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Reconfiguring a firm's knowledge: three essays on how different modes to reconfigure knowledge impact the value of innovation

Advisor: Paola CILLO

Co-Advisor: Dovev LAVIE

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Alessio DELPERO

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THESIS ABSTRACT

This work analyses the implications that different modes a firm can choose to reconfigure its knowledge base across knowledge domains have on the value of the innovation it generates.

In each chapter, we consider two knowledge domains, one established, which represents the firm's domain of operation, one emerging, which represents a knowledge domain that is new to the firm and different from the one of operation.
Reconfigured knowledge elements can either flow from the emerging domain into the firm to be applied to innovate in the established domain, a process known as knowledge search, or from the firm into the emerging domain in order to innovate there, a process known as knowledge deployment. The first two chapters of this work take the former perspective, the third one the latter.

The first chapter describes how different search modes that firms may adopt to acquire new knowledge elements from an emerging knowledge domain impact the value of new products that apply these elements in the established one.
Leveraging on the literature on learning modes and on time of entry, we define direct and indirect search as two modes that firm may adopt to acquire knowledge from the same emerging domain, and we propose a "U" shaped relation between the intensity of direct search and the value of innovation and an inverted "U" shape relation between the intensity of indirect search and the value of innovation. Furthermore, we show that when direct and indirect search are adopted simultaneously, both non-linear relations attenuate.

Although it is known that firms searching for new knowledge in an external knowledge domain may have ex-ante incentives to acquire knowledge elements that can be either general or specialist in nature, it is not clear what are the ex-post consequences on the value of innovation of choosing one type of knowledge over the other. There is indeed a trade-off in terms of advantages and disadvantages that general and specialist knowledge elements have on the value of the inventions they generate.

The second chapter takes the perspective of a firm that sequentially searches for new knowledge in an external domain and considers the implications of different characteristics of the generality the new elements on the value of the invention, according to the place occupied by each element in the firm's sequential knowledge search.

We propose that the level of generality of an element acquired from a new domain has a direct negative effect on the value of the inventions it generates, but that this negative effect decreases as the firm moves forth in the sequential knowledge search. By contrast, the generality of an element that occupies a preceding place in the sequential knowledge search has a positive indirect effect on the value of the invention generated by applying a subsequent element. Moreover, this positive indirect effect increases if the subsequent element is specialized.

The third chapter changes perspective and considers the implications for the value of innovation that a firm generates in an emerging domain it enters when choosing different modes for deploying the knowledge it has developed in the established domain. Knowledge reconfiguration from an established to an emerging domain can happen via co-deployment when a knowledge element from the established domain is applied in the emerging domain while being continuously applied also in the established domain, or via transfer, when a knowledge element from the established domain is applied in the emerging domain but its application in the established domain is discontinued. These two modes for reconfiguring across domains might be combined with modes for reconfiguring within the emerging domain, such as recombining or discarding elements. We identify the impact of each combination of modes on the value of innovation according to the relatedness between the established and the emerging domain. We further compare the outcome of transfer with the outcome of co-deployment at each level of relatedness.

Our results suggest that, in order to obtain superior innovation, firms that enter an emerging domain should evaluate transfer versus co-deployment according to the relatedness of the two domains and to the reconfiguration activity they plan to conduct within the emerging domain.

CHAPTER 1

Carving Innovation: Effects of Different Search Modes on Value of New Products.

With Paola Cillo, Bocconi University

Identifying the drivers of the value of innovation is of utmost importance being value one of the major determinants of the innovation's success (Aaker & Jacobson, 1994; Jacobson & Aaker, 1987; Phillips, Chang, & Buzzell, 1983; Sethi, 2000; Garvin, 1988) and a leading indicator of economic growth (Hasan & Tucci, 2010). Nevertheless, these drivers are still unclear in the context of firms innovating via knowledge search.

Knowledge search in new domains, defined as the acquisition by a firm of external knowledge from knowledge domains that are different from the one where the firm habitually operates, is a crucial component to reconfigure the firm's knowledge base and foster innovation (Ahuja & Lampert, 2001; Fleming, 2001; Leiponen & Helfat, 2010; Levinthal & March, 1993; Levitt & March, 1988; March, 1991).

Scholars studying the relation between knowledge search and the value of innovation have devoted their attention mainly to three aspects: the dichotomy between local and distant search (Rosenkopf & Nerkar, 2001), the openness to different knowledge sources, and the depth of search in each source (Dahlander, O'Mahony, & Gann, 2013; Jeppesen & Lakhani, 2010; Katila & Ahuja, 2002; Laursen & Salter, 2006; Leiponen & Helfat, 2010).

These insightful perspectives explain the relationship between external search and the value of innovation focusing on "where" and "how much" new knowledge is acquired, but overlook two essential aspects. The first is the evidence of firms operating in the same domain who search the same sources but obtain different results in the value of their innovative output. The second is “how” searching firms acquire external knowledge.

A change in perspective that considers different search modes that a firm can adopt to explore an external domain allows us to identify new drivers of the value of innovation that previous literature has overlooked and to extend the applicability of the framework to a context where competing firms strategically search the same external domain.

In the broader context of organizational learning and time of entry, different modes to learn have been identified juxtaposing firms that learn experientially to firms that learn vicariously (Levitt & March, 1988; March & Olsen, 1975), and comparing early with late entrants (Lieberman & Montgomery, 1988). A similar distinction is also possible in the narrower context of knowledge search. Indeed, a firm can search an external knowledge domain directly by exploring an external domain, but also indirectly by waiting for the knowledge from the external domain to be applied in the firm’s domain of operation by other organizations.

By answering the question: “how do different modes to search for knowledge in a new external domain affect the value of an innovation generated in the firm’s current domain of operation?” this paper highlights that direct and indirect search pose different trade-offs in terms of advantages and disadvantages to a searching firm that adopts external knowledge to innovate in its current domain of operation. On the one hand, direct search helps the firm to gain a deeper understanding of the new knowledge, but it entails a higher cost in terms of the uncertainty and the liability of newness that direct searchers pay when applying the external knowledge in the current domain of operation for the first time. On the other hand, indirect search limits the firm’s ability to understand the knowledge available in the external domain, but, it entails less uncertainty and less liability of newness due to the benefit that indirect searchers draw from prior applications of the external knowledge in the domain of operation, where they innovate.

We explain how, in light of these trade-offs in advantages and disadvantages, the intensity with which firms pursue each search mode triggers absorptive capacity (Cohen & Levinthal, 1990) and negative transfers (Finkelstein & Haleblian, 2002; Novick, 1988) with different magnitudes. The net effect of these two mechanisms, which respectively affect positively and negatively the value of innovation, links the intensity of each search mode to the overall value of the innovation generated.

We propose an (inverted) “U” shape relation between the intensity of direct (indirect) search and the value of innovation, implying that high levels of intensity might either enhance or harm the value of innovation according to the selected search mode. We also propose that direct and indirect search in a single external domain are not mutually exclusive, but that a searching firm can mix these two modes. Our results show that a mixed search mode attenuates the non-linear relationship between search intensity and the value of innovation, mitigating the risk of achieving an inferior value but also a superior one.

This work complements the literature on knowledge search by confirming that some of the drivers linking search to the value of innovation have not yet been considered and proposing search modes as one of them. Furthermore, it clarifies that searching firms face ex-ante trade-offs that depend on the search mode that they plan to implement, and that search might have negative implications. Finally, it highlights a nexus among the streams of literature on knowledge search, learning modes, and time of entry, while exposing differences between these perspectives that create exciting opportunities for research.

From a practitioner's standpoint, the non-linearities that we propose generate a non-trivial situation that deserves to be clarified to facilitate the optimization of the return on the firm's investment in knowledge search.

To corroborate our claims, we analyze data from the ski manufacturing industry from 1998 to 2009, when external knowledge was imported from the snowboard manufacturing industry and applied to new models of skis.

THEORY AND HYPOTHESES

Innovating firms frequently search outside their boundaries to acquire external knowledge and modify their knowledge base (Capron & Mitchell, 2009; Eisenhardt & Martin, 2000; Helfat et al., 2013; Helfat & Peteraf, 2015; Karim & Capron, 2016; Teece, 2007). This external search represents a critical activity when planning to introduce new products by changing the core technical and user service features of existing ones (Katila & Ahuja, 2002; Saviotti & Metcalfe, 1984).

Firms tend to search domains where they have prior experience, such as the industry where they operate (Cohen & Levinthal, 1990; Helfat, 1994; Levinthal & March, 1993; March, 1991; Nelson & Winter, 1982; Rosenkopf & Nerkar, 2001; Sorensen & Stuart, 2000; Stuart & Podolny, 1996). Nevertheless, as the novelty extractable from these local domains exhausts, the search may extend into unexplored domains represented by related product-markets (Helfat & Raubitschek, 2000), such as related industries, that share skills or resources (Robins & Wiersema, 1995; Rumelt, 1982; Tanriverdi & Venkatraman, 2005), technologies, or customers (Davis, Robinson, Pearce, & Park, 1992; Pitts & Hopkins, 1982) with the firm's domain of operation.

The resulting framework depicts a firm searching for new knowledge in a domain that is different but related to its domain of operation, and importing this new knowledge into the domain of operation to innovate there.
The ski manufacturers that innovated their ski models by searching for new knowledge in the snowboard domain, or the mobile phone producers that used knowledge from digital imaging to generate phones equipped with cameras, represent a practical example of this framework.

Although searching related domains is an acknowledged practice of innovating firms, many questions on the implications of this activity are still unanswered, and several aspects that link knowledge search with the value of the innovation generated remain unclear.
The relationship between knowledge search and the value of innovation has been studied focusing mostly on the characteristics of the external domain in terms of relatedness with the firm's domain of operation (Rosenkopf & Nerkar, 2001), or in terms of the number of sources available (Dahlander et al., 2013; Jeppesen & Lakhani, 2010; Laursen & Salter, 2006; Leiponen & Helfat, 2010)
These frameworks adequately explain the heterogeneity in the value of the innovative output when firms adopt different search behaviors in selecting the external domain source of the new knowledge but have limited applicability to situations where firms operating in a domain adopt similar search behaviors targeting a common external domain.
These similar search behaviors, which can be again found in our example of ski manufacturers searching the snowboard domain or mobile phone producers exploring digital imaging, are quite common across competing firms. Indeed, every time firms face

highly uncertain decisions, as it is the case of innovating via external knowledge, economic and social forces - such as information cascades, social learning, or institutional isomorphism - push firms to adopt similar behaviors (Banerjee, 1992; Bikhchandani, Hirshleifer, & Welch, 1992, 1998; DiMaggio & Powell, 1983; Lieberman & Asaba, 2006).

In this diffused context of similar search behaviors, the drivers of the value of innovation remain unexplored, making two questions arise spontaneously: what are the factors related to the external search that explain different values across innovative products that apply the same external knowledge? How do these factors affect the value of innovation?

In the next sessions, we propose that different search modes that a firm may adopt to acquire knowledge from a related domain have an impact on the value of the innovative products that apply the new knowledge in the domain where the firm usually operates. Specifically, we explain and empirically test how the ski manufacturers who searched directly versus indirectly the snowboard domain generated new models of skis that, ceteris paribus, had different values.

Search Modes to Acquire Knowledge from a Related Knowledge Domain

Following an epistemological conceptualization of knowledge, a knowledge domain is composed of knowledge elements that represent justified true beliefs in that domain. These elements, and the network of interdependencies among them, represent the knowledge available in the domain (Carnabuci & Bruggeman, 2009; Guan & Liu, 2016; Yayavaram & Ahuja, 2008).

This conceptualization highlights two factors that a firm must consider when searching for new knowledge in a related domain: the search intensity and the search mode.

The search intensity concerns the number of elements (and the entailed interdependencies) that the firm extracts from the related domain. Indeed, a firm can search with higher intensity and acquire more elements or with lower intensity and acquire fewer elements.

The search mode concerns how the elements are acquired: directly, indirectly, or both.

Different modes to acquire new knowledge have been identified in the literature on organizational learning, which shows that firms can learn either from their direct experience (Argote, 1999; Lieberman, 1984; March & Olsen, 1975) or vicariously imitating rivals (Levitt & March, 1988; Miner & Haunschild, 1995; Posen, Lee, & Yi, 2013).

Even though organizational learning is a broader context that contemplates firms altering their knowledge base via external knowledge but also recombining the knowledge they already have, it offers a good starting point to identify modes in the narrower setting of knowledge search, which focuses only on knowledge coming from outside the boundaries of the organization.

When searching in a related domain, a firm can acquire a single knowledge element directly or indirectly. Direct search is the action taken by a firm to acquire an external knowledge element exploring the related domain and extracting the element to apply it in the domain where the firm operates. Indirect search is the action taken by a firm to acquire an external knowledge element from a related domain only after it has been previously applied in the firm's domain of operation by other organizations such as competitors, suppliers, lead users.

A practical example from the ski manufacturing industry is the deep side-cut shape, which was the dominant design in snowboarding since the late 1970s and was applied to skis in the mid-1990s. Whereas some firms such as Elan and K2 acquired this knowledge directly from snowboards, others acquired it indirectly after it was first applied to skis by these pioneers[1].

