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Technological entry in new niches: Diversity, crowding and generalism

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ABSTRACT

Entry in new technological domains is essential for the long-term performance of firms. Therefore, it is important to understand the conditions that increase the likelihood that firms enter, and further explore, new technological domains. Some recent studies have started to unpack these issues by looking at the environmental conditions in a new technological domain that pull firms into it. In this paper, we complement these studies by looking at the environmental conditions in the firm's *current* technological domain that *push* firms into new domains. We do it from the perspective of *technological ecology*, by looking at how technological *diversity* and *crowding* in the firm's current technological niche, as well as firm's knowledge *generalism*, affect the likelihood that the firm enters, and further explores, new technological niches. To test our hypotheses, we rely on an empirical setting based on U.S. patents by 340 firms in the pharmaceutical industry. We propose a novel and advanced approach that, by leveraging a vast set of technological classifications, extracts technological niches from the patent system as they evolve over time.

1. Introduction

Entry in new technological domains is essential for the long-term performance of firms (Leten et al., 2016): it can bring firms a new series of technological innovations that can serve as new opportunities or options, which can be subsequently exploited through further upscaling and commercialization activities (Ahuja and Lampert, 2001), and it can also expand the repertoire of problem-solving skills (Hargadon and Sutton, 1997) that prevent lock-in during times of competence-destroying technological change (Tripsas, 1997; Tushman and Anderson, 1986). In this way, a firm's entry into new technological domains stimulates corporate rejuvenation and contributes to its future growth and long-term survival chances (Katila and Ahuja, 2002; King and Tucci, 2002). Entry in new technological domains, therefore, may serve as an important source for a firm's competitive advantage. Despite these strategic benefits, however, data suggest that not all firms enter new technological domains, and not all of those who enter innovate again after such entry (e.g., see Malerba and Orsenigo, 1999).[1] [2] Therefore, a better understanding of the entry in new technological domains is necessary, to shed light on these paradoxical findings (Leten et al., 2016).

An established perspective on these issues builds on resource arguments (Barney, 1991; Penrose, 1959). In a nutshell, this perspective centers on the (firm-level) insight that the resource base of the firm—for example, its technologies—determines both the direction and magnitude of entry, typically in function of resource synergies between the current and the new domain (Breschi et al., 2003; Leten et al., 2007; Nesta and Saviotti, 2005; Peteraf, 1993). This perspective has enriched our understanding of entry dynamics as the basis of firm's growth leading to competitive advantage. Yet, as argued by Leten et al. (2016), this view is fundamentally incomplete, because it overlooks the role played by the broader technological environment that surrounds the firm and that also influences its innovation initiatives. With the aim of unpacking the role of environmental conditions, these scholars have

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[1] In a demographic study on Schumpeterian patterns of innovation, Malerba and Orsenigo (1999) showed that entry in new technological classes tends to be common mainly among 'lateral' entrants, typically established firms engaged in a process of technological diversification. In addition, they showed that a large fraction of entrants is 'occasional' rather than 'persistent', meaning that only a few of them continue to patent after entry. These results hold across a variety of classes.

[2] Moreover, there seems to be a discrepancy between observed levels of product diversification and the extent of technological diversification via the entry in new domains. This makes technological diversification, and what drives it in the first place, a phenomenon worth of further studies.

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thus examined the conditions in the *new* technological domain, by looking at how the richness of opportunities in the new domain *pulls* firms into it (Leten et al., 2016). By analyzing patent data of R&D intensive firms, they have found that the richness of opportunities in the *new* domain encourages entry while competition discourages it, and that firms are heterogeneously positioned depending on the configuration of their knowledge base.

The combined importance of pull and push factors in technology (Dosi, 1982; Mowery and Rosenberg, 1979; Van den Ende and Dolfsma, 2005) requires us to complement the study of Leten et al. (2016) by examining the conditions in the *current* technological domain that *push* firms into new domains. Given the complexity of inventive problems (Baumann et al., 2019; Fleming and Sorenson, 2001; Ganco, 2017) combined with bounded rationality (Simon, 1955, 1962), firms tend to search 'locally' within their current domains (Greve, 1996; Levinthal and March 1993; Levinthal, 1997; March, 1991), and this exposes them to localized niche pressures. This requires a niche theory, which we borrow from the technological ecology literature (Coccia, 2019a; Coccia and Watts, 2020), based on which we operationalize current and new technological domains with the specific construct of current and new *technological niches* (Podolny and Stuart, 1995; Van den Oord and Van Witteloostuijn, 2017). In ecology, the concept of niche was introduced to describe a particular configuration of scarce resources and of a population of biological entities, and how the population itself responds to this configuration (Elton, 1927; Popielarz and Neal, 2007). In innovation, a technological niche refers to a configuration of resources in the technological space and of a population of firms that, in different degrees, depend on these resources for their viability (Podolny and Stuart, 1995). More precisely, we define a technological niche as a system consisting of several related technological inventions (in the form of patents) apportioned into categories (technological subclasses) (Van den Oord and Van Witteloostuijn, 2017).

To unpack push factors under the lens of technological ecology, we propose three basic hypotheses. First, we argue that a higher degree of *technological diversity* in the firm's current niche, by increasing the degree of technological opportunities, positively affects the likelihood that the firm enters in a new niche via patenting. Since the niche is new-to-the-firm, it takes time for the firm to react to such entry by further exploring the niche, as shown by multiple examples from different industries: that is why we want to understand what the post-entry drivers of further exploration are. We thus argue that, conditional on entry in the new niche, a higher degree of *technological crowding* in the firm's current niche, by increasing the degree of technological competition, positively affects the likelihood that the firm opts to further explore the new niche via subsequent patenting. We then argue that firms are heterogeneously positioned depending on the degree of *generalim* of their knowledge base: while generalism increases their ability to take advantage of technological opportunities, thus positively moderating the effect of technological diversity on the likelihood of entry, it also decreases their exposition to competitive niche pressures, thus negatively moderating the effect of technological crowding on the likelihood of exploration. To test our hypotheses, we rely on an empirical setting based on U.S. patents by 340 firms in the pharmaceutical industry. We propose a novel and advanced approach that, by leveraging a vast set of technological classifications, extracts technological niches from the patent system as they evolve over time.

The rest of the paper is organized as follows. In Section 2 we develop the theoretical framework. In Section 3 we explain the study design. In Sections 4 and 5 we present the key findings. In the last section we discuss the implications and limitations, and then conclude.

2. Theoretical framework

2.1. Evolutionary ecology of technology

Evolutionary models of technology are well-established in the innovation tradition (Arthur, 2009; Basalla, 1988; Nelson and Winter 1982; Utterback, 1994; Ziman, 2000), thanks to a renewed interest in the similarities between biological and technological evolution (Cattani and Malerba, 2021; Cattani and Mastrogiorgio, 2021) that have prompted some to suggest that evolutionary principles underlie all types of complex systems (Coccia, 2017, 2018, 2019b; Hodgson, 2002). A central debate in this tradition revolves around the sources of opportunities in new domains (Kneeland et al., 2020), which according to some lie at the micro-level (Gavetti, 2012), while others have stressed the role of environmental factors (Andriani et al., 2017; Dosi, 1982; Leten et al., 2016; Winter, 2012).[3]

An emerging stream of research unpacks environmental factors from the perspective of ecology, a field of investigation that studies the interactions between focal entities—biological or technological—in their respective environmental niches, and that is being proposed as a platform from which we can better understand evolutionary processes in technology (Coccia, 2019a; Coccia and Watts, 2020). This stream of research, also known as 'technological ecology', centers on the concept of 'technological niche' and on the dynamics that take place inside it (Podolny and Stuart, 1995; Van den Oord and Van Witteloostuijn, 2017).

Technological niches: basic concepts. As argued by Schot and Geels (2007), "in evolutionary theories, radical technical change is often explored […] as a process that proceeds in small steps or as a process that is accomplished by a great leap forward which opens new markets and creates new branches of industry", at the expense of a theory that explains these radical changes "in a more differentiated and nuanced way, working towards a *niche theory*" (pg. 617, emphasis added). There is, nevertheless, an emerging literature that links evolutionary theories of innovation with the research on niches (Andriani and Cohen, 2013; Schot and Geels, 2007), with the aim of understanding how niches (and the dynamics that take place inside them) are conducive to innovations and act as "incubation rooms for radical novelties" (Geels, 2005: pg. 684). An example is the recent work of Coccia, 2019a (see also Coccia and Watts, 2020), who examines technological evolution from the perspective of 'technological parasitism', referring to a taxonomy of ecological interactions between technologies in their niches.[4]

A key concept in this literature is that of 'technological niche' (Podolny and Stuart, 1995). The concept of niche is of key importance in organizational ecology, where it has been used to analyze how the forces of legitimacy and competition give rise to an inverted U-shaped relationship between density and the entry of organizations in a niche (Carroll and Hannan, 2000; Hannan and Freeman, 1977), having received a widespread attention from both an empirical (Baum and Singh, 1994; Khurshid et al., 2020; Podolny and Stuart, 1995; Podolny et al., 1996) and theoretical standpoint (Hannan et al., 2007; McPherson, 2004; Van Witteloostuijn and Boone, 2006). Contemporaneously with its application to organizational phenomena, but certainly in a less extensive way, the niche concept has been applied to technology too. The concept of 'technological niche' was introduced by Podolny and Stuart (1995), with the aim of studying how the structural relationships between a set of innovations affect the relevance, and impact, of these. More works followed, starting to disentangle how technologies in a

[3] This debate has deep roots in evolutionary biology, where it relates to the tension between gene-centric and contextual perspectives on evolution (Gould, 2007). For a summary, see Cattani and Mastrogiorgio (2021).

[4] This literature studies how niche mechanics lead to radical change, like the emergence of a new socio-technical regime. It does it within different paradigms about the evolutionary nature of radical change, like natural selection (Saviotti, 1996) and 'Generalized Darwinism' (Hodgson, 2002; Coccia, 2019a), punctuated equilibrium/speciation (Levinthal, 1998), and niche construction (Odling-Smee et al., 2003). Despite these interesting directions, "it is surprising that little systematic attention has been given to the topic of niches in evolutionary theories of technological change" (Schot and Geels, 2007: pg. 606).

niche are in a relationship of both 'competition' and 'mutualism' (Pistorius and Utterback, 1997), of which there can be different degrees (Coccia, 2019a; Coccia and Watts, 2020). For a comprehensive review of these approaches, we refer to Van den Oord and Van Witteloostuijn (2017).

What is a technological niche? In biology, a niche refers to a configuration of scarce resources (like food) and to a population of interacting biological entities (like mammals) competing for these (Elton, 1927; Odling-Smee et al., 2003; Popielarz and Neal 2007). A *technological niche*, instead, refers to a configuration of resources in the technological space—thus technologies, typically in the form of patents—and to a population of firms that, in different degrees, depend on these for their viability: more precisely, we define a technological niche as a *system consisting of several related technological inventions (in the form of patents) apportioned into categories (technological subclasses)* (Van den Oord and Van Witteloostuijn, 2017).[5] Equating patents with niche-level resources is quite established in the literature (Kovacs et al., 2021; Podolny and Stuart, 1995; Van den Oord and Van Witteloostuijn, 2017: pg. 2), as it acquires relevance in specific industries—like the pharmaceutical one, for instance—that heavily rely on patents, which thus represent essential resources for firms. The multi-billion monopolies afforded by drugs' patents and the often-recurring patent races (and wars) among firms are, in this regard, illustrative.[6]

Building on the distinction between environmental factors and firm-level factors, we will study what environmental factors, at the level of the firm's current technological niche, affect firm's trajectories into new areas of the technological space, thus increasing the likelihood that the firm enters, and further explores, new technological niches. The environmental push factors that we explore are technological diversity and technological crowding at the niche level. Whereas, at the firm-level, we consider the firm's degree of knowledge generalism. Fig. 1 illustrates our framework, whose mechanisms are further explained below.

- Current niche's technological diversity and entry in a new niche

The concept of diversity features a prominent role in a variety of disciplines (Dwertmann et al., 2016), including ecology (Coccia, 2018; McCann, 2000; Van den Oord and Van Witteloostuijn, 2017) and innovation studies at the intersection of science, technology and research policy (Cui and O'Connor, 2012; Hao et al., 2020; Haelg, 2020; Nowotny et al., 2001). A comprehensive review of diversity, and of the possible ways to approach the phenomenon, can be found in Page (2011) and Stirling (2007). What seems to be established, across this variety of fields, is that the value of a system increases as a function of its diversity. Indeed, in the innovation context, it is often claimed that technological diversity correlates with creative outcomes, thus leading to novelty generation and other advantages, like the ability of the system to generate options and 'hedge bets' against future changes. This has brought attention on the need to 'open up' technological systems (Chesbrough et al., 2006; Huizingh, 2011), also making them more diverse (Stirling, 2007). Building on these arguments, we here argue that technological diversity, operating at the level of the current niche of the firm, fosters creative outcomes that take the form of a firm's entry in a new niche. That is, higher technological diversity in the firm's current niche increases the likelihood of firm's entry in a new niche.

