2016), we complement prior insights showing that regional entry into new technology domains does not only depend on the level of relatedness between technology fields, but also on regional capabilities to search widely within their invention activities and by the extent they reuse previously exploited knowledge. Regions may exhibit similar levels of relatedness yet differ substantially in how they search for and combine knowledge, indicating that our search measures capture a distinct dimension of regional innovation processes.[16] This also adds a novel perspective to the literature calling for a dynamic extension of the proximity framework (Balland et al., 2015; Boschma, 2017; Martin, 2010) and encouraging further work on the wide range of sources, risks, and mechanisms underpinning new regional path development (Corradini, 2019; Hassink et al., 2019). Our results similarly complement recent studies on the role of relatedness in the first occurrence of regional breakthrough technologies (Boschma et al., 2023; De Noni & Belussi, 2021), showing how

the degree of cognitive proximity in the region co-defines these dynamics alongside their patterns of search breadth and depth. Thus, we suggest that introducing a more nuanced discussion of knowledge search processes may allow to further strengthen our understanding of the mechanisms of knowledge recombination and regional technological change.

From a policy perspective, this paper adds to recent contributions on the effective application of Smart Specialisation policy (Foray et al., 2009; McCann & Ortega-Argiles, 2015) showing that support should target related capabilities in the region to facilitate the development and entry of new technologies (Hidalgo, 2023). Our results also provide initial evidence of the importance to consider knowledge search dimensions in policy design as a means to support regional technological diversification. For example, policies fostering cross-sector collaboration, interdisciplinary research programmes, and interregional knowledge exchange may strengthen search breadth (Barzotto et al., 2019). Similarly, research and development (R&D) subsidies to consortia with diverse partners, which are likely to widen search patterns, may better support regional diversification (Mewes & Broekel, 2020). By contrast, policies connected to search depth may focus on long-term R&D investments, specialised research infrastructures, and the consolidation of regional expertise within key technological domains. The appropriate policy mix is also likely to depend on regional characteristics; this broader approach to knowledge search may also offer more flexibility to regions trapped between different levels of economic complexity and development (Hidalgo, 2023). Extending the attention to regional search patterns in processes of knowledge recombination may thus reinforce and expand the toolkit available for Smart Specialisation strategies, offering additional opportunities for designing more context-specific policies that better support regional diversification and long-term innovation capacity.

Our results should be considered in light of various limitations of the paper, that open important avenues for future research. While our analysis identifies inverted 'U'-shaped effects for both regional search breadth and regional search depth, further work is needed to unpack the mechanisms underlying these patterns. In particular, while we present theoretically grounded interpretations for these non-linear relationships, empirically testing the specific mediating mechanisms remains an area for future research. Building on the proximity framework (Boschma, 2005), these differences may also reflect the configuration of multiple dimensions of proximity shaping regional knowledge interactions. For instance, while we focus on patent citations to capture knowledge flows and measure key features of search processes, knowledge recombination and learning also occur through inventors' mobility and co-inventors' networks (Breschi & Lissoni, 2009; Kogler et al., 2023). As such, the insights presented in this study could be reinforced by further research exploring how such networks can define key features and characteristics of search processes and capabilities, both from a cognitive as well as a geographical perspective. Moreover, as we focus on within-region estimates of technological search breadth and search depth processes, our analysis does not provide insights on the differential effects of institutional dimensions across regions. Yet, institutional arrangements, collaborative infrastructures, and the governance of innovation networks that define regional innovation systems (Cooke et al., 1997; Storper, 2018) may also play an important role in shaping regional search capabilities and the ability of regional actors to coordinate knowledge search and effectively recombine diverse knowledge sources within regional innovation systems (Cooke et al., 1997; Isaksen, 2015; Storper, 2018). While our insights mostly aim to reflect processes of path diversification and new path creation, the role of technological search should also be explored across other forms of new path development, such as path renewal, upgrading or extension (Grillitsch et al., 2018; Hassink et al., 2019). Further studies could also complement our approach based on cognitive proximity within patent citations by looking at the spatial dimension of technological search breadth and search depth, as partly considered at the firm level (Ahuja & Katila, 2004; Wang, 2015). To offer more nuanced and specific insights for policy, technological search capabilities should also be explored through a comparative perspective focused on lagging-behind regions (Barzotto et al., 2019; De Noni et al., 2018), or regions at different levels of the complexity ladder (Pinheiro et al., 2022). Finally, while we mitigate potential reverse causality and omitted-variable bias by relying on the temporal ordering from backward citation search to patent output, a complementary lagged specification, as well as time-invariant and time-varying high-dimensional fixed effects, our identification strategy cannot fully solve endogeneity concerns. This reflects a persistent empirical gap within the wider EEG literature. Accordingly, we support the call by Bathelt and Storper (2023) for more causal evidence on the mechanisms underlying processes of regional technological diversification.