Furthermore, whereas Elan acquired the knowledge about deep side-cut shape directly from the snowboard, it indirectly acquired from the same domain the knowledge about the twin-tip construction, which was initially applied to ski by lead users.

This condition reveals that, just like experiential and vicarious learning that are not mutually exclusive but coexisting within an organization (Baum & Dahlin, 2007; Posen & Chen, 2013; Schwab, 2007; Simon & Lieberman, 2010), if we consider multiple elements available in a related domain, a searching firm can extract part of the knowledge directly and part indirectly.

Thus, we propose that a searching firm can also choose a mixed search mode where direct and indirect search are pursued simultaneously with different search intensities.

Overall, in the resulting framework, a searching firm may decide to acquire from a related domain a greater or a lower number of knowledge elements either directly, indirectly, or mixing the two modes. The selected mode and the number of elements acquired identify what we call direct search intensity, indirect search intensity, and mixed search intensity.

[1] The Elan SCX was the first commercialized deep side-cut ski.

Before analyzing how the intensity of each search mode affects the value of innovation, it is necessary to highlight that, even though the search modes that we propose resonate with the learning modes proposed in the existing literature, the former differ from the latter in at least two relevant aspects. Firstly, the concept of indirect search is not necessarily limited to imitating rivals, as proposed in the literature on learning modes, but it extends to any entity that might import knowledge from a related domain: it can be rivals but also lead users or suppliers.

Secondly, whereas the literature on learning modes considers knowledge from a related domain as well as knowledge already present within the firm or from the firm's domain of operation, search modes apply only to knowledge imported from a related domain.

This narrower focus, which might appear as a drawback, allows us to highlight the positive as well as the negative implications entailed in each search mode and to identify the mechanisms that link the intensity of each search mode to the value of innovation. These aspects are intractable when adopting a broader framework.

Advantages and Disadvantages of Direct and Indirect Search: Different Trade-offs

Despite essential differences that we will describe in detail, direct search intuitively resonates with the concept of first entry in a new domain and indirect search with late entry. To the extent that a similarity between these concepts holds, the advantages and disadvantages of being a first or a late entrant (Lieberman & Montgomery, 1988, 1998) also apply to the proposed search modes.

When considering technology and innovation, the disadvantages of being a first mover derive mostly from the uncertainty entailed in using external knowledge in a new context for the first time (Lieberman & Montgomery, 1988). This uncertainty increases the liability of newness (Dobrev & Gotsopoulos, 2010; Robinson & Min, 2002; Stinchcombe, 1965; Tellis & Golder, 1996) paid by first-movers with respect to late entrants, who can instead observe the first applications of the external knowledge and learn from the outcome generated by first movers to reduce the uncertainty they face.

The advantages of being a first mover derive from the ability to resolve uncertainty steering the technological evolution of the domain where the new knowledge is applied towards a trajectory that is more aligned with the first entrant's knowledge base (Lieberman & Montgomery, 1988; Wernerfelt & Karnani, 1987). Steering the change in a knowledge domain hampers the ability of late adopters of the new knowledge to adapt to the change via imitation (Siggelkow, 2001), creating a disadvantage for late entrants that increases with the complexity of the external knowledge (Rivkin, 2000)[2].

To the extent that direct searchers are first movers in adopting the external knowledge in the domain of operation and indirect searchers are late entrants, the advantages and disadvantages that we just described can be applied to our framework. Direct searchers can access all the knowledge available in the external domain but cannot observe prior applications of this knowledge in the domain of current operations. This condition poses to direct searchers a trade-off between the advantage of gaining a deeper understanding of the knowledge available in the external domain, with the deriving ability to extract the maximum value from this knowledge when applying it to

[2] There are also other factors that are exogenous to a firm's strategy and are more related to the environment where the firm enters. Examples are the pace of technological evolution and IP protection. In the discussion session, we will acknowledge the role played by these factors and the possible extensions of this paper. We do not include their specific analysis in order to contain the complexity of the paper without harming its fundamental contribution.

innovate in the domain of operation and steer the innovation in the latter, and the disadvantage of facing greater uncertainty and the liability of being the first to apply external knowledge in a different domain.

Indirect searchers face the opposite trade-off. On the one hand, they are exposed to a lower uncertainty as they can observe prior applications of the new knowledge elements in the current domain and identify potential improvements of these applications. On the other hand, they have limited access to the knowledge available in the related domain, as they can acquire only those elements that have been previously applied in the current domain by other organizations. This limitation inhibits the ability of indirect searchers to apply the new knowledge correctly as well as to accurately imitate prior applications in the current domain (Rivkin, 2000; Siggelkow, 2001).

Consider a ski manufacturer searching the snowboard domain and acquiring four knowledge elements respectively on deep sidecut, twin-tip shape, width, and construction materials. If all the elements are acquired directly, the ski manufacturer can observe all the interdependencies among these elements in the snowboard domain and gain a full understanding of this knowledge in its original context. It can, for example, realize that a twin-tip shape could be combined with different sidecuts, widths, and materials according to the purpose of the board[3].

On the other hand, when it first applies these elements to create a twin-tip ski, the direct searcher has to select a combination of sidecut, width, and material based on its

[3] A twin-tip snowboard to perform maneuvers on sliding features adopts a combination of these elements that is different from a twin-tip snowboard to perform maneuvers on jumps, the former being built with softer materials, a more symmetric sidecut, and wider construction.

experience in the snowboard world, which might be inappropriate in the ski domain without proper adjustments[4].

Whereas a direct searcher is likely to figure out the negative implications of misapplied combinations of snowboard elements in the ski domain only ex-post from the feedback received by its prototypes, an indirect searcher can observe these implications ex-ante, testing the direct searcher's products and observing the feedback of lead users[5]. Thus, an indirect searcher faces less uncertainty when applying the same knowledge and can improve on the direct searcher's first applications.

On the other hand, in the plausible event that direct searchers have not imported all the elements from the snowboard domain (in our example could be only sidecut and twin-tip shape), the pool of elements available to indirect searchers to be acquired is smaller and limited only to these elements. This restriction makes those knowledge elements that have not yet been imported (in our example width and construction materials) intractable to indirect searchers.

Even when direct searchers import all the elements from a domain, part of the knowledge of the related domain remains intractable for indirect searches as embedded in the interdependencies among elements that are not replicated in the other domain. Indeed, for a given combination of twin-tip shape, width, and material, snowboards have experimented with different sidecut shapes, but only a part of them is initially applied to skis and made available to indirect searchers. Therefore, many combinations remain

[4] Since when performing areal maneuvers skiers exploit the reactivity and torsion of their tools differently than snowboarders, whereas twin-tip snowboard devoted to jumps use carbon inserts in specific parts, twin-tip skis devoted to jumps need carbon insert in different parts according to the width of the ski. Copy-pasting the application of carbon inserts from snowboard to ski without necessary adjustment harms the performance of skis.

[5] A twin-tip ski that uses carbon inserts in the wrong parts receives reviews that make clear to indirect searchers that carbon inserts must be adjusted when transferred from snowboard to skis.

available only to direct searchers who can access all the interdependencies in the related domain.

Although direct and indirect search, as we have described them so far, resemble early and late entry, and so do their advantages and disadvantages, these search modes differ from the time of entry modes for at least two critical aspects. Firstly, whereas first and late entry are mutually exclusive in the focal firm, direct and indirect search in a domain may coexist within a firm. Secondly, whereas early or late entry is a binary condition where a firm is either an early entrant or not, direct and indirect search are continuous constructs that can be implemented with different levels of intensity according to the number of elements acquired using one mode or the other. In our example, a ski manufacturer can search more intensively and acquire all the four elements that we proposed, or less intensively and acquire only some of them. In both cases, it can acquire all the elements directly, all the elements indirectly, or some directly and some indirectly.

The coexistence of direct and indirect search within a single firm justifies a framework that considers also mixed search modes that are not contemplated in the literature on time of entry and advocates for an analysis of the advantages and disadvantages in this case. Furthermore, the possibility of adopting different levels of intensity for each search mode calls for a better understanding of how the trade-offs change with the intensity of each search mode.

Overall, depicting direct and indirect search intensity as orthogonal and continuous variables, versus conceptualizing them as mutually exclusive and dichotomous as done by the literature on time of entry, offers an excellent opportunity to analyze how the proposed trade-offs affect the value of innovation when the search intensity and the search mode change.

To perform this analysis, we must now delve into the mechanisms that link, at the light of the proposed trade-offs, the intensity of each search mode to the value of the innovation it generates, and explain that the intensity of direct, indirect, and mixed search triggers with different magnitudes absorptive capacity (Cohen & Levinthal, 1990) and negative transfers (Finkelstein & Haleblian, 2002; Novick, 1988).

These two mechanisms respectively impact the value of the innovation positively and negatively, with the sum of the positive implications of absorptive capacity and the negative implications of negative transfers showing the net effect that each level of search intensity has on the value of innovation for each search mode.

In the next sessions, we recall the definitions of absorptive capacity and negative transfers and, using the conceptual model described in figure 1, explain how these two constructs mediate the relation between the intensity of each search mode and the value of innovation. The model will then be tested empirically for each search mode.

Insert figure 1 about here

Absorptive Capacity, Negative Transfers, and their Mediation of the Relation between Search Intensity and the Value of an Innovation.

Absorptive capacity was defined by Cohen and Levinthal (1990) as the ability to value, assimilate, and commercially utilize new external knowledge. Since greater absorptive capacity allows for better uses of the new knowledge acquired from an external domain, absorptive capacity has positive implications on the value of innovation

(Chen, Lin, & Chang, 2009; Fabrizio, 2009; Ferreras-Méndez, Newell, Fernández-Mesa, & Alegre, 2015). Furthermore, since a firm's absorptive capacity to acquire knowledge from an external domain increases when more knowledge from the domain is added to the firm's knowledge base, absorptive capacity is positively related to the intensity of search (Cohen & Levinthal, 1990; Harlow, 1949; Kim, 1997; Lindsay & Norman, 1977; Zahra & George, 2002).

Thus, in a sequence of relations that sees absorptive capacity growing with search intensity and the value of an innovation growing with the level of absorptive capacity, the value of innovation increases with the intensity of search, as depicted in figure 1.

Negative transfers suggest instead that behaviors learned in a knowledge domain can generate negative consequences when applied with no adjustment to a different context (Finkelstein & Haleblian, 2002; Novick, 1988; Zahavi & Lavie, 2013). Firms tend to make unwarranted analogies across different applications of knowledge, thus overlooking adjustments that are necessary to reach a satisfactory level of quality in new products when applying new knowledge in a context that is different from the original one. Negative transfers emerge when three conditions are met (Finkelstein & Haleblian, 2002): (1) two situations share superficial similarities but have significant underlying differences; (2) because the situations are perceived as similar, behavior from a past situation is transferred to the new situation; (3) because the situations have significant underlying differences, the transfer of behavior is inappropriate, and performance outcomes are poor (Ellis, 1977).

Since, by definition, related domains share similar skills, resources, common technologies, or customers, but are profoundly different in the sense that they represent two separate knowledge domains, our context of knowledge search in a new domain is particularly subject to negative transfers. Indeed, the superficial similarities between the current and the related domain generate unwarranted analogies when transferring knowledge from the latter to the former, resulting in inappropriate behaviors and poor performance outcomes.

Thus, negative transfers harm the value of the innovation generated using new knowledge from the external domain in the current domain of operation, with the harming effect growing with the magnitude of negative transfers.

In parallel, since each new knowledge element imported from the external domain increases the likelihood of making unwarranted analogies, the magnitude of negative transfers increases with the number of elements imported from the external domain. Therefore, a higher level of search intensity leads to a greater magnitude of negative transfers.

Overall, in a sequence of relations that sees negative transfers growing with search intensity and the value of innovation diminishing with the level of negative transfers, the value of innovation diminishes with the search intensity, as depicted in figure 1.

At first sight, it appears that the positive effect of absorptive capacity and the negative effect of negative transfers, both increasing with search intensity, compensate each other with a net effect on the value of innovation that is fundamentally null. Nevertheless, the proposed analysis does not account for different search modes and the trade-off they entail.

Therefore, accurate conclusions on the net effect can be drawn only after adding search modes to the picture and carefully analyzing which mechanism dominates at each level of search intensity for each search mode.

Accordingly, we now turn our attention to describe how absorptive capacity and negative transfers grow with search intensity in the case of direct, indirect, or mixed search, in light of the different trade-offs faced by each mode.

We start from the opposite condition faced by direct and indirect searchers to set the contingencies that make absorptive capacity and negative transfers grow at different rates with intensity. We explain that direct searchers, who have access to the complete knowledge available in the external domain but lack references to prior applications of this knowledge in the current domain, see absorptive capacity growing with increasing margins and negative transfers growing with diminishing margins as intensity increases. Afterward, we describe that indirect searchers, who have access only to part of the knowledge in the external domain but can observe prior applications this knowledge in the current domain, see absorptive capacity growing with diminishing margins and negative transfers growing with increasing margins as intensity increases. Finally, we describe that absorptive capacity and negative transfer tend to grow more linearly with intensity when firms adopt a mixed search mode.

Direct Search Intensity and the Value of Innovation

We have discussed that absorptive capacity and negative transfers grow with search intensity. We now consider the rate of growth of each mechanism at different levels of direct search intensity.