With reference to a system (a technological niche) consisting of several related elements (technological inventions, in the form of patents) apportioned into categories (technological subclasses), we define diversity as a system-level property (see Stirling, 2007). More specifically, we define diversity as the disparity of categories of which the system is composed. That is, diversity refers to the degree in which categories can be distinguished from each other, and the more disparate are the categories, the greater is the diversity of the system.[7] When the technological diversity in a firm's current niche (that is, the disparity of the technological subclasses that compose the niche) increases, the novel ways in which underlying technological-knowledge elements can be recombined with other ones increase exponentially, through a process of 'combinatorial explosion' that is exemplified by Kauffman (2000)'s Lego blocks: when their disparity goes up, the novel ways in which they can be assembled increases exponentially, leading to an expansion of the 'adjacent possible' into which the assembly could advance. This is due to the hierarchical nature of technology: the fact that an invention is made of disparate components while at the same time is a component of other inventions and, in turn, of larger disparate sub-classes that are combinable too (Baldwin and Clark, 2000; Simon, 1969). In fact, as argued by Fleming (2001), "because every invention can be incorporated in further recombinations, the combinatorial potential will grow explosively" and "the set of potential combinations […] becomes essentially infinite" (pg. 119; Weitzman, 1996).[8]

A specific mechanism through which technological diversity in the firm's current niche leads to firm's entry in a new niche is that increasing technological diversity in the firm's current niche means that, due to increasing disparity, the niche potentially becomes less integrated. Therefore, more technological diversity, without any accompanying integrative measures (Baldwin and Clark, 2000; Lawrence and Lorsch, 1967), also means more technological incoherence across the niche (Yayavaram and Ahuja, 2008). The result is that increasing technological diversity makes it more difficult for those firms that are based in the niche to search across all potential new opportunities for recombination.[9] Consequently, when the search space becomes exceedingly scattered, the likelihood that inventors will be swamped by the absence of integrative links increases, making it difficult for them to distinguish the value of one opportunity from another (Goldenberg et al., 1999). Therefore, firms—and their inventors—will "lose the ability to explore some parts of the space of designs—in effect, the architects will restrict the search, declaring some parts of the design space to be out of bounds" (Baldwin and Clark, 2000: pg. 69).

Yet, whereas technological diversity may impede search and

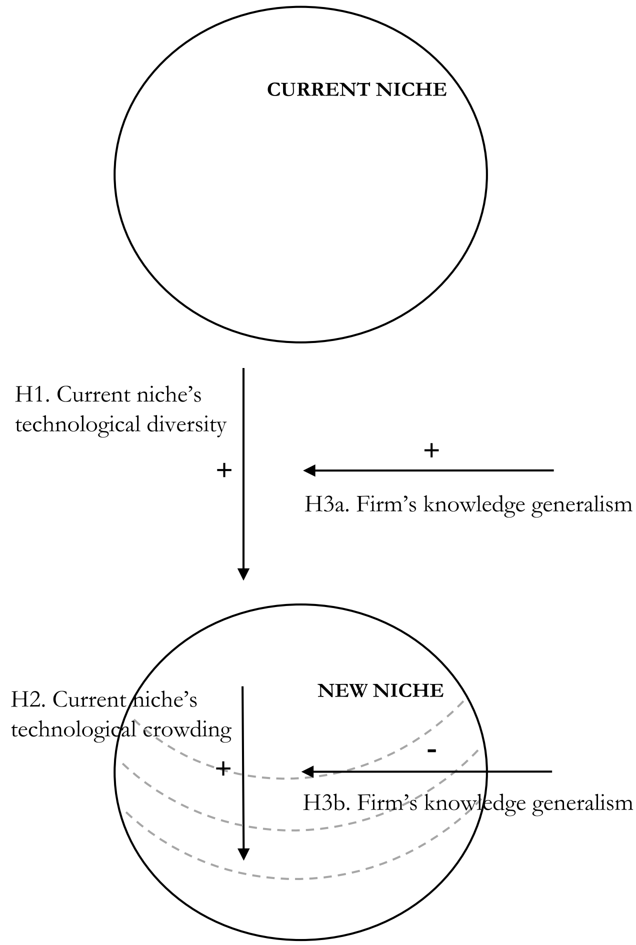
[5] As explained in the empirical section, we identify niches by clustering technological subclasses, based on their 'co-occurrences' in patent documents (representing 'distances' between subclasses).

[6] In fact, our study focuses on the pharmaceutical industry.

[7] Diversity has three main dimensions: variety, disparity, and balance. Variety is the number of categories, disparity is the difference among them, balance is how elements are distributed across the categories. Diversity increases when variety and disparity increase and when the elements are evenly distributed (Stirling, 2007). Standard approaches to diversity, like the Herfindal index, are based on the distribution of elements across categories and thus capture only one, specific, dimension of diversity (Stirling, 2007). Moreover, variety and balance cannot be properly characterized "without first considering *disparity*" (Stirling, 2007: pg. 710, emphasis added): that is, listing several categories, over which elements are distributed, requires an ex-ante assessment of disparity, which thus acquires priority in the order of relevance of the different dimensions of diversity. That is why we opted for conceptualizing diversity in terms of disparity.

[8] We assume that firms can get access to technological knowledge owned by other firms in a technologically diverse niche. There are three main reasons. First, even if knowledge is partly tacit and protected by patents, it 'spills' out of firm boundaries, as shown by the research on knowledge spillovers (Jaffe, 1986; Jaffe et al., 2000). Second, patents are public documents that reveal new, codified knowledge and therefore 'signal' new opportunities for innovation for firms' inventors (Arundel, 2001; Hsu and Ziedonis, 2013). Third, patent data are being used as proxies of a broader theoretical construct (in our case, technological diversity). This is in line with the innovation tradition, which makes an extensive use of patent data to measure very different aspects of technological knowledge that is used by other entities, even if this knowledge is protected.

[9] As argued by Yayavaram and Ahuja (2008), while the lack of integration in a technological space allows firms to search 'in depth' inside a cluster, it limits the 'breadth' of search across clusters.



Higher technological diversity in the firm's current niche positively affects the likelihood of firm's entry in a new niche. Conditional on entry, higher technological crowding in the firm's current niche positively affects the likelihood of firm's further exploration of the new niche. Firm's knowledge generalism positively moderates the diversity effect while it negatively moderates the crowding effect.

Fig. 1. Illustration of the theoretical framework.

recombination on the one hand, paradoxically it can also spur the creation of new inventions on the other hand. As shown by research in cognitive psychology, when the search space becomes ill-structured due to diversity, adhering to a cognitive frame of reference that limits the scope of search also enhances some other crucial dimensions of creativity, eventually enabling firm's inventors to achieve distant recombination and long search paths, or simply recognize the unexpected (Goldenberg et al., 1999; Kneeland et al., 2020; Perkins, 1981). For example, in studies on causal reasoning in science it is found that those experiments with many controls can be crucial for science, as they help inventors and scientists to develop a sensitivity for the unusual and to obtain novel findings (see Dunbar and Fugelsang, 2005). Some innovation scholars have thus stressed that "only a deep dive can produce breakthroughs" (Kaplan and Vakili, 2015: pg. 1435), siding with a 'foundational' view of invention, according to which local search attempts can also be the basis of detecting anomalies, and thus produce breakthroughs.[10] All this implies that technological diversity in the firm's current niche, producing a less integrated search space that limits the scope of search, activates different paths of inventive creativity, making a firm's inventors more prone to notice the unusual, which increases the likelihood of firm's entries in new niches. This leads to our first hypothesis.

H1. *A higher degree of technological diversity in the firm's current niche increases the likelihood of firm's entry in a new niche.*

- Current niche's technological crowding and exploration of the new niche

The concept of crowding features a prominent role in ecology studies, where it refers to the spatial distribution of organisms inside a niche with respect to scarce resources, which in turn affects the dynamic of the niche itself (Sun et al., 2012).[11] In technological ecology (Podolny and Stuart, 1995; Stuart, 1999; Van den Oord and Van Witteloostuijn, 2017), technological crowding refers to the spatial distribution, or 'positioning' (Barroso et al., 2016), of firms inside a technological niche,

[10] In line with the argument of Kuhn (1970) that the accumulation of anomalies leads to the emergence of novelty, in the form of new paradigms (Dosi, 1982).

[11] As argued by Sun et al., 2012 (see also Van den Oord and Van Witteloostuijn, 2017), the "distribution of nutrients as well as interactions on a spatial scale […] can have important impact on dynamics of ecological populations" (pg. 11161).

which consists of technologies—in the form of patents—that constitute the resources on which firms depend for their process of invention. Since invention consists of recombining previous technologies and knowledge components, these pieces of prior art represent fundamental building blocks for the firms operating in the niche (Van den Oord and Van Witteloostuijn, 2017). More precisely, technological crowding refers to the extent to which a firm specializes in a technology area that is densely populated by other firms, as expressed by the degree of overlap (on the prior art) of firms' knowledge bases (Podolny and Stuart, 1995). Building on these arguments, we here argue that technological crowding, operating at the level of the current niche of the firm, evokes effort on the part of the firm to distinguish its activities "from the initiatives of technologically adjacent organizations" (Stuart, 1999: pg. 747) through the exploration of new niches. That is, higher technological crowding in the firm's current niche increases the likelihood of firm's exploration of the new niche, in which the firm entered previously.

More specifically, we argue that, when technological crowding increases, competitive pressure from technologically adjacent firms increases (Baum and Singh, 1994; Hannan et al., 2007; Podolny et al., 1996). A key mechanism through which competitive pressure increases is related to knowledge spillovers (Jaffe, 1986; Jaffe et al., 2000) in the form of codified and tacit knowledge (Breschi and Malerba, 1997), which are not only received and absorbed but increasingly also leak away to more and more technologically-adjacent firms in the niche.[12] Whereas trust between a small group of partners may form a key mechanism for the exchange of tacit knowledge (Gilsing and Nooteboom, 2006), a larger and overlapping group of firms will make it become more difficult to keep tacit knowledge proprietary and to rely on secrecy for its appropriation (Teece, 1986). The implication is that it may become more difficult to create valuable and difficult-to-imitate technologies, as competing firms may just free-ride on a firm's inventive efforts. This will potentially erode a firm's competitive advantage. Consequently, firms need to look for new sources of competitive advantage that can lead to future growth. This makes them become more likely to engage in riskier behavior through a range of organizational actions (Afuah, 2001; Aghion et al., 2006; Benner and Tushman, 2003; Birkinshaw et al., 2007), including the exploration of new technological niches.[13] Consequently, when technological crowding increases, a firm's incentive to engage in riskier and distant exploration, beyond its current niche, increases too. In sum, when technological crowding increases, the firm may opt to further explore the new niches in which it entered previously. This suggests that, conditional on entry, technological crowding linearly affects the exploration of the new niche. This leads to our second hypothesis.

H2. *Conditional on entry in a new niche, a higher degree of technological crowding in the firm's current niche increases the likelihood of firm's further exploration of the new niche.*

- The role of firm's knowledge generalism

A variety of firm-level, positional, characteristics may moderate the relationship between niche-level drivers and a firm's entry and exploration of new niches. An important firm-level characteristic is the degree of firm's knowledge generalism. The concept of generalism, central in ecology studies (Stuart, 1999; Van Witteloostuijn and Boone, 2006) and innovation (Melero and Palomeras, 2015), refers to the scope of innovative competences and to the distinction between "specialist organizations that choose narrow and homogeneous" areas and "generalist organizations [that] choose targets composed of heterogeneous" areas of the technological space (Carroll et al., 2002, pg. 7). As discussed in the literature, being a generalist implies trade-offs (Teodoridis et al., 2019): for example, to invest time, resources and capabilities in several areas, maybe at the cost of having only a limited understanding of each; or, conversely, to invest in a specific area, at the cost of missing the big picture and being unable to 'connect the dots'.

Therefore, from a conceptual point of view, knowledge generalism is likely to positively moderate the entry response to increasing degrees of niche-level technological diversity. In fact, knowledge generalism, by granting access to a wider set of innovative competences (Fleming et al., 2007; Hargadon and Sutton, 1997; Taylor and Greve, 2006), helps the firm to establish those missing *integrative* links between the sparse and (apparently) incoherent elements of a technologically diverse niche. In this way, we expect that knowledge generalism strengthens the effect of technological diversity on firm's entry in a new niche. But, on the other side, knowledge generalism is likely to negatively moderate the exploration response to increasing degrees of niche-level technological crowding. In fact, a narrow-scope firm, by having all its activities concentrated in a single area of its current niche,[14] is more likely to explore new niches to react to increasing crowding levels in the current niche, as a way of spreading the risk of being active in a single area that becomes increasingly crowded. On the other hand, the generalist has more options to "shift the emphasis across [its current] set of activities [...] in response to different conditions" (Stuart, 1999: pg. 755). That is, we expect that the generalist is less likely to explore new niches to react to increasing crowding levels in the current niche, being such firm active in several areas, meaning that the pressure to spread the risk is less pronounced. In fact, empirical research has shown that internally diversified firms may see less value in external exploration, due to a variety of reasons, including weaker incentives to react against increasing crowding pressures (Srivastava and Devi, 2011). In this way, we hypothesize that knowledge generalism weakens the effect of technological crowding on firm's further exploration of the new niche. This leads to our third hypothesis:

H3a. *Firm's knowledge generalism positively moderates the effect of niche-level technological diversity on firm's entry in a new niche.*

H3b. *Firm's knowledge generalism negatively moderates the effect of niche-level technological crowding on firm's further exploration of the new niche.*

3. Study design

3.1. Data and sources

Our data come from the Compustat, NBER and USPTO databases. We rely on an empirical setting based on the pharmaceutical industry. This industry is particularly fit for our study, due to the tendency of pharmaceutical firms to focus on their current niches, thus being particularly subject to niche pressures (Petrova, 2014).[15] In order to obtain pharmaceutical patents, we first identify Compustat firms belonging to the pharmaceutical industry and therefore to SIC codes 2833–2836. Second, we match Compustat firms to their portfolios of patents obtained from the NBER and USPTO databases. Third, we match patents to their

[12] Knowledge spillovers are unobservable, which explains why economists quantify them with patent citations (Jaffe et al., 2000). This means that the degree of overlap of firms' knowledge bases on the prior art, consisting of backward patent citations (see the crowding measure), captures, at least in part, the degree of knowledge spillovers among firms. But knowledge spillovers are just *one type* of competitive pressure to which technologically adjacent firms are exposed. Another type is related to appropriability regimes: in a nutshell, regimes of patent protection create pressure to patent more aggressively, to establish priority of invention, especially in dense areas of the technological space where firms also patent strategically (Stuart, 1999).