Notes

1. ICRIOS provides harmonised patent data from PATSTAT. For more information on ICRIOS and the underlying harmonisation process, see Coffano and Tarasconi (2014).
2. Results are fully robust to a Poisson pseudo-maximum likelihood (PPML) specification, which takes into account the non-negative nature of our dependent variable, whilst retaining our full set of fixed effects, thus avoiding the incidental parameters problem in the presence of fixed-effects for logit models.
3. To further address potential omitted variable bias, we also consider the inclusion of region–time and ICP class–time fixed effects to control for any unobserved region-variant and technology-variant heterogeneity. Results are reported in Table 4.
4. In line with recent literature (Miguelez & Morrison, 2023), observations are set to missing if RTA = 1 in time period $t - 1$ or in the first period of the analysis, as *REG_ENTRY* can no longer occur.
5. Similarly to *REG_ENTRY*, observations are set to missing once a region has a breakthrough or when breakthroughs occur in the first period of the analysis (Boschma et al., 2023).
6. Relatedness is computed using the EconGeo package in R (Balland, 2017). Results are consistent when using co-occurrence probabilities or the Jaccard index to compute relatedness.
7. While both *NPAT* and *TECH_CLAIMS* are highly correlated to the number of backward citations, it is possible our search measures may be mechanically related to the number of backward citations. To address this potential concern, we replicated all our models including a control for the total number of backward citations at the region–technology–period level. Results are fully robust to this specification and are available upon request.
8. We also explored gross value added (GVA) and GVA growth in alternative specifications, yielding fully consistent results.
9. Variance inflation factor (VIF) values are consistently below the 5 threshold, suggesting multicollinearity is not a concern in the study.
10. While we calculate relatedness in line with the extensive literature on this concept for consistency, it is also possible to consider an alternative approach aimed at capturing more directly knowledge flows as reflected by patents citations in line with the suggestion of Bathelt and Storper (2023), and as implemented by Miguelez and Moreno (2018) in the context of related variety. Accordingly, we also calculated a measure of relatedness based on technological classes within patent citations. This alternative specification for *RELATED* provides fully consistent results.
11. Estimates presented are based on the top 5% of the distribution of forward citations. Following Boschma et al. (2023), we have considered for robustness different breakthrough thresholds, specifically the upper 1% and 10% of the distribution. Our results are fully consistent across these alternative specifications. Estimates are reported in Table A2 in Appendix A in the supplemental data online.
12. These are reported in Figure A1 in Appendix A in the supplemental data online.
13. This also allows us to introduce in the dataset observations for UK and Swiss regions, which are not covered in the AREDCO database on regional statistics.
14. All reported models, including the lagged specifications, are fully robust to this approach.
15. We also explored results splitting the sample across median GDP levels. This yields consistent results as those reported based on regional patents.
16. This is as also supported by the low correlations between relatedness and search measures reported in Table A1 in Appendix A in the supplemental data online.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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