Direct search intensity and absorptive capacity

Knowledge elements belonging to a knowledge domain are connected, creating a knowledge network described by the interdependencies among knowledge elements in the domain (Carnabuci & Bruggeman, 2009; Guan & Liu, 2016; Yayavaram & Ahuja, 2008).

Since elements have more than one interdependence with the other elements in the domain, when direct search intensity increases and a greater number of elements is acquired, the number of interdependencies entailed in these elements that the firm acquires grows more than proportionally. This proportionally greater number of interdependences acquired when search intensity increases, enhances the expansion of the firm's knowledge base toward the new domain, making absorptive capacity grow with it.

There is indeed a recursive relationship between organizational learning and absorptive capacity, as increased learning in a specific area enhances the organizational knowledge base in that area, which further increases absorptive capacity and, thus, facilitates future learning in that domain (Autio, Sapienza, & Almeida, 2000; Barkema & Vermeulen, 1998; Lane, Koka, & Pathak, 2006).

Thus, absorptive capacity grows with an increasing rate with search intensity. However, this relation is possible only when the searching firm has access to all the elements and interdependences available in the external domain, a condition that we described as typical of direct searchers.

Therefore, although absorptive capacity grows at any level of direct search intensity, as direct search intensity increases, the firm's knowledge base grows more than proportionally toward the external domain due to the increasing number of interdependences among elements entailed in each new element acquired, boosting the recursive effect that links direct search intensity and absorptive capacity, which grows faster,

Overall, the higher the level of direct search intensity, the greater the marginal rate with which absorptive capacity grows, as depicted in the top-left quadrant of figure 2.

Insert figure 2 about here

Direct search intensity and negative transfers

We described that negative transfers grow with the number of knowledge elements imported from the external domain into the domain where the firm operates, as the likelihood of misapplying knowledge increases. Nevertheless, to properly understand how negative transfers grow with intensity, it is necessary to consider also the likelihood of making unwarranted analogies and overlooking necessary adjustments when transferring a knowledge element across domains, a necessary condition for negative transfers to manifest.

At lower levels of direct search intensity, the searching firm acquires a limited number of knowledge elements but does not fully understand their applications and interdependencies neither in the current domain nor in the external one. This lack of understanding of the proper use of the searched elements in both domains increases the likelihood of making unwarranted analogies and overlooking necessary adjustments when transferring an element across domains. A ski manufacturer that directly acquires only the knowledge element on the width of snowboards but ignores the elements on sidecut, twin-tip, and materials, is more likely to misapply this element to skis, as it has no information on the combinations that make the element work effectively[6].

As direct search intensity increases, the searching firm's understanding of the acquired knowledge increases as well, at least in the related domain, and the likelihood of unwarranted analogies related to each extra knowledge element acquired reduces (Finkelstein & Haleblian, 2002; Perkins & Salomon, 1992). If a ski manufacturer directly acquires an element on width and an element on construction material, it is less likely to overlook the fact that wider skis perform better when combined with specific materials that make them softer while containing the torsion.

Other adjustments related to the same elements may still be required and overlooked when transferring each element from snowboard to ski[7], justifying the continued increase of negative transfers with intensity, but the improved ability to spot and execute part of these adjustments due to a better understanding of the knowledge in the related domain, reduces the rate of growth.

Thus, as direct search intensity increases, negative transfers keep cumulating with each new knowledge element acquired, but they do so at a decreasing rate due to an improved understanding of the knowledge in the related domain that reduces the likelihood of making unwarranted analogies entailed in each element.

Overall, adopting direct search, negative transfers grow with search intensity at a decreasing marginal rate, as shown by the mid-left quadrant in figure 2.

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[6] Wider skis perform only in specific purposes and if constructed with specific materials. The first applications of increased width to skis, which overlooked the other elements, generated products that were unusable on groomed runs because too wide and with no sidecut, and at the same time unskiable in deep snow because too stiff. The overall value of the product was very low.

[7] Increased width is applied to snowboards also for people with longer feet, this would be a misapplication to skis independently of the material used.

The net effect of absorptive capacity and negative transfers in the case of direct search

In order to identify the overall effect of direct search intensity on the value of innovation, we compare the positive effect of absorptive capacity and the negative effect of negative transfers and highlight the net result of their sum.

Absorptive capacity grows with direct search intensity at increasing marginal rate; this relation is transferred to the value of an innovation, which increases with search intensity following the same shape of absorptive capacity[8], as shown by the top curve in the bottom-left quadrant in figure 2.

On the other hand, negative transfers grow with direct search intensity at a decreasing marginal rate and harm value, which decreases with search intensity at a decreasing marginal rate mirroring the relation between direct search intensity and negative transfers, as shown by the bottom curve in the bottom-left quadrant in figure 2[9]. Starting from a given level of value of innovation represented by the origin of the axis in the bottom-left quadrant in figure 2, absorptive capacity makes the value grow with search intensity according to the relation that links absorptive capacity to search intensity, and negative transfers make the value decrease with search intensity according to the relation that links negative transfers to search intensity.

The net effect of direct search intensity is given by the sum of these two effects and is described by the middle curve in the bottom-left quadrant in figure 2. At low levels of search intensity, negative transfers prevail with a consequent decrease in the value of

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[8] We assume a linear relation between potential absorptive capacity and realized absorptive capacity Zahra and George (2002), non-linearity in the relation between these two constructs might change the way in which absorptive capacity mediates the relation between search intensity and quality. Overlooking this aspect opens the doors to future research on the topic, but should not affect the value of our contribution.

[9] The curve is flipped comparted to the quadrant above, due to the negative effect that negative transfers have on the value of innovation.

innovation with respect to the value baseline. This relative magnitude explains the descending left side of the curve. As search intensity increases, negative transfers still prevail, but their growth rate slows down. On the other hand, absorptive capacity grows faster and starts compensating for the harming effects of negative transfers. This relative magnitude explains turning point A and the rising right side of the curve, allowing us to claim that:

H1: When firms implement pure direct search, there is a U-shaped relationship between search intensity and the value of new products.

Indirect Search Intensity and the Value of Innovation

We now describe how the growth of absorptive capacity and negative transfers changes when considering indirect search intensity.

Indirect search intensity and absorptive capacity

When an organization transfers for the first time a knowledge element from the related domain into the domain of innovation, it acts as a “gatekeeper” that somehow adapt the element to the context where the innovation takes place. This adaptation facilitates the understanding and the acquisition of the same element by those who acquire it subsequently (Allen, 1977; Cohen & Levinthal, 1990; Tushman & Katz, 1980).

Indirect searchers, who access the knowledge elements after they have been applied and adapted in the current domain, are facilitated in understanding these elements with respect to direct searchers, who acquire the same elements from the related domain. This facilitation enhances indirect searchers’ ability to value, assimilate, and commercially utilize knowledge from a related domain, making absorptive capacity grow at a faster rate with indirect search intensity than with direct search intensity.

On the other hand, whereas the recursive relation between search intensity and absorptive capacity that we described is well defined for firms that search directly and have access to all the knowledge elements and interdependences available in the new domain, it is not applicable to indirect searchers, who can access only a limited amount of elements in the related domain.

The reduced pool of knowledge elements available to indirect searchers with respect to direct searchers implies that, when indirect search intensity reaches beyond the threshold where all the knowledge elements previously applied by direct searchers have been acquired, each extra element does not move the firm's knowledge base any closer to the related domain. Therefore, absorptive capacity grows more slowly as indirect search intensity increases.

This decreasing growth of absorptive capacity also manifests when the pool of elements available for indirect search is sufficiently large, and exhaustion might not be an issue.

Indeed, imitative behaviors, such as indirect search, are effective only at low levels of intensity, when only a few elements are imported, and complexity remains low (Rivkin, 2000)-

When more elements from a related domain are applied to innovate, the combinations of elements and their interdependencies increase; this leads to an increase in the complexity of the knowledge applied to innovate (Simon, 1962). Once the intensity of search increases beyond a certain threshold, and with it the complexity of the knowledge acquired, fundamental aspect to understand and apply the new knowledge and the entailed interdependencies remain intractable and undiscernible using an imitative approach typical of indirect search (Rivkin, 2000).

Therefore, when indirect search intensity reaches beyond the level where no new elements are available or where complexity becomes excessive for a proper understanding via indirect search, absorptive capacity grows at a lower rate in absolute terms and vis a vis direct search.

Overall, absorptive capacity grows at a high rate for low levels of indirect search intensity due to the facilitated acquisition of elements acquired indirectly versus directly. However, the rate of increase of absorptive capacity diminishes as the level of indirect search intensity increases. Thus, absorptive capacity grows with indirect search intensity at a decreasing marginal rate, as shown by the top-mid quadrant of figure 2.

Indirect search intensity and negative transfers

We have described how indirect searchers deal with new knowledge that has been previously applied in the current domain by other organizations. Consequently, compared to direct sarchers, not only indirect searchers can observe the outcomes of previous applications of the related knowledge in the new context reducing uncertainty (Lieberman & Montgomery, 1988; Wernerfelt & Karnani, 1987), but they can also improve on previous misapplications (Ingram & Baum, 1997; Kim & Miner, 2007; Miner, Kim, Holzinger, & Haunschild, 1996).

This benefit of indirect versus direct searchers, makes negative transfers grow more slowly with indirect search intensity than with direct search intensity.

Nevertheless, indirect searchers cannot observe the original applications of the knowledge elements in the related domain, as they can access them only after they have been applied in the domain of innovation. This limitation harms the indirect searchers' understanding of the original purpose of an element, making unwarranted analogies more likely.

Problems deriving from increased unwarranted analogies manifest more strongly at high levels of indirect search intensity, where combinations of knowledge elements become complex in terms of the number of elements and their interrelatedness, and the understanding of the aspects entailed in the acquired knowledge in its original domain become increasingly relevant.

Thus, once indirect search intensity grows beyond a certain threshold, the likelihood of unwarranted analogies accumulates, and negative transfers grow faster.

Overall, negative transfers grow at a low rate for low levels of indirect search intensity due to prior applications of the new knowledge in the domain of innovation. However, the rate of growth increases indirect search intensity due to the limited understanding of the knowledge in the related domain. Therefore, negative transfers grow with indirect search intensity at an increasing marginal rate, as in the mid quadrant of figure 2.

The net effect of absorptive capacity and negative transfers in the case of indirect search

We showed that the relation between indirect search intensity and absorptive capacity grows with decreasing margins (top-mid quadrant in figure 2). This relation translates into a positive effect on the value of the innovation, as described by the top curve in the bottom-mid quadrant in figure 2. On the other hand, negative transfers grow with indirect search intensity at an increasing marginal rate (mid quadrant in figure 2), translating into a negative impact on the value of innovation as described by the bottom curve in the bottom-mid quadrant in figure 2.

As in the case of direct search intensity, the net effect of indirect search intensity on the value of innovation is the result of the sum of the two effects, which is described by the middle curve in the bottom-mid quadrant in figure 2.

At low levels of search intensity, absorptive capacity prevails, making the overall value increases with intensity. This situation explains the growing right side of the relation between search intensity and value. At intermediate levels of intensity, whereas the growth of absorptive capacity slows down, that of negative transfers speeds up. This difference in magnitude explains the marginal decrease of the middle curve that leads to turning point B. At high levels of search intensity, whereas absorptive capacity grows very slowly, negative transfers boost, and so does their negative impact on value. The stronger effect of negative transfers harms the value of innovation and leads to its decrease, as represented by the descending right side of the middle curve in the bottom-mid quadrant in figure 2. Overall:

H2: When firms implement pure indirect search, there is an inverted U-shaped relationship between search intensity and the value of a new product.

Mixed Search Intensity and the Value of Innovation

We described how direct and indirect search in a single external domain can coexist within one organization. This condition generates a mixed search mode where the searching firm simultaneously implements direct and indirect search in a single related domain.

When firms adopt a mixed search approach, the advantages and disadvantages of direct and indirect search manifest simultaneously but, for the same total number of knowledge elements acquired (same intensity), with a lower magnitude with respect to pure direct or pure indirect search.

Going back to our example, if a ski manufacturer acquires all the proposed four elements directly, it has access to all their interdependencies in the external domain, but it cannot observe the outcome of prior combination in the domain of innovation. On the other hand, if it acquires two elements directly and two indirectly it has access to all the interdependences entailed in the elements acquired directly and only the interdependencies evident in the domain of innovation of those elements acquired indirectly, but it can observe the outcome of prior applications in the domain of innovation of the elements acquired indirectly. A similar argument on advantages and disadvantages can be applied if we compare a pure indirect searcher with a mixed searcher.

Therefore, although with a lower magnitude with respect to pure direct and indirect searchers, mixed searchers partly benefit from a facilitated understanding and observed applications of the elements acquired indirectly, and of a broader knowledge base and a clearer understanding of the necessary adjustments of the elements acquired directly. The former benefits prevail at lower levels of intensity, the latter at higher levels.

We now analyze how absorptive capacity and negative transfers grow with the intensity of a mixed mode given the described trade-off between advantages and disadvantages.

Mixed search intensity and absorptive capacity

At low levels of intensity, absorptive capacity grows faster with mixed search intensity than with pure direct search intensity due to the facilitated understanding of the elements in the mixed search that are acquired indirectly. However, it also grows slower with mixed search intensity than with pure indirect search intensity due to the elements in the mixed search that acquired directly, which are more difficult to understand.