[13] Other possible actions are strategic reorientation, market change, product/process/practice innovation, collaboration with new prospective partners, or vertical integration.

[14] That is, by 'having all the eggs in one basket'.

[15] For example, GlaxoSmithKline specializes on infectious diseases, while Eli Lilly on psychiatric disorders.

technological classifications. In order to build niches, we use technological classifications at the 'main-line subclass' level,[16] and thus at a more fine-grained level than three-digit classes (despite their coarse nature, three-digit classes are heavily used in the patent literature, with exceptions: e.g., Fleming and Sorenson, 2001). Overall, we use 61703 patents, belonging to 3276 main-line subclasses, and our main sample consists of 340 firms observed over time in an unbalanced panel.

3.2. Measures

Technological niches: a novel approach. Previous studies are based on the identification of technological niches with technological classes (Van den Oord and Van Witteloostuijn, 2017). We introduce a more dynamic, flexible and fine-grained measure of technological niches and thus follow an approach that, for the following reasons, is novel: first, our measure is still based on technological classes, but it also takes into account how firms combine these in their inventions; in other words, our measure is based on technological classes but it also takes into account how firms use these, therefore providing a more realistic picture of the technological space and of the distances that define different niches within it. Second, based on how it is calculated (see below), our measure allows us to capture how the technological space—and the niches within it—changes over time, thus linking with the idea of niches as dynamic (rather than stable) entities (see Andriani and Cohen, 2013). More specifically, our measure is based on the fact that a patent contains multiple technological classes, which means that the patent is based on combining the multiple types of knowledge that underlie these technological classes (Yayavaram and Ahuja, 2008).[17] The combination of knowledge reveals synergies among technological classes that can be translated into distances between them in the technological space: technological classes that are close to each other belong to the same technological niche, while technological classes that are distant from each other belong to different technological niches.[18]

To build our measure for a focal year, we follow these steps: we consider the universe of pharmaceutical patents granted during the 10 years preceding the focal year; we consider the universe of technological main-line subclasses appearing in these patents; we build the coupling network between technological main-line subclasses based on the number of co-occurrences in patents: technological main-line subclasses with frequent co-occurrences are close to each other and hence belong to the same technological niche, while technological subclasses with non-frequent (or absent) co-occurrences are distant from each other; hence, they belong to different technological niches. In addition, we do the following: the shortest distance is assigned between the two main-line subclasses with the highest frequency of co-occurrences, and larger distances between main-line subclasses are calculated proportionately—we label them 'co-occurrence distances'; a coupling network between main-line subclasses is therefore obtained, based on co-occurrence distances; the next step consists in calculating geodesics[19] between main-line subclasses weighted with their co-occurrence distances—we label them 'distances' (see endnote).[20]

To identify technological niches, we form clusters of main-line subclasses using an agglomerative hierarchical procedure. This is a bottom-up procedure, as it consists of starting with each main-line subclass in its own cluster and in progressively merging pairs of clusters. In this procedure, a major challenge consists in determining the number of clusters. We realized that many standard clustering procedures are not fit for determining this number.[21] [22] Therefore, we determine this number of clusters using the following procedure. The procedure consists in looking at how a fitness function decreases—with respect to a linear function—as the number of clusters increases, where the fitness function proxies the stability of the clusters (which is, by logic, maximum when there is only one cluster and minimum when there are all possible clusters). More precisely, we look at the maximum difference between the fitness and the linear function and consider the corresponding number of clusters as the target one. This is the number in correspondence of which the fitness function starts to decrease more rapidly than the linear trend, hence identifying the point after which subsequent clustering becomes marginal.

Based on this procedure, the number of clusters/niches varies from 31 to 51 depending on the year, with an average of 40.6 technological niches. For instance, the number of technological niches is 35 in year 1995, as illustrated in Fig. 2, where each niche has a different colour. Interestingly, the average number of technological niches (40.6) matches with the number of therapeutic areas mentioned in Nerkar and Roberts (2004: pg. 785): based on the IMS (Intercontinental Medical Statistics) database, they identify 45 major therapeutic areas, that however do not correspond to the 85 therapeutic areas of USPTO class 514.[23] Our matching seems to indicate that our algorithmic procedure captures niches that correspond (in number) to the major therapeutic areas identified by Nerkar and Roberts (2004). To further investigate this issue, we apply the clustering procedure to some specific therapeutic areas based on Nerkar and Roberts (2004), such as the 'menstrual disorder' area (corresponding to technological class 514/899), which is clustered by our algorithm together with the related 'contra conceptive' area (514/841) in the first level of the clustering tree. This cluster is then grouped with the 'blood substitute' (514/832) and 'blood plasma extender' (514/833) areas, which are clearly related too. This is an

[16] Technological subclasses have some specific properties. One of these properties is the 'indent level' of the subclass. Quoting from the US classification manual, the indent level "is shown as a series of zero or more dots (periods) immediately preceding the title of the subclass in the class schedule. A subclass having an indent level of zero (i.e., no dots) is called a *mainline subclass*. [Therefore], a mainline subclass *has no parent subclass*. A mainline subclass *directly depends from the class and inherits all the properties of the class*". For more details, see: https://www.uspto.gov/sites/default/files/patents/resources/classification/overview.pdf.

[17] As noted by Yayavaram and Ahuja (2008), assuming that the technological subclasses assigned to patents are elements of knowledge is quite common in the patent literature: as they stress, "the USPTO makes these class assignments. Unlike citations, class assignments should be less prone to bias, as identifying the technology class is likely to be easier than identifying the patents that constitute prior art. Although the USPTO decides which classes are to be assigned to a patent, the researcher or the firm decides which technology elements are to be used in an invention" (Yayavaram and Ahuja, 2008: pg. 346).

[18] Therefore, it is relatively easy for a firm that is patenting in class x to patent in classes that, based on co-occurrences, are close to x.

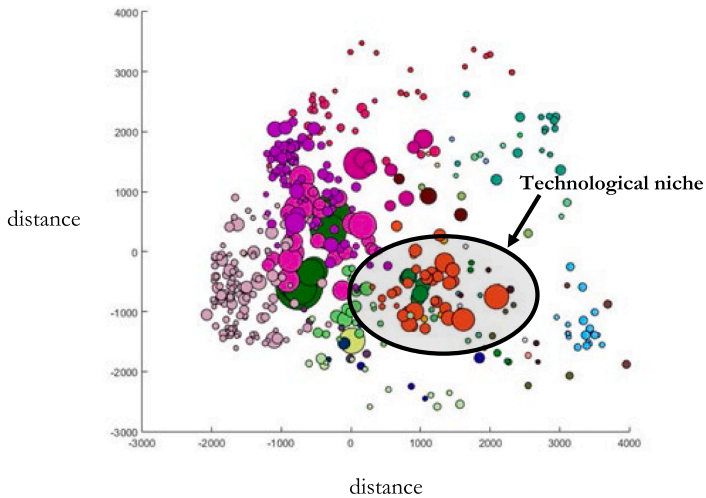
[19] A geodesic is the shortest path between any pair of nodes in a network.

[20] The reason of building a second coupling network based on geodesics is that a coupling network based on co-occurrences would not allow us to assign distances to main-line subclasses that are isolated.

[21] Procedures such as the Calinski-Harabasz evaluation, or those based on silhouette analysis, stability of clusters, homogeneity of clusters' size, within- and across-clusters differences, et cetera.

[22] Some procedures reveal unstable patterns, perhaps due to the underlying structural characteristics of the patent system that disrupt optimization, such as the existence of technological classes that refer to chemical structures *and* other classes that refer to therapeutic functions (or to other sources of intrinsic heterogeneity).

[23] Technological subclasses inside a class, like class 514, consist of both 'functional areas' (referring to the molecular and chemical structure of the invention) and 'application areas' of technology (referring to therapeutic areas). When matching firms' patents to technological subclasses, we did not distinguish between functional areas and application areas, for three main reasons. First, because application areas are lower in number than functional areas. Second, because functional areas, although indirectly and un-observably, may be linked with therapeutic applications, considering that different molecular and chemical structures may radiate into different therapeutic applications. Third, because our theoretical constructs (niche diversity and crowding) do not require us to distinguish between functional areas and application areas.



Two-dimensional representation of distances among technological main-line subclasses (represented by circles), of the frequency of patenting inside them (size of circles), and of clusters/niches (groups of circles with the same colours). The niches refer to year 1995.

Fig. 2. Niches in the technological space.

Table 1 (A)
Descriptive statistics.

Variable	Mean	S. Dev	Min	Max	Median	Skew.
Entry	0.429	0.495	0.000	1.000	0.000	0.285
Exploration	0.444	0.501	0.000	1.000	0.000	0.218
Technological diversity	-1.393	0.645	-2.416	1.064	-1.498	0.855
Technological crowding	-1.480	2.196	-10.033	2.797	-1.218	-0.924
Generalism	0.156	0.145	0.020	1.000	0.111	3.226
Firm R&D	0.522	1.018	0.000	19.855	0.267	9.867
Firm sales	0.978	2.197	0.000	87.500	0.582	31.462
Firm age	7.698	6.530	1.000	36.000	5.500	1.496
Firm size	6.364	16.395	0.000	107.517	0.165	3.107
Number of previous niches	0.204	0.174	0.025	0.903	0.150	2.085
General speed of patenting	2.443	4.292	0.000	40.333	1.176	4.928
Number of patents	158.8	516.4	2.000	5805.0	11.000	5.393
Targeted entries	0.136	0.434	0.000	4.000	0.000	4.012
Niche centrality	6994.8	762.5	5062.9	8474.8	6936.5	-0.083
Number of entries	0.679	0.964	0.000	5.000	0.000	1.588
Scientific references (pull factors)	0.163	1.114	-3.584	3.829	0.140	-0.457
Number of firms (competition)	22.868	39.776	0.000	266.000	8.000	3.273
Technological diversity (Herfindal)	1.480	0.372	0.563	2.316	1.488	0.078

indication that our clustering procedure also forms meaningful clusters, as it groups therapeutic areas (and their corresponding classes) according to their similarity.

Entry and exploration. We define entry as a firm's entry in a technological niche that is new-to-the-firm and, in addition, features a slow, post-entry, reaction time. The firm enters in a new niche meaning that it patents in the new niche for the first time, which in turn means that the patent is fully or partially classified in the new niche. We also consider the firm's reaction time: the underlying logic is that, when the niche in which the firm enters is new-to-the-firm, the firm will need time to react after the entry, to understand the new niche and analyze its potential before allocating additional resources for further exploration. In addition, as shown in the results and discussion section and related appendix, such entries have special features due to a variety of underlying inventive processes that may delay post-entry exploration. An example is that of Corning's entry from specialty glass into fibre optics: after it entered the new niche for the first time, it took time for the firm to further explore it. Corning's manufacturing of specialty glass was based on a 'vapour deposition' method that resulted useful in the manufacturing of glass fibres. Corning's glass fibres were embodied in a set of key entry patents granted in 1973. After these entry patents, though, Corning had to figure out several challenges that slowed down further development until the 80s, like the technical challenges related to high production temperatures and the reflective index of glass (Cattani, 2006). Other examples of time lags in the development of technology come from different industries, like the video tape-recorder, Du Pont's Kevlar, and

Intel's Pentium microprocessor (Garud and Nayyar, 1994).