At high levels of intensity, absorptive capacity grows faster with mixed search intensity than with pure indirect search intensity due to the recursive effect of a broader knowledge base deriving from the portion of direct search. However, it grows slower with mixed search intensity than with pure direct search intensity due to the intractability of some interdependences that limits the expansion of the firm's knowledge base deriving from the portion of indirect search.

Overall, the relation between mixed search intensity and absorptive has a less deep curvature than that of firms that adopt a pure direct or indirect search, as described by the dotted lines in the top-right quadrant of figure 2. Increasing or decreasing margins may persist according to the prevalence of direct or indirect search intensity in the mix and disappear when the two modes are balanced.

Mixed search intensity and negative transfers

At low levels of intensity, negative transfers grow slower with mixed search intensity than with pure direct search intensity due to the portion of elements acquired indirectly, whose previous application in the current domain is observable. However, they grow faster with mixed search intensity than with pure indirect search intensity due to the portion of elements acquired directly that does not have prior applications in the new domain.

At high levels of intensity, negative transfers grow faster with mixed search intensity than with pure direct search intensity due to the portion of elements acquired indirectly that limits the full understanding of the original application of the new knowledge in the related domain. However, they grow slower with mixed search intensity than with pure indirect search intensity due to the portion of elements acquired directly that improves the understanding of the new knowledge in its original domain and highlight differences and necessary adjustments when moving knowledge across the domains.

The curvature representing the relation between mixed search intensity and negative transfers attenuates with respect to pure direct and indirect search intensity, as described by the dotted curves in the mid-right quadrant of figure 2. Once again, the curvature tends to disappear when direct and indirect search intensity are balanced in a mixed mode.

The net effect of absorptive capacity and negative transfers in the case of mixed search

The simultaneous reduction in the curvatures of the relationship between absorptive capacity and mixed search intensity and of negative transfer and mixed search intensity is expected to transfer to the net effect that the two mechanisms have on the value of innovation.

Comparing the net effect of mixed search intensity with that of direct search intensity, we notice that, at low levels of intensity the dominance of the negative effect of negative transfer over absorptive capacity is reduced by the fact that negative transfers grow more weakly and that absorptive capacity grows more strongly when a portion of elements is acquired indirectly.

Similarly, at high levels of intensity, the dominance of absorptive capacity over negative transfers is reduced by the fact that absorptive capacity grows more weakly and negative transfers grow more strongly when a portion of elements is acquired indirectly.

Overall, the net effect of mixed search intensity on the value of innovation with respect to the net effect of pure direct search intensity is depicted by the top dotted line in the bottom-right quadrant of figure 2.

A similar analysis applies when comparing the net effect of mixed search intensity with that of indirect search intensity.

When indirect searchers acquire some elements directly, the positive effect of absorptive capacity over negative transfers at low levels of intensity diminishes, and so does the negative effect of negative transfers over absorptive capacity at a high level of intensity. This effect is depicted by the bottom dotted line in the bottom-right quadrant of figure 2 and allows us to claim:

H3a: When firms implement a mixed approach of direct and indirect search, the U-shaped relation between direct search intensity and value of innovation is attenuated.

H3b: When firms implement a mixed approach of direct and indirect search, the inverted U-shaped relation between indirect search intensity and value of innovation is attenuated.

METHODS

At the light of our analysis, the model proposed in figure 1 can be specified for the intensity of each search mode summarizing the relations that we described, as shown in figure 3.

In this session, we empirically measure the total effect of the intensity of each search mode on the value of the innovation and describe how the non-linearity of this relation is captured by the parallel mediation of absorptive capacity and negative transfers, which grow non-linearly with search intensity.

Data and Sample

To validate our hypotheses, we analyze data from the ski manufacturing industry from 1998 to 2009, when external knowledge was imported from the snowboard manufacturing industry and applied to new models of skis. This setting is particularly suitable to support our theory for several reasons. First, snowboard manufacturing is clearly a related knowledge domain to ski manufacturing due to the similarities between the two industries. Second, it is chronologically evident that certain knowledge flowed from snowboard into the ski and not vice versa. This non-biunivocal relationship between the two industries avoids confounding effects that spill-overs from the current domain into the related one might create. Third, it is relatively simple to isolate technologies and product lines that adopted snowboard related knowledge and influenced other ski models.

We collected data on the ski models available on the market from 1998 to 2009, which represents the right setting for our analysis as search in the snowboard sector heterogeneously started across ski manufacturers in 1998. We stopped our data collection in 2009 as this year represents the second season after the last evident adoption of snowboard related knowledge in the ski sector. After 2009, confounding effects do not allow a clear isolation of applications of snowboard related knowledge to ski products.

Our data are longitudinal in nature as we monitor each ski model during its lifetime.

Information on ski models comes from two primary sources: Sciaremag, the main Italian ski magazine, and Ski Canada Mag, the main Canadian ski magazine. Each of these two magazines publishes a yearly buyer's guide that gathers information about ski models available on the market in the next winter season. From these sources, for the whole period object of our analysis, we obtained 4898 ski models spread across 49 brands. Some ski models are dropped during the analysis due to a lack of information on some variables. However, this happens randomly across brands and years.

The use of product data allows us to propose a first attempt to measure negative transfers, which, to our knowledge, have been proposed theoretically, but never explicitly tested empirically.

Measures

Dependent variable, value of innovation. We use the natural logarithm of the firm's suggested price to market of each ski model as a proxy for value of the new product. Erdem, Keane, and Sun (2008)show that brands use price to signal higher value of their products. This practice is common in the ski industry, making price a convincing signal of value. Indeed, each year, between January and February, ski manufacturers participate in two major exhibitions where companies display their products for the next season, get consumer feedback about their innovations, and compare the output of their R&D departments with competitors. The information gathered at these exhibitions is than used to set the price of the products for the next season and communicate them to magazines that publish buyer's guides around late September. Hence, prices in the guides reflect a brand's assessment of the value of its products, compared to those of competitors. The price data we use come from these buyer's guides.

Using price instead of more conventional measures for the value of innovation, such as forward citations of patents, allows us to shift the analysis from patents to products, offering several significant advantages in our context. Firstly, since several ski manufacturers such as Line and Armada have little to no patenting activity, focusing on patents would lead to a loss of information on the role of these players, who are key innovators in the industry despite their limited patent portfolio. Secondly, since we are considering indirect search as a basic construct, we must account for the fact that indirect search involves an imitative component and entails possible variations of the inspiring product. These aspects cannot be adequately extracted from patents but can be disentangled by focusing on products[10].

On the other hand, since the price of a ski might be driven by factors that are different from the innovation behind the product, using price as a proxy for value might raise some concerns. Indeed, factors related to specific manufacturers or to the complexity and the profit margin, such as brand equity, the ski's target market (i.e. beginners, intermediate, advanced skiers), and the ski's purpose (i.e. racing, touring, freeskiing), affect the price.

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[10] It can be argued that backward patent citations could reveal an imitative behavior. Nevertheless, much important information would be lost using patent citations due to the borad nature of patents versus the precise nature of products. An example can be found in one of the first patent on sidecut, which quotes "A ski according the present invention has an exaggerated tip between 1.5 to 2.25 times the narrowest point of the waist and an exaggerated tail with a ratio of 1.05 to 2.14 times the narrowest point of the waist"; citing this patent tells us nothing on whether the product is using a sidecut where the tip is 1.5 or 2.25 times the narrowest point of the waist, a distinction that makes a substantial different in the product according to its purpose, and that is extremely relevant if the aim is considering the proper understanding and application of knowledge. Our data on products allow us to capture the precise measure of the sidecut of each ski model and, thus, to extract a precise information on how knowledge elements are combined and how these combinations evolve within and across products. The increased precision of the information entailed in products is necessary to measure our constructs.

To cope with these concerns and give validity to our measure, we add control variables (described later) that capture the effect of all these factors.

Independent variables, direct search intensity. We consider all patents filed by ski and snowboard manufacturers in the category coded A63C in the CPC classification of USPTO. This code contains 87.3% of the snowboard related patents and 61.1% of the ski related ones. We do not consider other categories because they refer mostly to accessories such as boots, ski carriers, ski lockers, and articles related to the use of skis that are beyond the scope of our analysis.

Within A63C, we isolate the patents filed by Burton, which is a pure and by far the most innovating snowboard manufacturers, as the benchmark to identify the knowledge that mostly expands the boundaries of the snowboard industry. We then analyze all the patents that each ski manufacturer filed in this category and perform a similarity analysis of the abstracts of these patents with each of Burton's patents in the years up to the one of the filing date by applying the LDA algorithm (Blei, Ng, & Jordan, 2003)[11]. Kaplan and Vakili (2015) explain that patent abstracts are a valid source of information to perform text analysis with LDA for two main reasons. Firstly, abstracts must be 150 words or less, which allows for similarity in size across documents; secondly, as defined by USPTO itself, "they have the purpose of enabling the public to determine quickly from a cursory inspection, nature and gist of the tech disclosure"[12].

[11] We preferred a topic-based algorithm over a word based one (i.e. TF-IDF), as we are interested in finding patents that treat the same arguments as Burton's patents, but that are not necessarily similar to the latter. There are two main reasons behind this choice: firstly, two patents might treat the same snowboard topic but use different words; secondly, two patents might treat two different topics about snowboarding (i.e. materials and shape) and we want to identify how related to snowboards these two patents are and not how similar they are. LDA allows us to capture these aspects (Blei et al., 2003).

[12] Although patent abstracts have been used in prior literature and prove effective to measure patent similarity (Arts, Cassiman, & Gomez, 2018; Kaplan & Vakili, 2015), there is debate in the literature on whether abstracts are

The similarity score of each ski manufacturer's patent to each Burton's patents goes from 0 to 1, where 0 represents very dissimilar patents, which in our case means pure ski patents, and 1 very similar patents, which in our case means pure snowboard patents. The similarity scores of each patent with Burton's patents up to the focal year are then summed by firm to obtain the cumulative similarity of each ski manufacturer's patent portfolio to Burton's patent portfolio up to that year. The resulting measure captures how much ski manufacturers have directly searched the snowboard knowledge domain, which in our framework is direct search intensity. The higher the similarity score, the more intensely the ski manufacturer has directly explored the snowboard domain.

Since products issued in a specific season rely on the knowledge acquired up to the previous year, the actual variable used in the model is the t-1 lag of this variable.

Despite some limitations related to this measure, such as the fact that we capture an application of knowledge and not the knowledge actually acquired from a related business, in this context, we consider it a more precise measure than the more widely used patents backward citations, which would face the same issue but raise even more concerns. There are at least two important reasons why backward citations could be misleading in this context. Firstly, whereas citations are dichotomous (a patent is either

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the right source to perform a text analysis on patents. On the one hand, abstracts entail the described advantages over other parts of patents such as claims, which are written in a language even good parsing algorithms tend to fail miserably at (Parapatics & Dittenbach, 2011); on the other hand, abstract lose their value when they are written to obfuscate the real content of the patent, a common practice in industries where firm performance in tightly related to IP protection.
In the specific context of the fairly simple ski and snowboard industries, this drawback does not manifest, as the value of the innovation is embedded in the product and not in the IP protection (non-patenting firms still perform well), and abstracts reflect the real content of the patent. Therefore, abstracts appear to be an appropriate choice to avoid technical problems while exploiting the advantages of synthesis of main topics of the patent in a standardized length.

cited or not), a similarity analysis allows us to grasp how much of a patent is in another patent in terms of topics treated on a continuous scale. This continuous nature enables a more precise and weighted description of the knowledge common across patents and avoids issues related to the fact that two patents might cite the same patent but for different aspects of its knowledge. Secondly, the influence of a cited patent on a focal patent depends on the number of generations between the two and on an arbitrary weight that can be assigned to generations that are closer or more distant to the focal patent (Corredoira & Banerjee, 2015). In our context, we have no specific hints on how to set this weight, risking misrepresentation of the influence of a cited patent on the focal one.

Independent variable, indirect search intensity. We consider the cumulative number of ski models produced by each ski manufacturer adopting snowboard knowledge after the introduction in the market of the first product to apply that knowledge. Again, we use the t-1 lag value, as products marketed at time t rely on knowledge acquired indirectly up to t-1.

Indirect search is measured at the product level and not at the patent level for two main reasons. Firstly, as discussed, not all the ski manufactures patent, even more so when they just improve on pre-applied combinations of elements; secondly, an analysis of products is more coherent with the fact that indirect searchers may leverage on tests and feedbacks of prior applications of the knowledge in the ski domain to improve on them.

Control variables. In order to use price as a valid proxy for the value of innovation, we control for several factors other than innovation that affect the price of skis.

Price changes according to the technical skills of user segments. Skis for beginners are cheaper than those for experts. For this reason, we control for the target segment of each new product including a “*level*” variable based on 9 categories identified in one of our sources according to the skills of the final user, and classified as: beginners, intermediate, advanced, experts, from beginner to intermediate, from beginner to advanced, from intermediate to advance, from intermediate to expert, from advanced to expert.

We also control for the categories representing the purpose of the ski, as skis for experts built for competitions might have a different price from skis for experts built for touring. In order to capture this aspect, we classify skis according to their under-boot width, with narrower skis being race-oriented and wider skis being free-riding oriented. This purpose is captured by a “*width*” variable based on 5 categories according to the width of the ski waist: 73 mm or narrower, from 74 to 88 mm, from 89 to 99 mm, from 100 to 110 mm, and 111 mm or wider.

Another aspect that directly affects the price is whether the ski is sold with or without binding, with the latter option being the most expensive. In order to control for this aspect, we included a “*binding*” binary variable that takes value 1 when skis are sold with bindings or plates.

Other than the variables mentioned above, which affect the price by impacting the productive and commercial components of each ski mode, some aspects may impact the very value of the innovative component included in the price and must be considered.

Some ski manufacturers also produce in sectors different from ski and snowboard (i.e. inline skates, tennis rackets, cross country skis). Although these businesses are domains more distant than snowboard, it is reasonable to think that their exploration might broaden the knowledge base of a firm that acquires elements from them, thus increasing the firm's absorptive capacity and consequently increasing value. This aspect is controlled by inserting the "*other domains*" binary variable, which equals 1 when the firm operates in businesses different from ski or snowboard.

The "*boots*" binary variable controls instead for ski manufacturers that produce also ski boots, as they may leverage the idea of synergies between the two tools to increase value.

The value of innovation may depend not just on the external knowledge acquired, but also on new applications of each firm's internal knowledge. To control for this aspect, we insert the variable "*ski patents*" that measures the one year lagged cumulative number of pure ski patents (0 similarity with Burton's patents) filed by each firm up to the focal year.

Finally, the model includes year and brand fixed effects to control for decisions on price and overall value that depend on a firm's specific strategy or specific years.

Absorptive capacity and negative transfers: we use a principal component analysis to weigh aspects of several different variables that we could use and that we believe embed negative transfers and absorptive capacity.

Leveraging on the longitudinal nature of our data, we can observe if a ski model has been updated or has remained the same across years. Absorptive capacity originates from four components. The first one represents the cumulative number of each brand's new products in the product line; this measure allows us to capture the number of applications of external knowledge, which enhance absorptive capacity. Since applications of external knowledge are important not just in absolute terms but also in terms of the proportion of successful outcomes over the total attempts, the second component is the percentage of new products that remained the same during their lifetime. This component captures the fact that, at least in this industry, unsuccessful products are either discarded or updated and discarded shortly after the update, whereas successful products remain unchanged for several years. The ratio with respect to the total number of products is necessary to compare firms that have product lines of different sizes and to capture nuances different from the absolute number of new products typical of the first component. The third component represents how many years each product persists in the product line; a prolonged presence indicates a valid commercial application of the new knowledge and higher absorptive capacity. The final component is the cumulative number of pure ski patents assigned to each firm, which captures the firm's familiarity with combining knowledge and is positively related to absorptive capacity[13].

We construct negative transfers relying on two main components. The first one represents the percentage of each brand's products that have been updated in the period of observation; when firms misapply external knowledge, they try to fix their mistakes by updating the products. This component captures how many products have been subject to a misapplication of external knowledge. We use a percentage instead of the absolute value, as it helps to better control for mistakes that might be due to reasons different from negative transfers, such as production issues or a broader product line. The second component is the cumulative number of products that had a life span in the

[13] The most used measures of absorptive capacity relay on the stock of patents. As we did for other measures, we account for this methodology inserting patents in the measure, but we weight this factor and use it in combinations with other factors because our context includes non-patenting firms that anyway have a certain endowment of absorptive capacity. Accounting for factors at the product level, allows us to measure the absorptive capacity of these firms.

market shorter than the average life span of the brand's products. A shorter lifetime indicates that the firm acknowledges that the product did not meet value expectations, capturing the misapplications of external knowledge.

The correlation of the main variables that are simultaneously used in the analysis is provided in table 1.

Model

We exploit the longitudinal nature of our data and apply a panel regression with year and brand fixed effect to control for possible endogeneity deriving from the firm's time-invariant characteristics and time effects that are not captured by our control variables[14]. The resulting model that expresses the relation between direct and indirect search intensity and the value of new products is formalized as:

$$(1)\ Ln(price)_t = \beta_0 + \beta_1 Direct_{t-1} + \beta_2 Direct_{t-1}^2 + \beta_3 Indirect_{t-1} + \beta_4 Indirect_{t-1}^2 + Controls + FE + e$$

Where: *Ln(price)* is the natural log of price, which proxies value; *Direct* is the direct search intensity; *Indirect* is the indirect search intensity; *Controls* are all the listed control variables and *FE* are brand and year fixed effects.

Following Haans, Pieters, and He (2016), to highlight how the impact on the value of new products changes when firms adopt mixed search modes that imply direct and indirect search, we extend the described model including the interaction of the squared

[14] Given the multilevel nature of our model, where we try to explain an outcome at a product level with a variable of interest at the firm level, we could choose between a multilevel model (i.e. HLM) with random effect or a fixed effect model. Results are consistent between the two models, but we propose only the fixed effect as more conservative in coping with unobserved variability.

value of direct search intensity (indirect search intensity) with the linear value of indirect search intensity (direct search intensity). The model becomes:

$$(2)\ Ln(price)_t = \beta_0 + \beta_1 Direct_{t-1} + \beta_2 Direct_{t-1}^2 + \beta_3 Indirect_{t-1} + \beta_4 Indirect_{t-1}^2 + \beta_5 Direct_{t-1}^2 \times Indirect_{t-1} + \beta_6 Indirect_{t-1}^2 \times Direct_{t-1} + Controls + FE + e$$

In order to attribute the results of these two models to the stated mechanisms, in a second step, we implement a bootstrap robust mediation model where negative transfers and absorptive capacity mediate the relationship between quality and direct/indirect search intensity. The mediation analysis captures the relation that links direct and indirect search intensity to negative transfers and absorptive capacity, and its translation into the value of new products. The mediated model is:

$$(3)\ NT_t = \beta_7 + \beta_8 Direct_{t-1} + \beta_9 Direct_{t-1}^2 + \beta_{10} Indirect_{t-1} + \beta_{11} Indirect_{t-1}^2 + Controls + FE + e$$

$$(4)\ AC_t = \beta_{12} + \beta_{13} Direct_{t-1} + \beta_{14} Direct_{t-1}^2 + \beta_{15} Indirect_{t-1} + \beta_{16} Indirect_{t-1}^2 + Controls + FE + e$$

These two equations, where *NT* represents negative transfers and *AC* represents absorptive capacity, capture the relation of pure direct and pure indirect search intensity with absorptive capacity and negative transfers respectively. By adding the predicted values of NT and AC generated by these equations to the model proposed in equation 1, we highlight how much of the effect that links quality with direct and indirect search intensity is captured by absorptive capacity and negative transfers and if there is any effect that direct and indirect search still have when controlling for the mediating variables. The model becomes:

$$(5)\ Ln(price)_t = \beta_0 + \beta_1 Direct_{t-1} + \beta_2 Direct_{t-1}^2 + \beta_3 Indirect_{t-1} + \beta_4 Indirect_{t-1}^2 + \beta_{17} AC_t + \beta_{18} NT_t + Controls + FE + e$$

Finally, also in this case, we introduce the interaction of direct and indirect search proposed in equation 2, in order to capture the different growth of absorptive capacity and negative transfer in case of a mixed search approach with respect to a pure direct or indirect one. The model describing the relation that links absorptive capacity and negative transfers with direct and indirect search intensity in the case of a mixed approach becomes:

$$(6)\ NT_t = \beta_7 + \beta_8 Direct_{t-1} + \beta_9 Direct_{t-1}^2 + \beta_{10} Indirect_{t-1} + \beta_{11} Indirect_{t-1}^2 + \beta_{19} Direct_{t-1}^2 \times Indirect_{t-1} + \beta_{20} Indirect_{t-1}^2 \times Direct_{t-1} + Controls + FE + e$$

$$(7)\ AC_t = \beta_{12} + \beta_{13} Direct_{t-1} + \beta_{14} Direct_{t-1}^2 + \beta_{15} Indirect_{t-1} + \beta_{16} Indirect_{t-1}^2 + \beta_{21} Direct_{t-1}^2 \times Indirect_{t-1} + \beta_{22} Indirect_{t-1}^2 \times Direct_{t-1} + Controls + FE + e$$

Results

Table 2 represents the results of the panel analysis. Models 1 to 7 show the impact of each independent variable or controls. In light of the correlation between some of these variables expressed in table 1, the interpretation of the coefficients in these models is not conclusive due to the potential omitted factor bias and the weight that each variable has in computing the standard errors.

Indeed, the 0.57 correlation between direct and indirect search is particularly interesting to support the study of the direct, indirect, and mixed search approach, as it shows that firms may or may not combine the intensity of the two modes. However, it also implies that the omission of direct or indirect search from the model could bias the coefficients and create confounding effects[15].

In Model 8, which is the full model, the squared term of direct search intensity has a positive coefficient (b=0.0003, p<0.01) and the linear term has a negative coefficient (b=-0.0133, p<0.01). The two signs support the "U" shape relationship between direct search intensity and quality of new products proposed in hypothesis 1.

The squared term of indirect search intensity has a negative coefficient (b=-0.0001, p<0.05) and the linear term has a positive coefficient (b=0.0067, p<0.05). These findings support the inverted "U" shape relationship between indirect search intensity and quality of new products proposed in hypothesis 2.

Following Lind and Mehlum (2010), we confirm the non-linear relation by performing a "utest" in Stata, which checks that the slopes of the curves at the lowest and highest values of direct and indirect search intensity are sufficiently steep and that the turning point belongs to the interval included between the maximum and minimum value of direct and indirect search intensity.

The test confirms the U shape (p<0.01) and the inverted U shape (p<0.05).

Insert table 2 about here

In Model 9, we test for the interaction between direct and indirect search on the quality of new products. The interaction of the quadratic term of direct search with linear indirect search is negative (b=-0.00001, p<0.05), meaning that the interaction of direct

[15] The results are robust also omitting the variable Ski Patents, which is the one with the highest correlation with Direct Search. We also test for multicollinearity with Stata Collin command, and we found non-significant variance inflation factor for each coefficient of the full model (max value 2.61).

and indirect search reduces the non-linear effect between direct search and quality, in support of hypothesis 3a. Similarly, the interaction between the quadratic effect of indirect search and direct search is positive ($b=0.00001$, $p<0.05$), indicating that the interaction of indirect search with direct search attenuates the quadratic effect of indirect search on quality, in support of hypothesis 3b.

Table 3 reports the relation between direct and indirect search intensity and our mediating variables: absorptive capacity and negative transfers.

Insert table 3 about here

Model 10 shows the relationship between direct/indirect search and negative transfers. We find that direct search has a positive linear effect ($b=0.0317$, $p<0.05$) and a negative quadratic effect ($b=-0.0007$, $p<0.05$) on negative transfers. A marginal analysis of the slope supports our idea that negative transfers grow at a decreasing rate as direct search intensity increases.

As for indirect search, we find a positive linear effect ($b=0.0238$, $p<0.05$) but no quadratic effect ($b=-0.0001$, $p<0.79$), thus showing that the relationship that we proposed in mid quadrant of figure 1 for indirect search intensity does not grow with a growing rate, but linearly. Despite this discrepancy, hypothesis 2 may still be supported by the proposed mechanism if we can show that the relationship between indirect search intensity and absorptive capacity grows with decreasing margins as we theorized. The net effect of linearly growing negative transfers and concavely growing absorptive capacity may indeed generate an inverted U shape if the slope of the line crosses the slope of the curve.

In Model 11, we use absorptive capacity as the dependent variable. We find that direct search has a positive quadratic effect ($b=0.0006$, $p<0.10$) on absorptive capacity. This relationship, in association with a linear coefficient that is not statistically different from zero ($b=-0.0276$, $p<0.13$) supports our idea of absorptive capacity growing at increasing marginal rates as direct search increases.

As for indirect search, we find a positive linear effect ($b=0.0411$, $p<0.05$) and a negative quadratic effect ($b=-0.0008$, $p<0.01$), supporting our idea that absorptive capacity grows at a decreasing marginal rate as indirect search increases.

All these relations are supported by a marginal analysis (that we do not report for the sake of brevity).

So far, we have shown that direct and indirect search influence a) value and b) negative transfers and absorptive capacity. In order to test for the mediating role of negative transfers and absorptive capacity in the search intensity - value relationship, we provide a parallel mediation model (figure 3). Should we find that the effects that we have found in Model 8 of Table 2 for the coefficients of the squared terms of direct and indirect search diminish when negative transfers and absorptive capacity are added to the model, we would find support for mediation.

We test for this full model in Table 4. We add the predicted values of negative transfers and absorptive capacity from equations 3 and 4 and generate model 12. We find that negative transfers have a negative effect on value ($b=-0.3121$, $p<0.01$), while absorptive capacity has a positive effect ($b=0.1600$, $p<0.01$), which is aligned with our claim that negative transfers harm value, whereas absorptive capacity enhances it.

Insert table 4 about here

Furthermore, the squared terms of direct and indirect search become non-significant. The loss of significance supports the fact that the full non-linear effect that relates direct and indirect search to the value of innovation is captured by the mediating effect of (predicted) negative transfers and absorptive capacity, providing support to the mechanism that we proposed behind the first two hypotheses.