Regarding the firm's reaction time, we measure the time to arrive to another patent or not followed by any other patent. If the entry patent is followed by another patent, we count the number of months between the entry patent and the other patent in the same niche and compare it to the average speed of patenting between subsequent patents. That is, we measure if the time to arrive to the other patent is considerably longer than the average time occurring between subsequent patents of the firm in the same niche. More precisely, we measure if the firm's reaction time is more than two standard deviations (and thus significantly) longer than the time between subsequent patents in the same niche by the focal firm. If the entry patent is not followed by another patent, that means that the reaction time becomes indefinitely long. Therefore, entry does not imply that the firm patents at least twice in a new niche, because there could be a firm that patents only once and never does it again (until the end of our observed data). In other words, entry also includes instances of single patenting. That is why we analyze what pushes firms to further explore the niche, as we do in the second part of that analysis, where we look at the effect of crowding.[24]

Finally, we measure the firm's exploration of the new niche by looking at whether the firm patents in the new niche, conditional on having entered. That is, if the firm enters, it may further (and slowly) explore the niche or not. Therefore, we do not model the timing (or duration) of exploration, but only whether the firm further explores the niche or not. These variables have a dummy structure: the firm's entry is 1 if the firm enters in new niches, and 0 otherwise; the firm's exploration is 1 if the firm further explores the new niche, and 0 otherwise.

Technological diversity. The technological niche is a system consisting of several related technological inventions (in the form of patents) apportioned into categories (technological subclasses). Technological diversity is a niche-level property given by the 'disparity' (Stirling, 2007) of the technological subclasses that compose the niche. Ideally, we could measure disparity by calculating distances among subclasses in the technological space, but there isn't a straightforward distance metric that is incorporated in the raw patent classification system (Bar and Leiponen, 2012). Therefore, we build on Hidalgo and Hausmann (2009), who proposed a measure of the diversity of a country's economy that is becoming increasingly common in innovation studies (Morrison et al., 2017).

We measure the technological diversity of a niche as the degree to which the niche is composed of disparate technological subclasses: that is, technological subclasses that differ among each other as the result of being singular, or *distinctive*, which makes them less common. More specifically, we measure the technological diversity of a niche as the average distinctiveness of the niche's technological subclasses. The distinctiveness of a technological subclass, in turn, is a function of the number of firms that specialize into it, whereby 'firm specializing in a subclass' means that the firm's proportion of patents in the subclass is higher than the industry's proportion of patents in the subclass. Higher distinctiveness of a technological subclass, by requiring distinctive capabilities to operate into it, makes the subclass less common, as proxied by a lower number of firms that specialize into it and by the fact that these firms, thanks to their distinctive capabilities, are active in several other subclasses (see: Hidalgo and Hausmann., 2009; Hausmann et al., 2014).[25] To give a simple example, we could think about a distinctive technological subclass as a distinctive concept, or idea: a concept is distinctive when a few people are able to assemble it because they are gifted, so these gifted people are also able to assemble several other concepts, while other (less gifted) people are not able to do this, which means that the focal concept is truly distinctive (Hausmann et al., 2014).

The measure is constructed as follows:

$$nd_{it} = \frac{1}{S}\sum_{s=1}^{S} d_s$$

where nd stands for niche diversity, i stands for firm i, t stands for time t, S stands for the number of main-line technological subclasses in the niche, and d_s is the distinctiveness of technological subclass s, which is a function of the firms that specialize in the technological subclass and of the other technological subclasses in which these firms specialize, as explained above.[26] [27] The measure is calculated using previous data belonging to a 10-years window preceding t[28] and, as is Hausmann et al. (2014), is standardized. Summing up, according to the measure, when the average distinctiveness of the technological subclasses that compose the niche increases, the diversity of the niche increases.[29]

Technological crowding. To measure the niche's technological crowding, we follow the approach proposed by Stuart (1999). For a given firm in a niche at a given time, we measure crowding in terms of the overlap of the firm's patent portfolio with the patent portfolios of the

[24] Therefore, for the sake of clarity, entry is 1 if the firm enters a new-to-the-firm niche with a single patent or with a patent *slowly* followed by another patent, while it is 0 if the firm does not enter or it enters with a patent *immediately* followed by another patent. Does an increase in diversity increase the likelihood that entry takes the value of 1 (according to hypothesis 1)? Conditional on entry equal to 1, does an increase in crowding increase the likelihood that the first patent is *slowly* followed by other patents (according to hypothesis 2)?

[25] If firms are active in several other subclasses thanks to their distinctive capabilities, it is likely that the focal subclass is less populated because it (also) requires distinctive capabilities—thus being *truly* distinctive, instead of being less populated for other reasons, like firms' (dis)abilities or unwillingness to populate the subclass.

[26] To get a better grasp of how distinctiveness is calculated, we can think of firms and technological subclasses in terms of a matrix whose rows are firms and columns are subclasses, in which cell i,j is 1 if firm i specializes in subclass j and 0 otherwise. In a nutshell, high subclass distinctiveness means that the number of 1s in the respective column would be low (i.e., few firms are specialized in the subclass) and the number of 1s in the corresponding rows would be high (i.e., these firms specialize in many other subclasses). The matrix is the input of an iterative converging procedure, known as 'method of reflections', that extracts information from the matrix with the aim of improving the precision of the distinctiveness metric. For more details, we refer to Hausmann et al. (2014, pg. 24), Hidalgo and Hausmann (2009, pg. 10571) and related appendix.

[27] When firms are active in more than one niche, technological diversity is calculated as the weighted average diversity over all niches in which the firm is active, with weights given by the size (number of patents) of the respective niches.

[28] We use a 10-years window also for technological crowding and generalism. Patent research seems to rely on shorter windows but there is no accepted standard: e.g., see Yayavaram and Ahuja (2008) versus Fleming and Sorenson (2001). In un-tabulated analyses that were conducted in previous phases, we experimented with different time windows. We did not observe changes in the main results.

[29] As explained in the results section, we conduct a set of additional analyses, in which we replace the technological diversity measure with a standard Herfindal index. We thank one of the reviewers for this suggestion. The Herfindal index, though, captures just one specific dimension of diversity (Stirling, 2007): namely, the 'balance' of elements across the categories that compose the niche. Moreover, in our setting, the Herfindal index is based on unworkable assumptions: namely, that the different categories (subclasses), among which elements (patents or firms) are distributed, are 'equally different' among each other. However, patent subclasses are 'differently different' among each other because there is no distance metric that is incorporated in the raw patent classification system. Therefore, we cannot easily capture technological diversity in terms of variety, balance, or classical distances. That is why we opted for the Hidalgo and Hausmann (2009)' approach.

other firms in the niche at that time. We measure the overlap of patent portfolios in terms of common backward patent citations. Therefore, the measure is constructed as follows:

$$\mathrm{nc}_{\mathrm{it}} = \sum_{j=1}^{N} a_{ijt}$$

where nc stands for niche crowding, i stands for firm i, t stands for time t, and a_{ijt} is the overlap between the patent portfolio of firm i and another firm j in the niche at time t. a_{ijt} is the ratio between the backward citations that firm i's patent portfolio has in common with firm j's patent portfolio at time t and the total number of backward citations of firm i's patent portfolio.[30] [31] We take a logarithmic transformation of the measure that, like the previous ones, is calculated using a window of 10 years preceding t. Overall, the measure assumes that when a dyad of firms builds on common knowledge from the same patents, the spillovers and competitive pressure faced by firms increases.

Generalism. To measure firm's generalism, we use a Herfindahl index approach. For a given firm in a niche at a given time, we measure generalism in terms of the dispersion of firm's patents across the different technological subclasses that compose the firm's patent portfolio. Therefore, the measure is calculated as follows:

$$\mathrm{fg}_{\mathrm{it}} = \sum_{s=1}^{S} p_s^2$$

where fg stands for firm generalism, i stands for firm i, t stands for time t, S stands for the number of main-line subclasses in the portfolio, and p_s^2 is the share of firm's patents in subclass s. The index is bounded in the [0 1] interval and, when it decreases, generalism increases. Like the previous two measures, this measure is calculated using a window of 10 years preceding t. Overall, the measure assumes that when the dispersion of patents across the subclasses of the patent portfolio of the firm increases, knowledge generalism goes up.

Control variables. We introduce several controls in our models, to rule out factors that may be correlated with our independent variables and, at the same time, with entry and exploration.

First, we control for standard firm-level characteristics, as in previous research. We control for *firm R&D*, defined as research and development expenses over total assets. We control for *firm performance*, defined as sales over total assets. We control for *firm age*, defined as the number of years that the firm has been active in patenting. We control for *firm size*, defined as the logarithm of the number of employees.

Second, we control for more specific firm-level characteristics. We control for the *number of previous niches*, defined as the number of niches in which the firm was active before the focal year, because a firm may enter in a new niche just because before it was active in few niches, compared to a firm that may not enter in a new niche because before it was active in many niches (and fewer niches were thus 'left free' for entry). We control for the *general speed of patenting*, defined as the firm's average reaction time between patents and measured before the focal year, to rule out systematic sources of variation that may affect exploration. We control for the *number of patents*, defined as the size of the firm's patent portfolio before the focal year. We control for *targeted entries* in the focal year, to capture the firm's 'exploratory predisposition' towards niches, and thus control for the fact that entry in a new niche might be result from the intentional exploration of the (larger) technological landscape.[32]

Third, we control for niche-level features. We control for *niche centrality*: we consider a niche to be central when it is near to other niches. That is, a niche is near to other niches when there is a short distance—in terms of technological combinability—between the niche and the other niches. Therefore, when the niche is near to other niches, it should be easier for firms in the niche to enter the other niches. We also control, in the entry models of hypotheses 1 and 3a, for *technological crowding*, since entry in a new niche could be due to other reasons besides current niche's diversity, like current niche's crowding, which could push—and, broadly speaking, motivate—firms in a highly contested area to diversify into (and thus enter) a new niche. Similarly, we control, in the exploration models of hypothesis 2 and 3b, for *technological diversity*, since exploration of the new niche could be due to other reasons besides current niche's crowding, like current niche's diversity, which could enrich the set of available ideas, techniques, problem-solving tools—and, broadly speaking, abilities—needed to successfully explore the new niche. In addition, in the models of hypotheses 2 and 3b, we control for the *number of entries*, because entering in more than one niche may affect how the firm responds to crowding levels.

Finally, since we aim to complement prior work on environmental pull factors (Leten et al., 2016) by examining the effect of environmental push factors, we control for pull factors. According to our theory, conditional on entry in a new niche (spurred by the current niche's technological diversity), current niche's technological crowding *pushes* the firm to further explore the new niche. Yet besides being pushed towards it, the firm may explore the new niche because it is pulled by it due to its attractiveness. We thus control for pull factors, building on Leten et al. (2016), who suggest measuring variations between technological niches in technological opportunities "by differences in the importance of science as a source of relevant knowledge" (pg. 1271). More specifically, we approximated the degree of technological opportunities in niches by calculating the logged average number of citations to *scientific references* in patent documents (Leten et al., 2016).[33] In addition, we control for technological competition in the new niche, which could deter further exploration of the new niche—as shown in the work of Leten et al. (2016), thus offsetting the attractiveness effect. To measure the degree of technological competition in the new niche, we opted for a proxy given by the *number of firms* active in the new niche, whereby firm active in the new niche means that the firm has patented into the new niche in the 10 years preceding the entry event.

[30] To calculate technological crowding, we identify the niche (or niches) in which the focal firm is active, then we identify the other firms that are active in the niche(s), after which we calculate the overlap—in terms of common backward citations—of the focal firm's patent portfolio with those of the other firms that are active in the niche(s), according to the $\mathrm{nc}_{\mathrm{it}}$ formula.

[31] Since a_{ijt} is the *ratio* between common and total backward citations, and the number of total backward citations systematically increases with the number of firms' patents, the crowding measure is scaled. That is, the measure should not take higher values for firms that are part of a technological niche in which the other members of the niche have lots of patents. An alternative way to scale this measure could consist in comparing the observed share of common patent citations with an expected share of common patent citations based on the size of patenting in the niche and random assignment of citations. We leave it to future researchers, and we thank one of the reviewers for this suggestion.

[32] The dependent variable deals with entry in a technological niche that is new-to-the-firm and features a slow, post-entry, reaction time (due to outlier-type processes: see the first paragraph of 'results and discussion' and the related appendix), while this control deals with entries that do not have such features and thus aims to capture firm's exploratory predispositions (or targeted activities) towards new niches, with the aim of filtering out these exploratory predispositions from outlier patenting. The fact that a firm enters in a new-to-the-firm niche with slow, post-entry, reaction time, does not imply targeted entries in other niches; vice versa, targeted entries in other niches do not imply that the firm enters in a new-to-the-firm niche with slow, post-entry, reaction time.

[33] There are two main ways through which science creates technological opportunities: first, it enriches the toolbox of theories, data, and problem-solving techniques that industrial R&D can use; second, new scientific insights can open radically new trajectories (Leten et al., 2016).

3.3. Data analysis: models

To test hypotheses 1 and 3a, we run the following econometric models:

$$p\ (y_{i,t}=1)=\Phi(\alpha+\beta_1 nd_{i,t}+\beta_2 Z+\varepsilon_{i,t})$$

for hypothesis 1, where $y_{i,t}$ is a binary outcome equal to 1 if firm i at time t enters in a new niche as explained previously, and 0 otherwise, $nd_{i,t}$ is the technological diversity of the firm's current niche at time t, Z is the vector of control variables, $\varepsilon_{i,t}$ is the error term and ϕ is a probit function. For hypothesis 3a we augment the model as follows:

$$p\ (y_{i,t}=1)=\Phi(\alpha+\beta_1 nd_{i,t}+\beta_2 fg_{i,t}+\beta_3 nd_{i,t}fg_{i,t}+\beta_4 Z+\varepsilon_{i,t})$$

where $y_{i,t}$, $nd_{i,t}$ and Z are the same as before, $fg_{i,t}$ is the generalism of firm i at time t, $nd_{i,t}fg_{i,t}$ is the interaction between technological diversity and generalism.