In table 5, we show how negative transfers and absorptive capacity grow in case of mixed search. Models 13 and 14 test the interaction between direct and indirect search on negative transfers and absorptive capacity, respectively. To find support for the mechanisms that we proposed, we should find that the curvatures evident in Model 10 and 11 diminish. The interaction between the quadratic term of direct search and the linear term of indirect search goes in the expected direction as it is positive when explaining negative transfers ($b=0.000003$, $p<0.90$) and negative when explaining absorptive capacity ($b=-0.00003$,$p<0.22$), but is not significant in both models. The same is true for the interaction between the quadratic term of indirect search and the linear term of direct search, which is positive when explaining absorptive capacity ($b=0.00004$, $p<0.13$), but not significant.

Insert table 5 about here

In light of these results, despite the expected direction of the coefficients, we cannot draw conclusions on the link between the mechanisms that we proposed and hypotheses 3a and 3b.

DISCUSSION

In this paper, we propose that new knowledge from an external domain can be acquired directly, indirectly, or using a mix of these two approaches. We explain that the intensity of each mode has a non-linear effect on the value of the innovation that the searching firm generates applying knowledge from a related domain to its current domain of operation.

Understanding this relationship is of utmost importance not just because the value of innovation is a crucial measure of innovation performance, but also because the non-linearities that we found highlight that, to achieve innovation of superior value, firms should select the search mode in accordance to the intensity with which they can pursue that mode. Indeed, overinvesting in intensity might be detrimental for the value of innovation as pure indirect searchers achieve the best quality at intermediate levels of intensity and pure direct searchers at a high or a low level of intensity.

What might seem intuitively obvious is counterintuitive in practical terms: typically, firms pursue either highly intense indirect search, which looks safer and easier to achieve, or moderately intense direct search, which seems instead riskier and harder to achieve. However, our results show that these strategies hamper the value of innovation.

In addition to these practical implications, we believe that our analysis has important theoretical implications for organizational learning theory. Firstly, it extends the literature on knowledge search identifying new drivers of innovation performance that not only have been so far overlooked but that manifest also in contexts that are broader than those considered in the existing literature, as the case of competing firms searching a common knowledge domain.

Secondly, we support that the outcome of external knowledge search depends on absorptive capacity, but we also highlight the potential drawbacks of negative transfers.

Negative implications of knowledge search have received little attention in the literature, but deserve careful consideration to accurately understand what drives innovation performance.

In this matter, we could adequately describe the proposed mechanisms because we selected the value of innovation as the dependent variable instead of other standard measures of innovation performance, such as the amount of innovation generated, that would have hidden the presence of negative transfers, having this mechanism implications on quality but not on quantity.

Overall, our attempt to offer a detailed and comprehensive analysis of the mechanisms behind learning modes in the specific context of knowledge search, advocates for a deeper understanding of the implications of experiential and vicarious learning also in different contexts. Nevertheless, this kind of improvement can be achieved only by narrowing the focus onto specific sources of learning and by being precise in identifying the outcome variable, which is often defined in broad terms, such as innovation performance.

Lastly, by comparing search modes with early and late entrants, we identified a nexus between the streams of literature on organizational learning and time of entry, but at the same time, we clarified essential differences that open opportunities for new research.

We clarified that, differently from first movers and late entrants, we considered direct and indirect search as orthogonal. Future research might investigate limitations to this orthogonality, as it is not clear if and under what circumstances searching firms can freely adopt any mixed mode with any intensity.

Similarly, we have not discussed the conditions that bound our framework in light of the proposed mechanisms and trade-offs. Since negative transfers and absorptive capacity change with the complexity of the knowledge available in the external domain as well as with the relatedness between this domain and the firm's domain of operation, we expect these two variables to play an essential role in setting necessary contingencies for our theory. Theorizing on these contingencies and testing them in a context with heterogenous related domains that vary in relatedness and complexity, would extend our knowledge of the implications of search modes as well as confirm the net effect of the proposed mechanisms.

Even the literature on time of entry has shown that advantages and disadvantages related to early versus late entry are contingent on environmental factors of the new domain. These factors may inhibit the ability of competitors to imitate or leapfrog first movers (Fudenberg, Gilbert, Stiglitz, & Tirole, 1983; Jovanovic & Macdonald, 1994; Lee, Smith, Grimm, & Schomburg, 2000; Mansfield, Schwartz, & Wagner, 1981) or allow later adopters to exploit market opportunities more effectively through imitation rather than innovation (Carow, Heron, & Saxton, 2004; Golder & Tellis, 1993; Shankar, Carpenter, & Krishnamurthi, 1998). This aspect offers new opportunities for research bridging the literature on knowledge search with the literature on first-mover advantage.

In addition to these extensions, which arise from the nature and focus of this paper, we also acknowledge two main limitations that offer opportunities for future improvement. The first one derives from the lack of support of the mechanisms behind hypotheses 3a and 3b, which advocates for a better understanding of how mixed search intensity is linked to the value of innovation. It is in fact possible that negative transfers and absorptive capacity do not change with mixed search intensity the way we described, but with other non-linear relations that we could not capture and that attenuate the total effect of direct and indirect search intensity on quality. Another possible explanation is that the interaction of direct and indirect search creates non-linearities not just in the indirect effect that relates search intensity to absorptive capacity and negative transfers, but also in the second indirect effect that relates these mechanisms to the value of innovation, which we assumed as linear.

The second limitation is in the measures we used, which may appear non-conventional in the literature. This non-conventionality is not dictated just by the fact that new constructs may require new measures, but also by our attempt to adopt measures that best grasp the essence of the proposed concepts while making sense in the empirical setting identified by the ski and snowboard industries.

We chose to sacrifice conventionality in favor of a more realistic representation of the proposed concepts in the studied industry. Even though this offers a more realistic contribution in our context, we acknowledge that it might imply limitations in the generalizability of our findings. Nevertheless, it is our opinion that this drawback does not harm the validity of our findings and that, before focusing on generalizability, it is essential to prioritize the accurate description of the concepts that will be applied to different contexts.

Whereas this and the other proposed limitations set the boundaries of the validity of this paper, they also offer opportunities for future development.

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Figure 1

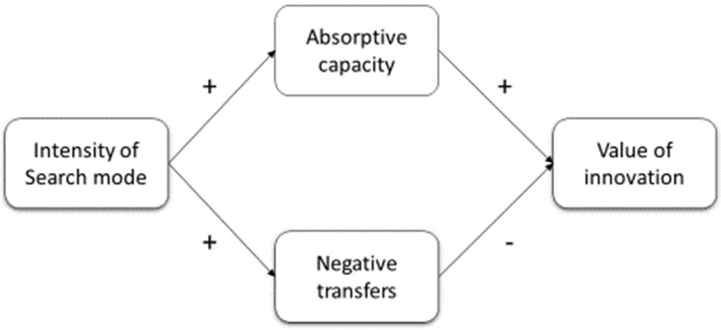

Figure 2

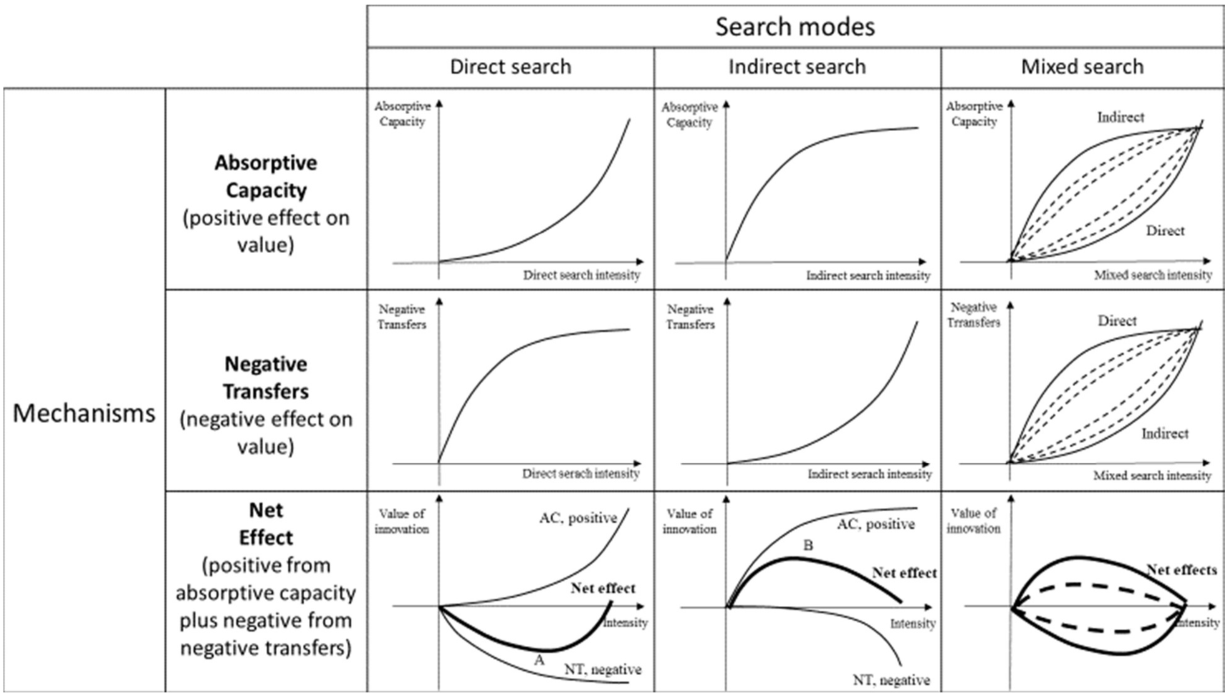

Figure 3

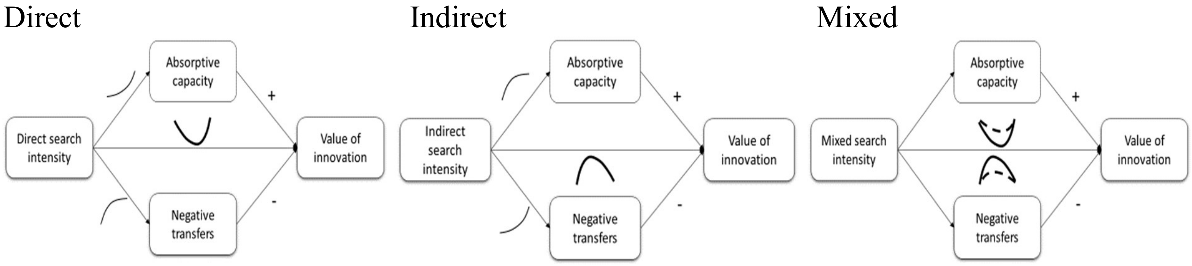

Table 1

Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Direct	1.000									
(2) Indirect	0.570	1.000								
(3) Other Domains	0.246	0.089	1.000							
(4) Boots	0.335	0.313	0.218	1.000						
(5) Ski Patents	0.700	0.343	0.431	0.411	1.000					
(6) Level category	-0.031	-0.056	0.031	0.014	0.020	1.000				
(7) Width category	0.100	0.172	-0.021	-0.053	-0.009	-0.046	1.000			
(8) Bindings	0.195	0.380	0.029	0.191	0.117	-0.014	-0.178	1.000		
(9) Year	0.299	0.656	-0.070	0.037	0.037	-0.064	0.298	0.440	1.000	
(10) Brand Id	0.303	0.048	-0.062	0.264	0.228	-0.049	-0.032	-0.054	-0.002	1.000

Table 2

Effects of search modes on quality of new skis

	Model 1 Price Coef./p	Model 2 Price Coef./p	Model 3 Price Coef./p	Model 4 Price Coef./p	Model 5 Price Coef./p	Model 6 Price Coef./p	Model 7 Price Coef./p	Model 8 Price Coef./p	Model 9 Price Coef./p
Direct	0.0001	-0.0009				-0.0120***		-0.0133***	-0.0174**
	(0.847)	(0.625)				(0.006)		(0.001)	(0.014)
Direct X Direct		0.0000				0.0003***		0.0003***	0.0010**
		(0.491)				(0.001)		(0.000)	(0.014)
Indirect			0.0008**	0.0037***			0.0053	0.0068**	0.0105***
			(0.040)	(0.001)			(0.124)	(0.044)	(0.009)
Indirect X Indirect				-0.0001***			-0.0001	-0.0001**	-0.0002***
				(0.006)			(0.179)	(0.030)	(0.004)
Other Domains					-0.3603***	-0.3382***	-0.3499***	-0.3272***	-0.3159***
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Boots					-0.1703***	-0.1829***	-0.1308***	-0.1465***	-0.1482***
					(0.000)	(0.000)	(0.010)	(0.001)	(0.001)
Ski Patents					0.0066	0.0062	0.0064	0.0079	0.0107
					(0.504)	(0.535)	(0.453)	(0.371)	(0.290)
Bindings					0.1940***	0.2017***	0.1883***	0.1978***	0.2000***
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Direct X Indirect									-0.0005
									(0.217)
Direct X Direct X Indirect									-0.0000**
									(0.024)
Indirect X Indirect X Direct									0.0000**
									(0.014)
Constant	6.6140***	6.6157***	6.5989***	6.5741***	6.8181***	6.7916***	6.7954***	6.7602***	6.7402***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
year FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes
brand FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes
level FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes
width FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes
R-squared	0.003	0.001	0.000	0.001	0.096	0.098	0.100	0.102	0.107
N	4125	4125	4137	4137	3290	3278	3290	3278	3278

s.e. are robust and clustered at brand id where included

* p<0.10, ** p<0.05, *** p<0.01

Table 3

Effects of pure direct and indirect search intensity on negative transfers and absorptive capacity

	Model 10 Negative Transfers Coef./p	Model 11 Absorptive Capacity Coef./p
Direct	0.0317**	-0.0276
	(0.02)	(0.13)
Direct X Direct	-0.0007**	0.0006*
	(0.03)	(0.07)
Indirect	0.0238**	0.0411**
	(0.05)	(0.01)
Indirect X Indirect	-0.0001	-0.0008***
	(0.79)	(0.00)
Other Domains	-1.0197***	1.8269***
	(0.00)	(0.00)
Constant	-1.9613***	-5.6392***
	(0.00)	(0.00)
Year FE	Yes	Yes
Brand FE	Yes	Yes
N	4625	4512

First column represents the effect of direct and indirect search intensity on negative transfers.
Second column represents the effect of direct and indirect search intensity on absorptive capacity
Standard errors are robust and clustered at brand level, p values in parentheses.
Coefficients are robust to bootstrap.
* p<0.10, ** p<0.05, *** p<0.01

Table 4

Total effect of search modes on quality of new products with mediation

	Model 12 Price Coef./p
Predicted Negative Transfers	-0.3121***
	(0.00)
Predicted Absorptive Capacity	0.1600***
	(0.01)
Direct	0.0011
	(0.61)
Direct X Direct	0.0000
	(.)
Indirect	0.0077***
	(0.01)
Indirect X Indirect	0.0000
	(.)
Other Domains	-0.6445***
	(0.00)
Boots	0.1468
	(0.56)
Ski Patents	0.0079
	(0.37)
Bindings	0.1978***
	(0.00)
Constant	7.0623***
	(0.00)
Year FE	Yes
Brand FE	Yes
Level FE	Yes
Purpose FE	Yes
N	3278

Standard errors are robust and clustered at brand level, p values in parentheses.
Coefficients are robust to bootstrap
* p<0.10, ** p<0.05, *** p<0.01

Table 5

Effects of mixed search modes on negative transfers and absorptive capacity

	Model 13 Negative Transfers Coef./p	Model 14 Absorptive Capacity Coef./p
Direct	0.0420**	-0.0289
	(0.02)	(0.28)
Direct X Direct	-0.0013	0.0020
	(0.32)	(0.19)
Indirect	0.0288**	0.0476**
	(0.03)	(0.01)
Direct X Indirect	-0.0001	-0.0016
	(0.93)	(0.15)
Direct X Direct X Indirect	0.0000	-0.0000
	(0.90)	(0.22)
Indirect X Indirect	-0.0002	-0.0009***
	(0.43)	(0.00)
Indirect X Indirect X Direct	0.0000	0.0000
	(0.77)	(0.13)
Other Domains	-1.0290***	1.8458***
	(0.00)	(0.00)
Constant	-1.9195***	-5.6670***
	(0.00)	(0.00)
Year FE	Yes	Yes
Brand FE	Yes	Yes
N	4625	4512

First column represents the effect of direct and indirect search intensity on negative transfer considering the interaction of direct and indirect search modes.
Second column represents the effect of direct and indirect search intensity on absorptive capacity considering the interaction of direct and indirect search modes
Standard errors are robust and clustered at brand level, p values in parentheses.
Coefficients are robust to bootstrap.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

CHAPTER 2

Sequential knowledge search: a "demand-side" perspective on the role of general versus specialist knowledge in sequential inventions.

Inventions are the result of new combinations of knowledge elements that were previously unconnected or of the reshuffling of connected elements in novel combinations (Fleming, 2001; Nahapiet & Ghoshal, 1998; Schumpeter, 1934). However, not all the knowledge elements composing a new combination have the same characteristics: some are more general and find application in more combinations, others are more specialist and applicable more narrowly (Bresnahan & Trajtenberg, 1995; Hall & Trajtenberg, 2004).

The contribution of general versus specialist knowledge to inventions has been studied extensively in the context of the markets where knowledge and technologies are traded (Arora & Fosfuri, 2003; Arora, Fosfuri, & Gambardella, 2002; Arora & Gambardella, 2010). In these markets, some firms supply knowledge that can be general or specialist, and other firms acquire it to innovate.

When studying these markets, scholars have focused principally on understanding the incentives faced by the suppliers of the market (Arora & Fosfuri, 2003; Gambardella & Giarratana, 2013; Gambardella & McGahan, 2010; Palomeras, 2007; Thoma, 2009). Little attention has been given to understand the perspective of the demand, that is those firms acquiring and recombining new knowledge to invent and compete in downstream product markets (Ceccagnoli & Jiang, 2013; Conti, Gambardella, & Novelli, 2019).

Indeed, inventing firms often create new combinations of knowledge elements by searching for new knowledge outside their boundaries and exploring new knowledge domains (i.e., new industries) where they have no prior experience (Leonard-Barton, 1992; Nonaka & Takeuchi, 1995; Simonin, 1997). This process goes under the name of knowledge search (Levinthal & March, 1993; March, 1991) and allows the searching firm to leverage on knowledge from an external domain to invent in the knowledge domain where it operates (Fleming, 2001; Helfat, 1994; Levinthal & March, 1993; Stuart & Podolny, 1996). An example in point is the adoption by mobile phone producers of knowledge from the digital imaging industry to create mobile phones equipped with cameras. Another case is provided by ski manufacturers who have acquired snowboard knowledge to generate new models of skis.

For searching firms, who innovate to compete in downstream product markets, understanding the implications of general versus specialist knowledge on the value of the inventions that they generate is of utmost importance, being value a source of competitive advantage and one of the major determinants of an innovation's success (Aaker & Jacobson, 1994; Jacobson & Aaker, 1987; Phillips, Chang, & Buzzell, 1983; Sethi, 2000).

Nevertheless, research on general knowledge has so far devoted limited attention to the perspective of the searching firms, and, on the other hand, research on searching firms has overlooked the implications of the generality of knowledge on the value of the inventions that the searching firm generates.

Bridging these two streams of literature is essential in light of a trade-off that different levels of generality of the external knowledge elements pose to a firm that wants to innovate via knowledge search. Indeed, whereas specialist knowledge elements entail less causal ambiguity (Simonin, 1999), which facilitates the integration with the firm's knowledge base (Grant, 1996), general knowledge offers a deeper understanding of the relations among elements in the new domain, allowing for a more effective search (Fleming & Sorenson, 2001).

The respective advantages and disadvantages of general and specialized knowledge suggest that different levels of generality trigger different mechanisms, namely negative transfers and absorptive capacity, and are best suited to different circumstances; a core circumstance being the place that a knowledge element occupies in the firm's sequential knowledge search in an external domain.

Since firms invent with a sequential approach that depicts subsequent inventions building on top of preceding ones (Ahuja, Lampert, & Novelli, 2013; Green & Scotchmer, 1995; Hopenhayn, Llobet, & Mitchell, 2006; Novelli, 2015; Scotchmer, 1991), also knowledge search is a sequential process to progressively explore more in-depth an external domain (Laursen & Salter, 2006).
This sequential view of in-depth knowledge search in a domain allows for proper identification of the impact of the advantages and disadvantages of generality on the value of inventions.

The paper takes the perspective of a firm initiating a sequential knowledge search in a new external domain and answers to the question: "how does generality versus specialization of a knowledge element that occupies different places in a sequential knowledge search affect the value of the inventions that a searching firm generates?". The paper aims at identifying the consequences of the initial steps of a searching firm in acquiring knowledge from a new external domain and highlights two effects of the trade-off that emerges from the generality of knowledge. The first is the direct effect that the generality of an element has on the value of the invention generated applying this element; the second is the indirect effect of the generality of a preceding element of the sequence on the value of a subsequent invention generated using a subsequent element in the sequential knowledge search.

By adopting a new measure of generality to better capture the idea of generality of knowledge within a knowledge domain, this work analyzes RIM's entire patent history. By leveraging on a change in the regulation of the patenting procedure introduced by the Leahy-Smith act in the US, it offers two important results: firstly, that general knowledge has a negative direct effect on the invention it generates, but this effect diminishes as the firm moves forth in the sequential knowledge search and applies subsequent elements in subsequent inventions; secondly, by contrast, that the generality of a preceding element has a positive indirect effect on the value of the subsequent inventions generated by subsequent elements and that this positive indirect effect increases if the subsequent element is specialized.

Overall, when firms initiate a search in a new domain, specialist knowledge has immediate positive implications on the value of inventions, but these positive implications diminish as the firm moves forth in sequential knowledge search. On the other hand, when search initiates with general knowledge, the positive implications do not manifest immediately, but only when subsequent knowledge is extracted from the same domain. Moreover, starting a search with a general knowledge revamps the positive effect of specialist knowledge elements that occupy subsequent places in the sequential knowledge search.

THEORY AND HYPOTHESES

Inventions result from combining knowledge elements that were previously unconnected (Fleming, 2001; Schumpeter, 1934). These new connections are often generated when a firm combines its knowledge base with new elements acquired by exploring external knowledge domains that are different from the one where the firm usually operates (Helfat & Raubitschek, 2000; Robins & Wiersema, 1995; Rosenkopf & Nerkar, 2001; Rumelt, 1982; Tanriverdi & Venkatraman, 2005).

This process, known as knowledge search (Levinthal & March, 1993; March, 1991), has been the object of several studies highlighting two crucial aspects: firstly, that firms may initiate a search for external knowledge in multiple knowledge domains (Dahlander, O'Mahony, & Gann, 2013; Jeppesen & Lakhani, 2010; Katila & Ahuja, 2002; Laursen & Salter, 2006; Leiponen & Helfat, 2010; Rosenkopf & Nerkar, 2001); secondly, that search in a given domain may have different levels of depth according to how many knowledge elements the firm extracts from that domain (Laursen & Salter, 2006).

These relevant findings offer the opportunity to highlight two relevant aspects of the search process that have not yet been considered. The first one being how the process to search more in-depth in a domain is practically implemented; the second one being the impact that different characteristics of the knowledge that is extracted from the external domain has on the value of the inventions that the firm generates.

Indeed, as we describe in detail in the next section, depth of search is not a lump event, but a progressive sequential process where the generality of each new elements acquired from the external domain affects the value of inventions differently according to the place that the element occupies in the sequence.

Sequential knowledge search in an external domain

Following an epistemological perspective, the knowledge available in an external domain object of a firm's search is composed of several multiple and different knowledge elements that a firm can extract to innovate (Fleming, 2001). The availability of multiple knowledge elements in a single external domain offers to a searching firm the possibility to explore this domain with a level of depth that increases with the number of elements that the firm extracts and applies to innovate (Laursen & Salter, 2006).

However, search has been theoretically described as myopic, meaning that searching firms tend to be cautious in exploring a domain (Helfat, 1994; Helfat & Raubitschek, 2000; Levinthal & March, 1993; Stuart & Podolny, 2007). Due to this cautiousness, an in-depth search can be conceptualized (and empirically observed) as a progressive process where more and more elements belonging to a domain are extracted step by step.

This progressive approach identifies and temporally ranks in a sequence the first and the subsequent elements that a firm extracts from each knowledge domain. The sequence resulting from searching a single knowledge domain is what this paper identifies as the *sequential knowledge search*. Thus, a searching firm adopts multiple sequential knowledge searches according to the number of external domains explored.

The idea of sequential knowledge search is supported by the simple observation of the different times with which a searching firm applies different pieces of knowledge from the same domain and by the fact that also a firm's inventions are sequential, with subsequent inventions building on top of preceding ones (Ahuja et al., 2013; Green & Scotchmer, 1995; Hopenhayn et al., 2006; Novelli, 2015; Scotchmer, 1991).
There is, in fact, parallelism between a firm's sequential inventions and the sequential knowledge search that contributes to generating them.

By observing the evolution of the mobile phone industry, it is easy to notice that companies introduced the first models of phones equipped with cameras by searching the digital imaging domain and extracting only those knowledge elements related to cameras and sensors. As these companies moved forth in the sequential knowledge search and extracted elements concerning, for example, zooming, stabilizing, and continuous shooting, they improved the initial inventions and introduced a sequence of mobile phones whose cameras had functions unseen in previous models.

This relation between sequential knowledge search and sequential inventions advocates for a better understanding of the implications that an element occupying a particular place in the sequence of search has on inventions occupying different places in the sequence of inventions.

Indeed, each element of the sequential knowledge search has two effects on sequential inventions. The most evident is the direct effect of a new element on the invention that the firm generates applying this element in new combinations. The second is the less evident indirect effect that the element has on the value of subsequent inventions generated by applying the subsequent elements of the sequential knowledge search.

As we discuss in detail in the next sections, these direct and indirect effects on the value of innovation depend on two combined aspects: the place occupied by the element in the sequential knowledge search and the level of generality of the element in its knowledge domain.