To test hypothesis 2 and 3b, we run the following econometric models:

$$p\ (y_i=1)=\Phi(\alpha+\beta_1 nc_{i,t}+\beta_2 Z+\varepsilon)$$

for hypothesis 2, where y_i is a binary outcome equal to 1 if firm i, conditional on entry, further explores the niche hereafter, and 0 otherwise, $nc_{i,t}$ is the technological crowding of the firm's current niche measured before entry (denoted by t), Z is the vector of control variables, ε is the error term and ϕ is a probit function. For hypothesis 3b we augment the model as follows:

$$p(y_i=1)=\Phi(\alpha+\beta_1 nc_{i,t}+\beta_2 fg_{i,t}+\beta_3 nc_{i,t}fg_{i,t}+\beta_4 Z+\varepsilon)$$

where y_i, $nc_{i,t}$ and Z are the same as before, $fg_{i,t}$ is the generalism of firm i measured before entry (denoted by t), $nc_{i,t}fg_{i,t}$ is the interaction between technological crowding and generalism.

4. Results and discussion

Descriptive statistics are reported in Table 1 (A) and correlations in Table 1 (B).[34] As we can notice in Table 1 (A), the mean value of entry is 0.42, while the mean value of the number of entries is 0.68. Since entries are in technological niches that are new-to-the-firm and feature a slow, post-entry, reaction time, we aimed to investigate if such entries have special features. To investigate this issue, we correlated our measure of entry with a replication of Kneeland et al. (2020)' measure of outlier patents, defined (in their paper) as those patents that differ significantly from other patents in the technological space, due to a variety of underlying—and special—inventive processes: namely, distant recombination, long search paths, or serendipity. We replicated that measure by defining outlier patents as those patents that differ significantly from other patents in the firm's technological knowledge base. The results, un-tabulated,[35] showed a substantial correlation between entries and outlier patents (Kneeland et al., 2020). This seems to indicate that entries are associated to the inventive processes that underlie outlier patenting: namely, distant recombination, long search paths, or serendipity (Kneeland et al., 2020). Due to lack of granularity in our data, we are certainly unable to identify *the* exact process, but entries do seem to exhibit special features. Entries seem to be associated with (underlying) serendipitous processes, thus raising interesting implications that are discussed in the final section. For more details, we refer to the Appendix contained in the Supplement, where we complement this replication exercise with a qualitative example and a text-mining analysis.

The results of hypotheses 1 and 3a are reported in Table 2, where model 4 reports the full specification of a panel probit regression with random effects and robust standard errors, based on a sample of 340 firms and 1954 firm-year observations. Model 5, instead, reports the full specification of a negative binomial model in which the dependent variable is, rather than a dummy, a *count* of how many times the firm enters in new niches. The binary outcome is equal to 1 if the firm enters in a new niche in year *t* or *t+1* or *t+2* as explained previously, and 0 otherwise, with a lag sufficient for the dependent variable to reflect eventual delays in the firm's processing of technological information. In robustness analyses (explained later), we vary the length of delays and our results do not change substantially. As we can see in model 4, the coefficient of technological diversity is positive and significant, which means that technological diversity is positively correlated with the probability of entering in a new niche with a lagged reaction, in line with hypothesis 1. To appraise the magnitude of the predictor, we also calculated the marginal effect, and found that the probability of entry increases by about 0.18 when technological diversity increases by one standard deviation, keeping all the other predictors constant at their means. Furthermore, as we can see in the same table, the coefficient of technological crowding is also positive and significant, suggesting that increasing competitive pressures in the current niche not only affect the decision to further explore new niches but also that of entering them. To test the moderating influence of generalism, we relied on the framework of Ai and Norton (2003) implemented as in Norton et al. (2004), which consists in checking the sign and significance of the cross-derivative of the conditional mean function with respect to the two interacted variables. Since generalism is based on a Herfindal index, meaning that generalism increases as the index decreases, a *negative* sign of the interaction coefficient is indicative of a positive moderation effect that would be consistent with hypothesis 3a. We found that the interaction coefficient is always negative (with a mean of about −0.24), in line with hypothesis 3a, and is significant for those firms with a predicted probability of entering a new niche below 0.3 or above 0.8, suggesting that generalism plays a role especially for firms with either a low or high likelihood of entry.

The results of hypotheses 2 and 3b are reported in Table 3, where model 5 reports the full specification. We test if, conditional on entry in a niche, the firm further explores the niche hereafter or not. The level of analysis is the firm-technology level, with one observation per new niche entered by a firm, and with the dependent variable measuring if the firm further patents in the new niche or not. Since the firm may have entered in more than one niche each year, a panel specification is not appropriate. We thus run standard probit regressions augmented with firm dummies and entry-year dummies.[36] Since the analysis is conditional on entry, the sample reduces to 133 firms and 1061 observations. Although we cannot draw strong conclusions, due to the different model specification and the reduced sample, model 5 shows that the coefficient of technological crowding is positive and significant, which means that technological crowding is positively correlated with the probability that the firm, conditional on entry, further explores the niche, in line with

[34] The matrix reports the correlations among predictors. In previous analyses, we computed the 'variance inflation factor' (VIF) of each predictor (unreported). VIF are computed to rule out multi-collinearity. In particular, the VIF of a predictor measures how much the variance of the estimated coefficient increases due to its correlation with the other predictors. In our case, all the VIF were below the value of 10 and, with a single exception, they were all ≤ 4. Based on VIF analysis, this indicates that multi-collinearity is not a concern.

[35] Available upon request to the authors.

[36] Since the analysis is at the firm-technology level, we could also include niche dummies, as suggested by a reviewer. We did not include niche dummies due to instances of perfect collinearity of niche dummies with entry-year dummies that, by removing observations from the regression model, significantly reduce the sample. For example, this happens when two firms enter the same niche in the same year and they are the only ones (since entries are rare events: see first paragraph of 'results and discussion'), where this implies that dummy vectors are in a deterministic relationship.

Table 1 (B)
Correlation matrix.

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1 Technological diversity	1														
2 Technological crowding	-0.1536*	1													
3 Generalism	0.0756*	-0.4426*	1												
4 Firm R&D	-0.0836*	-0.0864*	0.1082*	1											
5 Firm sales	0.1558*	-0.0568*	-0,0074	0.0832*	1										
6 Firm age	0.1914*	0.3680*	-0.3095*	-0.1290*	0.2098*	1									
7 Firm size	0.1850*	0.3683*	-0.2423*	-0.1266*	0.1549*	0.5198*	1								
8 Number of previous niches	0.2404*	0.5294*	-0.4397*	-0.1458*	0.1555*	0.7839*	0.7270*	1							
9 General speed of patenting	0.0785*	-0.3706*	0.3496*	0,0276	0.1148*	0.0464*	-0.1733*	-0.2649*	1						
10 Number of patents	0.1001*	0.3895*	-0.2144*	-0.0851*	0.1215*	0.6587*	0.6290*	0.7769*	-0.1603*	1					
11 Targeted entries	0,0086	0,0267	0,032	0,0443	-0,019	-0.1262*	0.0949*	-0.0492*	-0.0571*	-0,036	1				
12 Niche centrality	0.6058*	-0.1196*	-0.1255*	-0.1153*	0.1379*	0.1032*	0.1350*	0.2122*	-0.0459*	0.0635*	0.0510*	1			
13 Number of entries	0.0558*	0.1486*	-0.0561*	-0,0344	-0,0022	-0.0446*	0.1608*	0.0640*	-0.1321*	0,0398	0.1800*	0.0677*	1		
14 Scientific references	-0,0413	-0.0473*	0,0444	0,0445	-0,0336	-0.0643*	-0.0776*	-0.1041*	-0,0031	-0.0608*	0,0419	-0.0939*	0,0291	1	
15 Number of firms	-0.1246*	-0.0990*	0.1043*	0.0712*	-0.0460*	-0.1481*	-0.1334*	-0.1969*	0.0457*	-0.1272*	0.0447*	-0.1808*	-0,0137	0.5507*	1

*$p < 0.05$.

hypothesis 2. To appraise the magnitude of the predictor, we also calculated the marginal effect, and found that the probability of niche exploration increases by about 0.10 when technological crowding increases by one unit, keeping all the other predictors constant at their means. Furthermore, as we can see in the same table, the coefficient of technological diversity is also positive and significant, suggesting that increasing technological opportunities in the current niche not only affect the ability to enter new niches but also that of further exploring them. To test the moderating influence of generalism, we relied on the framework of Ai and Norton (2003) implemented as in Norton et al. (2004). Again, since generalism is based on a Herfindal index, meaning that generalism increases as the index decreases, a *negative* sign of the interaction coefficient is indicative of a positive moderation effect that would be inconsistent with hypothesis 3b. We found that the interaction coefficient is negative (with a mean of -0.02) for those firms with a predicted probability of exploring the new niche above 0.2 and is significant across the full range of variation of predicted probabilities. Since the sign is the opposite of the expected one, except for a few observations, hypothesis 3b is not supported.

5. Additional findings

We conducted several additional analyses. A first concern is related to the role of *strategic patenting*. Although we control for several variables, entry in a new niche (and the time elapsed between the first and the second patent in the same niche) can be due to other unobservable factors. A firm may pre-emptively—and thus strategically—file a patent in a new niche, just to prevent competitors from doing so, by occupying certain areas of the technological space. Typically, strategic patenting takes place in those areas of the technological space that are 'dense' (Shapiro, 2000; Von Graevenitz et al., 2011). To rule out strategic patenting, we identified the focal technological subclass of entry within the niche; then, we counted the number of firms populating the subclass, every year; then, we counted the number of firms populating the other subclasses and took the median; therefore, we classified the focal subclass as populated if the number of firms inside is higher than the median; based on this, we ran again the models by excluding entries in populated niches, thus ruling out entries that could be due to strategic patenting. The results, reported in model 3 of Table S1 in the Supplement, are in line with those of Table 2: technological diversity is positive and significant and the interaction between technological diversity and generalism is negative and significant, consistent with hypotheses 1 and 3a. The results also hold when considering the count of entries (rather than the entry dummy) as the dependent variable.[37]

A second concern is related to niche's technological diversity, which we measured as the disparity of the technological subclasses that compose the niche. We ran again the models, replacing technological diversity with an alternative measure based on a standard *Herfindal index*, with the aim of capturing another dimension of diversity—the balance of elements across technological subclasses—that is less important in our theory yet worth exploring.[38] More specifically, we measured technological diversity as follows: $nd_t = \sum_{s=1}^{S} p_s^2$, where S stands for the number of main-line subclasses in the niche, s denotes a subclass and p is the share of firms in the subclass: the higher is the dispersion of firms across subclasses, the lower is the Herfindal, the higher is technological diversity, meaning that a lower Herfindal leads

[37] Un-tabulated results. Results did not vary substantially when we considered the number of patents—rather than the number of firms—in a subclass, to estimate how much it is populated.

[38] We thank one of the reviewers for this suggestion.

Table 2
Main results (first and third hypothesis).Probit regression (models 1 to 4) and negative binomial regression (model 5).

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Technological diversity			0.239***	0.420***	0.403***
			(0.090)	(0.119)	(0.101)
Generalism		0.546	0.356	-0.694	-0.516
		(0.420)	(0.429)	(0.619)	(0.544)
Interaction diversity X generalism				-0.855**	-0.745**
				(0.367)	(0.339)
Technological crowding	0.130***	0.139***	0.145***	0.150***	0.132***
	(0.028)	(0.029)	(0.029)	(0.029)	(0.027)
Firm R&D	-0.011	-0.013	-0.012	-0.002	0.017
	(0.041)	(0.041)	(0.041)	(0.041)	(0.037)
Firm sales	-0.033	-0.034	-0.048	-0.047	-0.022
	(0.058)	(0.058)	(0.059)	(0.060)	(0.043)
Firm age	-0.026*	-0.024*	-0.024*	-0.021	-0.017
	(0.014)	(0.014)	(0.014)	(0.015)	(0.013)
Firm size	0.025***	0.025***	0.025***	0.024***	0.021***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
Number of previous niches	-3.385***	-3.254***	-3.562***	-3.787***	-3.294***
	(0.742)	(0.751)	(0.764)	(0.770)	(0.611)
General speed of patenting	-0.034**	-0.038***	-0.039***	-0.045***	-0.043***
	(0.014)	(0.014)	(0.014)	(0.015)	(0.016)
Number of patents	0.000***	0.000***	0.000***	0.001***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Targeted entries	0.332***	0.324***	0.326***	0.321***	0.130**
	(0.089)	(0.089)	(0.090)	(0.090)	(0.058)
Niche centrality	0.000***	0.000***	0.000***	0.000***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-1.402***	-1.566***	-0.402	-0.149	15.363
	(0.433)	(0.456)	(0.628)	(0.636)	(324.506)
Observations	1,954	1,954	1,954	1,954	1,954
Log likelihood	-1171	-1170	-1166	-1163	-2011

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$ (standard errors in parenthesis).

to an increase of entry—and, by implication, a higher Herfindal leads to a decrease of entry, thus implying a negative sign that is consistent with hypothesis 1.[39] [40] The results, reported in model 1 of Table S2 in the Supplement, show that the coefficient of the Herfindal index is negative and significant, consistently with hypothesis 1. The coefficients of generalism and of its interaction with technological diversity in models 2 and 3, though, become insignificant, thus providing mixing results for hypothesis 3a. These results show that, while firm's knowledge generalism plays a role when dealing with a technologically-diverse niche made of disparate subclasses, because it helps the firm to process disparate pieces of knowledge and establish integrative links among them (in line with hypothesis 3a), it doesn't when a niche is technologically-diverse in terms of balance of elements across subclasses: the reason is that this type of technological diversity does not say much to what extent these subclasses are close and related, or disparate and unrelated. In the end, this underscores that the Herfindal index has somewhat less fit with our theory.

In a third, additional, analysis we tried to capture the *impact of entry* through a study of forward citations. We measured and compared the Alpha centrality (Corredoira and Banerjee, 2015) of entries with that of more regular types of entries (that is, entries that are not characterized by a slow reaction time). Alpha-centrality measures the influence of a patent on future inventions by looking at both the direct and *indirect* forward citations (that is, citations of citations, citations of citations of citations, and so on). Interestingly, as we can see in Fig. S1, in the Supplement, entries are more influential than regular types of entries on future inventions, as reflected in a higher Alpha centrality for different levels of the α parameter, which weights the importance of indirect citations (the higher is the α, the higher is the weight assigned to indirect citations).

We also conducted a series of robustness checks. First, we ran again the models using different econometric specifications. In un-tabulated models, we tried with a logit specification (instead of the probit), and the main results did not change. Additionally, since the models of hypotheses 1 and 3a are based on a panel probit specification with random effects, we also ran a panel linear-probability specification with firm and time fixed effects. The results, reported in models 1 and 2 of Table S3 in The Supplement, are robust under this alternative specification, and remain robust under a panel logit specification with fixed effects, as reported in models 3 and 4 of the same table.[41] In another set of un-tabulated models, we tried to impose a series of conditions on our main dependent variable. More specifically, we measured entry by imposing longer and shorter lags on the dependent variable, to eventually reflect longer or shorter delays in the firm's processing of technological information. Interestingly, we noted stronger effects of technological diversity and of its interaction for longer lags, while for shorter lags the effect of technological diversity was significant only when we removed the interaction. This suggests that technological diversity relates to entry when longer time lags are considered, so that

[39] Alternatively, we could consider the dispersion of patents, rather than firms, across niche's subclasses. Anyway, patents belong to firms, so the dispersion of patents across subclasses is also captured by the dispersion of firms across subclasses. Moreover, by considering firms, we remove the effect due to uneven sizes of patent portfolios (e.g., one big subclass with many patents belonging to the same large firm that would artificially decrease diversity although there could be many other firms scattered across the remaining subclasses).

[40] The calculated measure is a linear transformation of the Herfindal index (Berrebi and Silber, 1985), given by 10*HHI. Without linear transformation, results remain significant and are stronger in magnitude.

[41] There isn't a command for a conditional fixed-effects model in probit, since there isn't a sufficient statistic allowing fixed effects to be conditioned out of the likelihood. In general, the interpretation of fixed effects in non-linear models faces several practical and methodological challenges (Greene, 2002).

Table 3
Main results (second and third hypothesis).Probit regression.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Technological crowding				0.169**	0.201*
				(0.079)	(0.111)
Interaction crowding X generalism					-0.170
					(0.411)
Generalism	0.558	1.132	1.882	2.697*	2.210
	(1.302)	(1.307)	(1.334)	(1.409)	(1.835)
Technological diversity	0.492*	0.467*	0.502*	0.524*	0.521*
	(0.258)	(0.260)	(0.272)	(0.274)	(0.274)
Firm R&D	0.011	-0.006	-0.002	-0.039	-0.030
	(0.125)	(0.124)	(0.124)	(0.132)	(0.133)
Firm sales	-0.112	-0.107	-0.153	-0.111	-0.118
	(0.176)	(0.179)	(0.183)	(0.185)	(0.185)
Firm age	0.042	0.057	0.037	0.024	0.021
	(0.056)	(0.056)	(0.058)	(0.058)	(0.058)
Firm size	-0.038**	-0.036**	-0.036**	-0.040**	-0.040**
	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)
Number of previous niches	-2.204	-1.660	-0.237	-0.601	-0.704
	(1.470)	(1.496)	(1.529)	(1.542)	(1.563)
General speed of patenting	-0.095	-0.123*	-0.120*	-0.140**	-0.140*
	(0.067)	(0.069)	(0.069)	(0.071)	(0.072)
Number of patents	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Targeted entries	0.202*	0.209*	0.251**	0.242**	0.244**
	(0.109)	(0.111)	(0.114)	(0.115)	(0.115)
Niche centrality	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of entries	-0.086	-0.082	-0.061	-0.061	-0.062
	(0.063)	(0.064)	(0.065)	(0.065)	(0.065)
Scientific references (pull factors)		0.269***	0.019	0.018	0.018
		(0.062)	(0.070)	(0.071)	(0.071)
Number of firms (competition)			0.012***	0.012***	0.012***
			(0.002)	(0.002)	(0.002)
Constant	15.667***	16.172***	18.612***	17.886***	18.032***
	(4.810)	(4.829)	(4.945)	(5.000)	(5.016)
Year dummies	Yes	Yes	Yes	Yes	Yes
Firm dummies	Yes	Yes	Yes	Yes	Yes
Observations	1,061	1,061	1,061	1,061	1,061
Log likelihood	-544	-534.1	-505.5	-503.2	-503.1

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$ (standard errors in parenthesis).

technological information can be processed. Second, as mentioned above, we measured entry in terms of a count of how many times the firm enters in a new niche. Again, we did not see changes in our results. We further tested the threshold of entry using one or three standard deviations rather than two and noted a stronger effect of technological diversity when using three standard deviations, a result that is also in line with our theory. For space purposes, all these robustness analyses are not reported here.

6. Conclusions, implications and limitations

Drawing from the technological ecology literature (Coccia, 2019a; Coccia and Watts, 2020; Van den Oord and Van Witteloostuijn, 2017), we developed hypotheses on how two conditions of a firm's current technological niche affect both the firm's entry in a new niche and its further exploration. We found that current niche's technological diversity has a positive effect on firm's entry in a new niche and that, conditional on entry, current niche's technological crowding has a positive effect on firm's further exploration of the new niche. These core findings from our study show that the conditions in a firm's current domain 'push' it into new domains. As we also control for 'pull' factors from the new domain, this indicates that not only the lure and attractiveness of the new domain shapes entry but that also a firm's current domain forms an important entry factor.

Moreover, we found that firm-level knowledge generalism positively moderates the effect of technological diversity on entry, especially for those firms with a predicted probability of entering a new niche that is either low or high. However, firm-level knowledge generalism does not negatively moderate the effect of technological crowding on exploration, as we hypothesized. This result is puzzling yet interesting, as it suggests that alternative mechanisms may play a role. A possible explanation is that, contrary to what we hypothesized, firms with a more generalist knowledge base are in reality *more* willing (and able) to explore new niches, thanks to their diversified knowledge base: this could explain why the observed effect is the opposite of the expected one. Taken together, these results suggest that generalist firms are more advantaged in front of the opportunities offered by an increasingly technologically diverse niche but *not* necessarily disadvantaged when responding to increasing crowding pressures in the niche. This may suggest that generalists, even if they spread their activities across different areas of the technological space (instead of having 'all the eggs in one basket'), aren't less likely to buffer, against increasing crowding levels, by further exploring new niches. That is, generalist firms seem to be more advantaged when both entering *and* exploring new technological niches.

Our paper offers several *contributions*. First, our study contributes to several streams of the innovation literature and to the debate on the evolution of technology (Arthur, 2009; Basalla, 1988; Nelson and Winter 1982; Ziman, 2000), which is receiving increasing attention (Cattani and Mastrogiorgio, 2021) due to the many similarities between biological and technological systems (Coccia, 2017, 2018, 2019b; Hodgson, 2002). As argued by some scholars (Schot and Geels, 2007), though, several processes underlying the evolution of technology remain understudied, whereas the notion of technological niche could represent a 'platform' for a better understanding (Coccia, 2019a; Coccia and Watts, 2020; Van den Oord and Van Witteloostuijn, 2017). Schumpeter, who has inspired the evolutionary tradition since the beginning, once famously coined the term 'recombination' as the search process that leads to new combinations (Schumpeter, 1939, 1942). A dominant stream in the innovation literature has adopted this definition when studying the creation of new innovations and their impact on firms, markets, and industries (Hargadon and Sutton, 1997; Phene et al., 2006). This literature assumes that, when recombining, firms act based on some degree of foresight. In other words, recombination is seen as formed by technological search activities that are conducted in anticipation of an existing opportunity domain. However, in Schumpeter's view and as recently shown by Kneeland et al. (2020), recombination can also consist in the creation of a new combination or application of an existing one in an entirely new technological domain, in ways that are not always foresighted or anticipated. Whereas the dominant focus in the literature has mainly been on the creation of new technologies through mostly targeted activities, much less emphasis has been placed on Schumpeter's third type of innovation, formed by the creation of new technologies in entirely new technological domains, in ways that are not always foresighted or anticipated (Schumpeter, 1942). Such processes suggest, though, that a firm's recombination activities may not be simply pulled by the new technological domain, because another type of mechanism also plays a role. Instead of the 'pull' by the new technological domain, as emphasized in the literature thus far (Leten et al., 2016), we have argued and shown that 'push' factors in the firm's current technological domain also matter. We have done it under the lens of technological ecology.

Related to the arguments above, our paper also contributes to the emerging literature on serendipitous innovation (Andriani et al., 2017; Cunha et al., 2010; Merton and Barber, 2004; Meyers, 2007; Murayama et al., 2015) and on the role of accidentality and un-intendedness in the innovation process (Austin et al., 2012; Seo et al., 2017). As shown in the Appendix contained in the Supplement, our measure of entry in new niches correlates with a replication of outlier patenting (Kneeland et al., 2020). This seems to indicate that entries in new niches are associated to the inventive processes that underlie outlier patenting: namely, distant recombination, long search paths, or serendipity, as also confirmed by the qualitative example and the text mining analysis. Based on this evidence, we believe that our paper contributes to the serendipity literature by showing how specific niche-level drivers (technological diversity), in combination with firm's knowledge generalism, are conducive to *possibly* serendipitous accesses in new niches, which could be seen as 'growth options' in new domains (Bowman and Hurry, 1993; Sakhartov and Folta, 2014) whose activation—via further niche exploration—is a function of crowding levels in the current niche. In this way, we unpack and shed light on some poorly understood mechanisms through which firms expand into new areas of the technological space. This, in turn, raises implications, like the need to abandon the linear model of R&D targeted towards restrictive goals and to substitute it with increasing freedom of experimentation in organizations. Another key implication is the adoption of research policies that foster technological diversity—and, consequently, serendipity—in niches, regions, and broader innovation ecosystems (Granstrand and Holgersson, 2020), thus unlocking the power of contextual drivers in the generation of novelty (Andriani et al., 2017). As noted by Morescalchi and Hardeman (2015), "technological diversity potentially offers the seeds for turning existing technologies into new and unexpected directions and therewith renders major opportunities to un-lock prevailing technological trajectories" (pg. 4). Despite the potential of diversity and the increasing adoption of research policies that specifically aim to cross-fertilize technologies (OECD, 2013), research on how diversity effects propagate across niches is still limited.

Our study has several managerial *implications* as well as policy implications. Regarding managerial implications, our study shows the importance of awareness that firms should have of the technological opportunities in their current niche as well as of the strategic behaviour that (some of) their competitors, operating in the same niche, can exhibit. To the extent that the current niche becomes more technologically diverse as well as crowded and hence competitive, more and more firms will start to pursue opportunities elsewhere. This implies for managers that when they tend to ignore other niches, they are likely to find out that others may have already entered one or more of these new niches (well) before them, and possibly have also built up a position herein through its further exploration. By the time they come to realize this, they may find out that they are already late in the game. This means that also when a firm's current niche is technologically diverse but still relatively uncrowded, managers should avoid to overly focus on this current niche, yet also spend enough time and attention on looking for new opportunities elsewhere and consider the potential entry, and subsequent exploration, of new niches, even though they may not feel the pressure at the current moment. Accomplishing such strategies is supported to the extent that a firm has a higher degree of knowledge generalism and related organizational arrangements, which contributes to seeing new opportunities, whereas it does also suppress the 'reflex' to stay only focused on a firm's current niche, as the results show.

Although our study relies on patent data from the U.S. pharmaceutical industry, it also informs technology and innovation policy in other countries. Innovation in the pharmaceutical industry follows largely a so-called 'science-based' innovation pattern (Marsili, 2001; Pavitt, 1984). This is a pattern that is characterized by a relatively strong dependency on external sources of knowledge for innovation such as universities, public research institutes and research-intensive firms (Coriat and Weinstein, 2001; Marsili, 2001; Nikulainen and Palmberg, 2010; Pavitt, 1984). This contribution of academic research is large and entails (highly) scientific, basic knowledge, often in highly codified form (Cohen et al., 2002; McMillan et al., 2000). This is a key sectoral characteristic that has a structure and life of its own in this industry (Coriat and Weinstein, 2001), making it also exceed the role of (some) national institutions that characterize a country's national system of innovation (Mowery and Nelson, 1999). This applies the more so for a science-based pattern like pharmaceuticals, as this is also (heavily) influenced by knowledge inflows from outside the national territory, and vice versa. This implies that our theoretical logic and the empirical regularities we have identified based on our dataset may also hold for other countries. Yet, a generic difference between the U.S. national system of innovation and most other countries' is that both the degree of technological opportunities and of competition among firms might be more pronounced in the U.S. (Mowery and Rosenberg, 1993). The consequence may be that our sample shows both higher degrees of technological diversity as well as higher degrees of technological crowding. Overall, this suggests that our findings and conclusions on the U.S. context may be like other countries in terms of kind, but not necessarily in degree. In other words, given some of the more generic similarities in pharmaceuticals across different countries, we expect our findings and conclusions to hold in terms of their underlying logic, yet we also expect differences as far the size of the pronounced effects of niche's technological diversity and crowding are concerned. We expect these effects to be generally somewhat less pronounced in most other countries than the U.S. because we expect the average levels of both niche diversity and crowding to be somewhat lower, due to a generally lower degree of technological opportunities and competition among firms. For other countries and their standing technology and innovation policy, this does offer an interesting and useful insight though, namely that an important way to stimulate more distant and larger types of innovations in their national system of innovation can be formed by increasing and stimulating technological opportunities and competition, as this can stimulate diversity and crowding in a domain. Whereas stimulating competition is generally not considered by innovation policy makers as a key instrument in their toolbox to boost innovation (e.g., Borras and Edquist, 2017), our study shows that it may be worthwhile to reconsider this assumption.

Our paper also has several *limitations*. First, from a theoretical viewpoint, we argue for an effect of technological diversity on entry and, conditional on entry, an effect of technological crowding on exploration. However, our results show that entry and exploration are also, respectively, affected by technological crowding and diversity, suggesting that a more comprehensive framework of how push factors interact among each other (and how push factors interact with pull factors) is highly needed, in order to better understand how firms grow in the technological space that surrounds them.[42 43] From an empirical viewpoint, a first limitation is that we only rely on patent data. Although patent data are being used in very innovative ways (Caviggioli, 2016; Huang and Su, 2019; Lee et al., 2020), they are also characterized by several shortcomings, like the fact that not all firm's inventions are patented, or that the assignment of technological classes to patents—based on which we build niches—can be imperfect. A second empirical limitation is that our sample is small, and our measures lack the granularity that is necessary to capture the underlying processes of invention. Although our entry measure correlates with that of Kneeland et al. (2020), we are not able to associate an entry to a specific underlying inventor-level process, like distant recombination, long search paths, or serendipity. This links to our third empirical limitation: the fact that we only focus on the macro-, meso- and firm-level aspects of entry in new niches and their exploration: a fine-grained analysis of the role played by inventors is a missing piece in our paper, and thus a possible starting point for future extensions based on our work.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.technovation.2022.102478.

References

Afuah, A., 2001. Dynamic boundaries of the firm: are firms better off being vertically integrated in the face of a technological change? Acad. Manag. J. 44 (6), 1211–1228.
Aghion, P., Griffith, R., Howitt, P., 2006. U-shaped relationship between vertical integration and competition: theory and evidence. Int. J. Econ. Theor. 2, 351–363.
Ahuja, G., Lampert, C.M., 2001. Entrepreneurship in the large corporation: a longitudinal study of how established firms create breakthrough inventions. Strat. Manag. J. 22 (6–7), 521–543.
Ai, C., Norton, E.C., 2003. Interaction terms in logit and probit models. Econ. Lett. 80 (1), 123–129.
Andriani, P., Cohen, J., 2013. From exaptation to radical niche construction in biological and technological complex systems. Complexity 18 (5), 7–14.
Andriani, P., Ali, A., Mastrogiorgio, M., 2017. Measuring exaptation and its impact on innovation, search, and problem solving. Organ. Sci. 28 (2), 320–338.
Arthur, B.W., 2009. The Nature of Technology. What it Is and How it Evolves. Allen Lane-Penguin Books.
Arundel, A., 2001. The relative effectiveness of patents and secrecy for appropriation. Res. Pol. 30 (4), 611–624.
Austin, R.D., Devin, L., Sullivan, E.E., 2012. Accidental innovation: supporting valuable unpredictability in the creative process. Organ. Sci. 23 (5), 1213–1522.

[42] We thank one of the reviewers for pointing this out.

[43] In a broad sense, our paper first looks at those conditions in the current niche—diversity—that stimulate firms' 'abilities' (broadly defined) to end up in new niches, then it looks at those conditions in the current niche—-crowding—that 'motivate' (in a broad sense) firms to further explore these new niches. Assuming that the timing of these two 'behavioral' dimensions is different, we keep them separated in the analysis. Nevertheless, a more comprehensive framework of how these two behavioral dimensions interact is needed, because firms' motivations and abilities may also respectively influence entry and exploration activities.

Baldwin, C., Clark, K., 2000. Design Rules: the Power of Modularity. MIT Press.
Bar, T., Leiponen, A., 2012. A measure of technological distance. Econ. Lett. 112, 457–459.
Barney, J., 1991. Firm resources and sustained competitive advantage. J. Manag. 17 (1), 99–120.
Barroso, A., Giarratana, M., Reis, S., Sorenson, O., 2016. Crowding, satiation, and saturation: the days of television series' lives. Strat. Manag. J. 37 (3), 565–585.
Basalla, G., 1988. The Evolution of Technology. Cambridge University Press.
Baum, J.A., Singh, J.V., 1994. Organizational niches and the dynamics of organizational founding. Organ. Sci. 5 (4), 483–501.
Baumann, O., Schmidt, J., Stieglitz, N., 2019. Effective search in rugged performance landscapes: a review and outlook. J. Manag. 45 (1), 285–318.
Benner, M.J., Tushman, M.L., 2003. Exploitation, exploration, and process management: the productivity dilemma revisited. Acad. Manag. Rev. 28 (2), 238–256.
Berrebi, Z.M., Silber, J., 1985. Income inequality indices and deprivation: a generalization. Q. J. Econ. 100 (3), 807–810.
Birkinshaw, J., Bessant, J., Delbridge, R., 2007. Finding, forming, and performing: creating networks for discontinuous innovation. Calif. Manag. Rev. 49 (3), 67–84.
Borras, S., Edquist, C., 2017. Holistic Innovation Policy. Theoretical Foundations, Policy Problems, and Instrument Choices. Oxford University Press.
Bowman, E.H., Hurry, D., 1993. Strategy through the option lens: an integrated view of resource investments and the incremental-choice process. Acad. Manag. Rev. 18 (4), 760–782.
Breschi, S., Malerba, F., 1997. Sectoral innovation systems: technological regimes, Schumpeterian dynamics, and spatial boundaries. In: Edquist, C. (Ed.), Systems of Innovation. Pinter.
Breschi, S., Lissoni, F., Malerba, F., 2003. Knowledge relatedness in firm technological diversification. Res. Pol. 32 (1), 69–87.
Carroll, G.R., Hannan, M.T., 2000. The Demography of Corporations and Industries. Princeton University Press.
Carroll, G.R., Dobrev, S.D., Swaminathan, A., 2002. Organizational processes of resource partitioning. Res. Organ. Behav. 24, 1–40.
Cattani, G., 2006. Technological pre-adaptation, speciation, and emergence of new technologies: how Corning invented and developed fiber optics. Ind. Corp. Change 15 (2), 285–318.
Cattani, G., Malerba, F., 2021. Evolutionary Approaches to Innovation, the Firm, and the Dynamics of Industries. Strategy Science, forthcoming.
Cattani, G., Mastrogiorgio, M., 2021. New Developments in Evolutionary Innovation: Novelty Creation in a Serendipitous Economy. Oxford University Press.
Caviggioli, F., 2016. Technology fusion: identification and analysis of the drivers of technological convergence using patent data. Technovation 55–56, 22–32.
Chesbrough, H., Vanhaverbeke, W., West, J., 2006. Open Innovation: Researching a New Paradigm. Oxford University Press.
Coccia, M., 2017. Sources of technological innovation: radical and incremental innovation problem-driven to support competitive advantage of firms. Technol. Anal. Strat. Manag. 29 (9), 1048–1061.
Coccia, M., 2018. A theory of classification and evolution of technologies within a generalized Darwinism. Technol. Anal. Strat. Manag. 31 (5), 517–531.
Coccia, M., 2019a. The theory of technological parasitism for the measurement of the evolution of technology and technological forecasting. Technol. Forecast. Soc. Change 141, 289–304.
Coccia, M., 2019b. Comparative theories of the evolution of technology. In: Farazmand, A. (Ed.), Global Encyclopedia of Public Administration, Public Policy, and Governance. Springer Nature.
Coccia, M., Watts, J., 2020. A theory of the evolution of technology: technological parasitism and the implications for innovation management. J. Eng. Technol. Manag. 55, 101552.
Cohen, W.M., Nelson, R.R., Walsh, J.P., 2002. Links and impacts: the influence of public research on industrial R&D. Manag. Sci. 48 (1), 1–23.
Coriat, B., Weinstein, O., 2001. The organization of R&D and the dynamics of innovation. Sectoral view. European Sect. Sys. Innov. (ESSY) Working Paper.
Corredoira, R.A., Banerjee, P.M., 2015. Measuring patent's influence on technological evolution: a study of knowledge spanning and subsequent inventive activity. Res. Pol. 44 (2), 508–521.
Cunha, M.P., Clegg, S.R., Mendonca, S., 2010. On serendipity and organizing. Eur. Manag. J. 28 (5), 319–330.
Cui, A.S., O'Connor, G., 2012. Alliance portfolio resource diversity and firm innovation. J. Market. 76 (4), 24–43.
Dosi, G., 1982. Technological paradigms and technological trajectories. Res. Pol. 11 (3), 147–162.
Dunbar, K.N., Fugelsang, J.A., 2005. Causal thinking in science: how scientists and students interpret the unexpected. In: Gorman, M.E., Tweney, R.D., Gooding, D.C., Kincannon, A.P. (Eds.), Scientific and Technological Thinking. Lawrence Erlbaum Associates Publishers.
Dwertmann, D.J.G., Nishii, L.H., Knippenberg, D., 2016. Disentangling the fairness and discrimination and synergy perspectives on diversity climate: moving the field forward. J. Manag. 42 (5), 1136–1168 (watts).
Elton, C., 1927. Animal Ecology. Sidgwick and Jackson.
Fleming, L., 2001. Recombinant uncertainty in technological search. Manag. Sci. 47 (1), 117–132.
Fleming, L., Sorenson, O., 2001. Technology as a complex adaptive system: evidence from patent data. Res. Pol. 30 (7), 1019–1039.
Fleming, L., Mingo, S., Chen, D., 2007. Collaborative brokerage, generative creativity, and creative success. Adm. Sci. Q. 52 (3), 443–475.
Ganco, M., 2017. NK model as a representation of innovative search. Res. Pol. 46 (10), 1783–1800.

Garud, R., Nayyar, P.R., 1994. Transformative capacity: continual structuring by intertemporal technology transfer. Strat. Manag. J. 15 (5), 365–385.
Gavetti, G., 2012. Toward a behavioral theory of strategy. Organ. Sci. 23 (1), 267–285.
Geels, F.W., 2005. Processes and patterns in transitions and system innovations: refining the co-evolutionary multi-level perspective. Technol. Forecast. Soc. Change 72 (6), 681–696.
Gilsing, V., Nooteboom, B., 2006. Exploration and exploitation in innovation systems. Res. Pol. 35 (1), 1–23.
Goldenberg, J., Mazursky, D., Solomon, S., 1999. Creative sparks. Sci. Mag. 285, 1495–1496.
Gould, S.J., 2007. Punctuated Equilibrium. Belknap Press.
Granstrand, O., Holgersson, M., 2020. Innovation ecosystems: a conceptual review and a new definition. Technovation 90–91, 102098.
Greene, W.H., 2002. The behavior of the fixed effects estimator in nonlinear models. NYU working paper. No. EC-02-05.
Greve, H.R., 1996. Patterns of competition: the diffusion of a market position in radio broadcasting. Adm. Sci. Q. 41 (1), 29–60.
Haelg, L., 2020. Promoting technological diversity: how renewable energy auction designs influence policy outcomes. Energy Res. Social Sci. 69, 101636.
Hao, B., Ye, J., Feng, Y., Cai, Z., 2020. Explicit and tacit synergies between alliance firms and radical innovation: the moderating roles of interfirm technological diversity and environmental technological dynamism. R. Manag. 50 (4), 432–446.
Hannan, M.T., Freeman, J., 1977. The population ecology of organizations. Am. J. Sociol. 82 (5), 929–964.
Hannan, M.T., Pólos, L., Carroll, G.R., 2007. Logics of Organization Theory: Audiences, Codes, and Ecologies. Princeton University Press.
Hausmann, R., Hidalgo, C.A., Bustos, S., Coscia, M., Chung, S., Jimenez, J., Simoes, A., Yildirim, M.A., 2014. The Atlas of Economic Complexity: Mapping Paths to Prosperity. The MIT Press.
Hargadon, A., Sutton, R., 1997. Technology brokering and innovation in a product development firm. Adm. Sci. Q. 42 (4), 716–749.
Hidalgo, C.A., Hausmann, R., 2009. The building blocks of economic complexity. Proc. Natl. Acad. Sci. U.S.A. 106 (26), 10570–10575.
Hodgson, G.M., 2002. Darwinism in economics: from analogy to ontology. J. Evol. Econ. 12, 259–281.
Hsu, D.H., Ziedonis, R.H., 2013. Resources as dual sources of advantage: implications for valuing entrepreneurial-firm patents. Strat. Manag. J. 34 (7), 761–781.
Huang, H.C., Su, H.N., 2019. The innovative fulcrums of technological interdisciplinarity: an analysis of technological fields in patents. Technovation 84–85, 59–70.
Huizingh, E., 2011. Open innovation: State of the art and future perspectives. Technovation 31, 2–9.
Jaffe, A.B., 1986. Technological opportunity and spillovers of R&D: evidence from firms' patents, profits, and market value. Am. Econ. Rev. 76 (5), 984–1001.
Jaffe, A.B., Trajtenberg, M., Fogarty, M.S., 2000. Knowledge spillovers and patent citations: evidence from a survey of inventors. Am. Econ. Rev. 90 (2), 2-15-218.
Kaplan, S., Vakili, K., 2015. The double-edged sword of recombination in breakthrough innovation. Strat. Manag. J. 36 (10), 1435–1457.
Katila, R., Ahuja, G., 2002. Something old, something new: a longitudinal approach of search behavior and new product introductions. Acad. Manag. J. 45 (6), 1183–1194.
Kauffman, S., 2000. Investigations. Oxford University Press.
King, A., Tucci, C., 2002. Incumbent entry into new market niches: the role of experience and managerial choice in the creation of dynamic capabilities. Manag. Sci. 48 (2), 171–186.
Kneeland, M.K., Schilling, M.A., Barak, A., 2020. Exploring uncharted territory: knowledge search processes in the origination of outlier innovation. Organ. Sci. 31 (3), 535–795.
Kovacs, B., Carnabuci, G., Wezel, F.C., 2021. Categories, attention, and the impact of inventions. Strat. Manag. J. https://doi.org/10.1002/smj.3271.
Khurshid, F., Park, W.Y., Chan, F.T.S., 2020. The impact of competition on vertical integration: the role of technological niche width. Bus. Strat. Environ. 29 (3), 789–800.
Kuhn, T., 1970. The Structure of Scientific Revolutions. Chicago University Press.
Lawrence, P.R., Lorsch, J.W., 1967. Organization and Environment: Managing Differentiation and Integration. Harvard Business School Press.
Lee, C., Jeon, D., Ahn, J.M., Kwon, O., 2020. Navigating a product landscape for technological opportunity analysis: a word2vec approach using an integrated patent-product database. Technovation 96–97, 102140.
Leten, B., Belderbos, R., Van Looy, B., 2007. Technological diversification, coherence, and performance of firms. J. Prod. Innovat. Manag. 24 (6), 567–579.
Leten, B., Belderbos, R., Van Looy, B., 2016. Entry and technological performance in new technological domains: technological opportunities, technology competition and technological relatedness. J. Manag. Stud. 53 (8), 1257–1291.
Levinthal, D.A., March, J.G., 1993. The myopia of learning. Strat. Manag. J. 14 (S2), 95–112.
Levinthal, D.A., 1997. Adaptation on rugged landscapes. Manag. Sci. 43 (7), 934–950.
Levinthal, D.A., 1998. The slow pace of rapid technological change: gradualism and punctuation in technological change. Ind. Corp. Change 7 (2), 217–247.
Malerba, F., Orsenigo, L., 1999. Technological entry, exit and survival: an empirical analysis of patent data. Res. Pol. 28 (6), 643–660.
March, J., 1991. Exploration and exploitation in organizational learning. Organ. Sci. 2 (1), 71–87.
Marsili, O., 2001. The Anatomy and Evolution of Industries: Technical Change and Industrial Dynamics. Edward Elgar Publishing.
McCann, K., 2000. The diversity-stability debate. Nature 405, 228–233.
McMillan, G.S., Narin, F., Deeds, D.L., 2000. An analysis of the critical role of public science in innovation: the case of biotechnology. Res. Pol. 29 (1), 1–8.
McPherson, M., 2004. A Blau space primer: prolegomenon to an ecology of affiliation. Ind. Corp. Change 13 (1), 263–280.
Melero, E., Palomeras, N., 2015. The Renaissance man is not dead! the role of generalists in teams of inventors. Res. Pol. 44 (1), 154–167.
Merton, R.K., Barber, E., 2004. The Travels and Adventures of Serendipity. Princeton University Press.
Meyers, M.A., 2007. Happy Accidents: Serendipity in Major Medical Breakthroughs in the Twentieth Century. Arcade Publishing.
Morescalchi, A., Hardeman, S., 2015. Diversity and the Technological Impact of Inventive Activity: Evidence for EU Regions. European Commission Technical Report.
Morrison, G., Buldyrev, S.V., Imbruno, M., Arrieta, O.A.D., Rungi, A., Riccaboni, M., Pammolli, F., 2017. On economic complexity and the fitness of nations. Sci. Rep. 7 (1), 1–11.
Mowery, D., Rosenberg, N., 1979. The influence of market demand upon innovation: a critical review of some recent empirical studies. Res. Pol. 8 (2), 103–153.
Mowery, D., Nelson, R., 1999. Sources of Industrial Leadership. Cambridge University Press.
Mowery, D., Rosenberg, N., 1993. The US national system of innovation. In: Nelson, R. (Ed.), National Innovation System, a Comparative Analysis. Oxford University Press.
Murayama, K., Nirei, M., Shimizu, H., 2015. Management of science, serendipity, and research performance: evidence from a survey of scientists in Japan and the U.S. Res. Pol. 44 (4), 862–873.
Nelson, R., Winter, S., 1982. An Evolutionary Theory of Economic Change. Harvard University Press.
Nerkar, A., Roberts, P.W., 2004. Technological and product-market experience and the success of new product introductions in the pharmaceutical industry. Strat. Manag. J. 25 (8–9), 779–799.
Nesta, L., Saviotti, P., 2005. Coherence of the knowledge base and the firm's innovative performance: evidence from the U.S. pharmaceutical industry. J. Ind. Econ. 53 (1), 123–142.
Nikulainen, T., Palmberg, C., 2010. Transferring science-based technologies to industry–does nanotechnology make a difference? Technovation 30 (1), 3–11.
Norton, E.C., Wang, H., Ai, C., 2004. Computing interaction effects and standard errors in logit and probit models. STATA J. 4 (2), 154–167.
Nowotny, H., Scott, P., Gibbons, M., 2001. Re-thinking Science: Knowledge and the Public in an Age of Uncertainty. Polity Press.
Odling-Smee, E.J., Laland, K.N., Feldman, M.W., 2003. Niche Construction: the Neglected Process in Evolution. Princeton University Press.
OECD, 2013. Innovation-driven Growth in Regions: the Role of Smart Specialization Strategy. OECD Publications.
Page, S., 2011. Diversity and Complexity. Princeton University Press.
Pavitt, K., 1984. Sectoral patterns of technical change: towards a taxonomy and a theory. Res. Pol. 13 (6), 343–373.
Penrose, E., 1959. The Theory of the Growth of the Firm. John Wiley and Sons.
Perkins, D.N., 1981. The Mind's Best Work. Harvard University Press.
Peteraf, M.A., 1993. The cornerstones of competitive advantage: a resource-based view. Strat. Manag. J. 14 (3), 179–191.
Petrova, E., 2014. Innovation in the pharmaceutical industry: the process of drug discovery and development. In: Ding, M., Eliashberg, J., Stremersch, S. (Eds.), 2014. Innovation and Marketing in the Pharmaceutical Industry. Springer.
Phene, A., Fladmoe-Lindquist, K., Marsh, L., 2006. Breakthrough innovations in the U.S. biotechnology industry: the effects of technological space and geographic origin. Strat. Manag. J. 27 (4), 369–388.
Pistorius, C.W.I., Utterback, J.M., 1997. Multi-mode interaction among technologies. Res. Pol. 26 (1), 67–84.
Podolny, J.M., Stuart, T.E., 1995. A role-based ecology of technological change. Am. J. Sociol. 100 (5), 1224–1260.
Podolny, J.M., Stuart, T.E., Hannan, M.T., 1996. Networks, knowledge, and niches: competition in the worldwide semiconductor industry, 1984-1991. Am. J. Sociol. 102 (3), 659–689.
Popielarz, P.A., Neal, Z.P., 2007. The niche as a theoretical tool. Annu. Rev. Sociol. 33, 65–84.
Sakhartov, A.V., Folta, T.B., 2014. Resource relatedness, redeployability, and firm value. Strat. Manag. J. 35 (12), 1781–1797.
Saviotti, P.P., 1996. Technological Evolution, Variety and the Economy. Edward Elgar.
Schot, J., Geels, F.W., 2007. Niches in evolutionary theories of technical change. J. Evol. Econ. 17, 605–622.
Schumpeter, J.A., 1939. Business Cycles: A Theoretical, Historical and Statistical Analysis of the Capitalist Process. McGraw Hill.
Schumpeter, J.A., 1942. Capitalism, Socialism and Democracy. Harper & Brothers.
Seo, H., Chung, Y., Yoon, H.D., 2017. R&D cooperation and unintended innovation performance: role of appropriability regimes and sectoral characteristics. Technovation 66–67, 28–42.
Shapiro, C., 2000. Navigating the patent thicket: cross licenses, patent pools, and standard setting. Innovat. Pol. Econ. 1, 119–150.
Simon, H.A., 1955. A behavioral model of rational choice. Q. J. Econ. 69 (1), 99–118.
Simon, H.A., 1962. The architecture of complexity. Proc. Am. Phil. Soc.
Simon, H., 1969. The Sciences of the Artificial. MIT Press.
Srivastava, M.K., Devi, R.G., 2011. When do relational resources matter? Leveraging portfolio technological resources for breakthrough innovation. Acad. Manag. J. 54 (4), 797–810.
Stirling, A., 2007. A general framework for analysing diversity in science, technology and society. J. R. Soc. Interface 4 (15), 707–719.

Stuart, T.E., 1999. A structural perspective on organizational innovation. Ind. Corp. Change 8 (4), 745–775.
Sun, G.Q., Zhang, J., Song, L.P., Jin, Z., Li, B.L., 2012. Patter formation of a spatial predator-prey system. Appl. Math. Comput. 218 (22), 11151–11162.
Taylor, A., Greve, H.R., 2006. Superman or the fantastic four? Knowledge combination and experience in innovation teams. Acad. Manag. J. 49 (4), 723–740.
Teece, D.J., 1986. Profiting from technological innovation: implications for integration, collaboration, licensing and public policy. Res. Pol. 15 (6), 285–305.
Teodoridis, F., Bikard, M., Vakili, K., 2019. Creativity at the knowledge frontier: the impact of specialization in fast- and slow-paced domains. Adm. Sci. Q. 64 (4), 894–927.
Tripsas, M., 1997. Unravelling the process of creative destruction: complementary assets and incumbent survival in the typesetter industry. Strat. Manag. J. 18, 119–142.
Tushman, M., Anderson, P., 1986. Technological discontinuities and organizational environments. Adm. Sci. Q. 31 (3), 439–465.
Utterback, J.M., 1994. Mastering the Dynamics of Innovation. Harvard Business School Press.
Van den Ende, J., Dolfsma, W., 2005. Technology-push, demand-pull and the shaping of technological paradigms-Patterns in the development of computing technology. J. Evol. Econ. 15, 83–99.
Van den Oord, A., Van Witteloostuijn, A., 2017. The population ecology of technology: an empirical study of U.S. biotechnology patents from 1976 to 2003. PLoS One.
Van Witteloostuijn, A., Boone, C., 2006. A resource-based theory of market structure and organizational form. Acad. Manag. Rev. 31 (2), 409–426.
Von Graevenitz, G., Wagner, S., Harhoff, D., 2011. How to measure patent thickets: a novel approach. Econ. Lett. 111 (1), 6–9.
Weitzman, M., 1996. Hybridizing Growth Theory. Proceedings of the American Economic Association.
Winter, S.G., 2012. Purpose and progress in the theory of strategy: comments on Gavetti. Organ. Sci. 23 (1), 288–297.
Yayavaram, S., Ahuja, G., 2008. Decomposability in knowledge structures and its impact on the usefulness of inventions and knowledge-base malleability. Adm. Sci. Q. 53 (2), 333–362.
Ziman, J., 2000. Technological Innovation as an Evolutionary Process. Cambridge University Press.

Further reading

Arts, S., Hou, J., Gomez, J.C>, 2021. Natural language processing to identify the creation and impact of new technologies in patent text: Code, data, and new measures. Res. Pol. 50 (2), 104144.