General versus specialist knowledge elements within a domain

Since inventions arise from combining or recombining knowledge elements (Schumpeter, 1934), these elements are linked with each other according to their joint applications in previous inventions (Fleming, 2001). Therefore, each element entails associational relationships with other elements through the links emerging from previous inventions. The web of associational relationships creates a knowledge network in which past combinatorial relationships are recorded (Carnabuci & Bruggeman, 2009; Guan & Liu, 2016; Yayavaram & Ahuja, 2008).

At the level of a single knowledge domain that a firm can search, the network of previous combinations of elements belonging to the domain represents the knowledge available for search (Granovetter, 1985). In this network, each element is a "node" and each combination of two knowledge elements in a prior invention is a "tie" (Wang, Rodan, Fruin, & Xu, 2014).

According to its position in the knowledge network, an element may have different characteristics of generality.

Arora and Gambardella (1994) define as general the knowledge that relates the outcome of a particular experiment to the outcomes of other, more distant experiments. Indeed, the number of relations that manifest in applied combinations of a knowledge element is the key aspect that identifies generality. General technologies, and the general knowledge they entail, find broader applicability with respect to specialist technologies (Gambardella & McGahan, 2010) and have the intrinsic characteristics of being applied in a more significant number of circumstances and, thus, relating a higher number of knowledge elements, either within or across knowledge domains (Hall & Trajtenberg, 2004).

In the proposed network conceptualization of knowledge where elements represent the nodes in a domain and the interdependences that relate these elements represent the ties linking the nodes, a higher number of interdependences upon an element signals a higher number of relations of that element with other elements and, thus, a greater generality of the focal element in the domain. In other words, an element in a more central position in the knowledge network pertaining to a knowledge domain is considered more general in that domain.

In the snowboard manufacturing industry, whereas the deep side-cut design is applied to the vast majority of models, the twin-tip design is a peculiarity of those models devoted to acrobatic maneuvers. Due to its broader set of applications within the snowboard domain, the deep side-cut knowledge is more general than the twin-tip one.

Overall, a searching firm can extract knowledge elements that are more general or more specialist in a domain, according to the number of interdependencies within the domain incident upon each element.

Therefore, at the time when ski manufacturers searched the snowboard knowledge domain to innovate their ski models in the 1990s, they could initiate a sequential knowledge search by applying the more general deep side-cut knowledge or the more specialist twin-tip one.

In the next sections, we describe that general and specialist knowledge elements entail advantages and disadvantages for the searching firm, and that this trade-off changes according to the place that these elements occupy in the sequential knowledge search.

General versus specialist knowledge elements in a sequential search

Not only general and specialist knowledge have been juxtaposed in the literature to compare their economic impact (Bresnahan & Trajtenberg, 1995), but also to understand their role in markets for knowledge and technology (Arora & Fosfuri, 2003; Arora et al., 2002; Arora & Gambardella, 2010).

These markets are an alternative to competition in downstream product markets for the firms offering knowledge for licensing (Arora & Fosfuri, 2003; Gambardella & McGahan, 2010), and are a source of novelty for those firms that search for external knowledge to innovate (Arora, Fosfuri, & Gambardella, 2000; Gans & Stern, 2003; Teece, 1986).

The effects of generality have been widely studied by taking the supply-side perspective and understanding the implications of generality for those firms that offer general or specialist knowledge to other firms that then use it to innovate.
For instance, scholars have suggested that the suppliers' costs of acquiring complementary downstream assets, the strength of intellectual property rights in protecting the suppliers (Arora & Ceccagnoli, 2006; Gans & Stern, 2003), and the transaction costs caused by incomplete contracting or undesired leakage of information (Arora et al., 2002; Fosfuri, 2006; Gambardella, Giuri, & Luzzi, 2007; Williamson, 1976), are critical factors affecting the decision of licensing knowledge with different levels of generality to other firms.

However, these markets for knowledge comprise also of a demand-side represented by those firms that search for general or specialist knowledge and use it to invent and compete in downstream product markets (Ceccagnoli & Jiang, 2013; Conti et al., 2019).

This demand-side perspective has received little attention in the context of general versus specialist knowledge; nevertheless, understanding the implications of general versus specialist knowledge from the perspective of a searching firm is of utmost importance. Indeed, first of all, searching firms rely on new knowledge to generate inventions finalized at competing and creating a competitive advantage in downstream product markets and, thus strive to understand how to generate inventions of the highest possible value in order to better succeed in these markets (Aaker & Jacobson, 1994; Jacobson & Aaker, 1987; Phillips, Chang, & Buzzell, 1983; Sethi, 2000).

In addition, the implications of the generality of knowledge on the inventions of a searching firm are not straight-forward, as there is a trade-off intrinsic in searching for knowledge with different characteristics of generality.

On the one hand, the contained span of specialist elements has the advantage of entailing less causal ambiguity (Simonin, 1999) that facilitates their integration within the innovating firm's knowledge base (Grant, 1996; Smith & Zeithaml, 1996). However, specialist elements have the disadvantage of entailing a limited set of the interdependencies and, thus, offering to the searching firm that uses specialist knowledge a restricted understanding of the potential applications of the knowledge available in the external domain (Fleming & Sorenson, 2001).

Overall, as we describe in detail in the next sessions, these characteristics of specialist knowledge reduce negative transfers of knowledge (Ellis, 1965; Finkelstein & Haleblian, 2002; Novick, 1988; Zahavi & Lavie, 2013) but limit the firm's absorptive capacity (Cohen & Levinthal, 1990).

On the other hand, general elements have the advantage offering a deeper understanding of the interdependencies among elements in the external domain, thus allowing for a more effective search (Fleming & Sorenson, 2001) and triggering internal mechanisms that enhance the firm's ability to work with new knowledge (Goldin & Katz, 1998). Nonetheless, elements with a broader span entail higher causal ambiguity (Simonin, 1999), are often perceived as less credible (Leahey, 2007; Teodoridis, Bikard,

& Vakili, 2019) and are more difficult to integrate into the firm's knowledge base (Grant, 1996; Smith & Zeithaml, 1996).

Overall, general knowledge brings higher negative transfers of knowledge but enhances the firm's absorptive capacity,

To properly understand how a searching firm can cope with this trade-off and generate inventions of superior value, this work highlights that the advantages and disadvantages of generality manifest differently according to the place that a general or specialist element occupies in a sequential knowledge search in an external domain, and to the place that an invention occupies in the firm's sequence of innovations.

Accordingly, this paper evolves in three parts: firstly, it considers the direct effect of the generality of a knowledge element on the invention that applies this element. Secondly, it describes how this direct effect changes as the firm progresses in the sequential knowledge search. Lastly, it considers the indirect effect that the generality of a preceding element has on the value of a subsequent invention generated by applying a subsequent element of the sequence.

In terms of our example, where a mobile phone producer initiates a sequential knowledge search by applying knowledge on digital sensors and proceeds in the sequence by acquiring knowledge on zooming and stabilizing, we consider three aspects.

The first one is the direct effect of the generality of the knowledge on sensors, zooming, and stabilizing on the value of the inventions that respectively apply these elements.

The second one is how this direct effect changes according to the place that the elements on sensors, zooming, and stabilizing occupy in the sequential knowledge search that sees sensors as the first element, zooming as the second, stabilizing as the third.

The third one is the indirect effect that the generality of the sensor knowledge (first in the sequence) has on the value of the inventions generated applying the zooming and stabilizing ones (subsequent in the sequence).

We proceed by describing that the positive or negative direction of these direct and indirect effects derive from a change in the firm's triggering of negative transfers and absorptive capacity according to the level of generality of the elements and their place in the sequential knowledge search.

The direct effect of the generality on the value of an invention. The negative impact of negative transfers

Negative transfers suggest that behaviors learned in a knowledge domain can generate negative consequences when adopted with no adjustment in a different context (Ellis, 1965; Finkelstein & Haleblian, 2002; Novick, 1988; Zahavi & Lavie, 2013). Indeed, when elements move across domains, they must be adjusted to fit the requirements in the domain of destination.

Thus, every time searching firms acquire knowledge from an external domain to apply it in their domain of operation, the value of the invention they generate is subject to the harming effect negative transfers, which manifest when the element moved across the domains is not correctly adjusted to fit the new context.

Although the adjustment of an element might appear obvious, unwarranted analogies that hide significant underlying differences between the two domains or the inability of the firm to perform the necessary adjustment might trigger negative transfers.

Thus, due to cognitive limitations and inertial forces that may constrain a firm's behavior, the application of the same element across domains might be inappropriate or inaccurate and harm the value of the invention it generates.

The cognitive limitation and the firm's ability to correctly adjust an element across domains depend on the generality of the element and its place in the sequential knowledge search.

Scholars have shown that when knowledge is narrow (Schmickl & Kieser, 2008) or specialist (Melero & Palomeras, 2015), the adaptation of knowledge to a new setting and new combinations is facilitated. Indeed, specialist knowledge in the external domain entails less causal ambiguity (Simonin, 1999), which facilitates the identification of effective adjustments and the integration and recombination in the firm's knowledge base of a specialist element (Grant, 1996) once it is imported and applied in the firm's current domain of operation.

The more identifiable adjustments entailed in a specialist element and its facilitated integration limit the formation of negative transfers and, thus, their harmful effects on the value of the invention that applies this element.

On the contrary, a more general element, which entails more considerable causal ambiguity, is appropriately adjusted and integrated with more difficulty and triggers a higher level of negative transfers that harms the value of an invention.

Overall, the higher the generality (specialization) of an element, the higher (lower) the level of negative transfers that harm the value of an invention.

H1: The higher the level of generality (specialization) of a knowledge element acquired from an external knowledge domain, the lower (higher) the value of the *invention a firm generates in its current domain of operations by applying this element.*

The evolution of the negative direct effect in the sequential knowledge search. The diminishing negative impact of negative transfers

Although the proposed reasoning is applicable to all the elements of a sequential knowledge search, as the firm progresses in the sequence and familiarizes with the knowledge available in the external domain, the causal ambiguity the firm faces diminishes.

From a cognitive standpoint, the familiarity the firm develops with a domain by applying preceding elements of the sequential knowledge search increases the firm's awareness of the knowledge in the domain when applying subsequent elements of the sequential knowledge search (Kogut & Zander, 1992). This increased familiarity enables the firm to better understand the relationships between the role of each element in the external domain and its outputs, thus reducing the overall causal ambiguity faced by the firm (Simonin, 1999).

The reduction in the overall causal ambiguity perceived by the searching firm as it moves forth in the sequential knowledge search also reduces the overall likelihood of negative transfers when extracting subsequent elements from the same external domain.

Therefore, since the magnitude of negative transfers is overall lower when applying subsequent elements of a sequential knowledge search with respect to preceding ones, also the marginal benefits deriving from specialist elements in reducing negative transfers diminish.

At the initial stages of a sequential knowledge search, the generality of a knowledge element triggers higher levels of negative transfers that harm the value of invention that uses this element, but, as the firm progresses in the sequential knowledge search and becomes familiar with the external domain, the overall likelihood of negative transfers diminishes, and so does the negative direct effect of generality on the value of an invention.

H2: The negative direct effect of the level of generality of a knowledge element from an external domain on the value of inventions generated in the firm's domain of operation diminishes with the increase of the place occupied by the element in the sequential knowledge search.

The indirect effect of the generality of a preceding element on the value of an invention generated by a subsequent element. The positive impact of absorptive capacity

When searching a new domain, the value of the inventions generated is subject to the firm's absorptive capacity, which is the ability to internalize, understand, evaluate, and apply external knowledge elements (Cohen & Levinthal, 1990).
This ability positively affects the value of an invention: firms with a higher absorptive capacity to search an external domain generate inventions of higher value when applying the knowledge from the domain.

When a firm initiates a search, its endowment of absorptive capacity depends on the knowledge base resulting from the experiences accumulated in the past. The more the firm's knowledge base is related to the external domain, the higher is the firm's ability to internalize, understand, evaluate, and apply the knowledge from the domain (Nooteboom, Van Haverbeke, Duysters, Gilsing, & van den Oord, 2007).

Being absorptive capacity the result of the firm's past experience, we have not considered the role of this construct when theoretically assessing the direct effect of an element on the inventions deriving from that element[16]. Indeed, even though each new knowledge element that the firm adds to its knowledge base from an external domain enhances the firm's absorptive capacity, the effects of this change do not manifest until the firm extracts and applies a subsequent element from that same domain.

Nonetheless, when considering the indirect effect of an element that occupies a preceding place in the sequential knowledge search on the value of an invention generated applying a subsequent element from the sequence, it is necessary to consider how the generality of the preceding element marginally affect the firm's absorptive capacity to identify, extract, and apply a subsequent element.

Fleming and Sorenson (2001) explain that having the "big picture" of a knowledge landscape enables inventors to conduct a more effective search than that performed when the vision of the knowledge landscape is more specialized. Furthermore, Melero and Paolmeras (2015) show that general knowledge places inventors in a better position to identify fruitful novel combinations, and Goldin & Katz (1998) describe how working

[16] If we consider absorptive capacity as path dependent following the characteristics of prior experience (Zahra & George, 2002), there might be an effect of the firm's absorptive capacity in acquiring also the first element in the sequential knowledge search. It could be that a firm is be better at acquiring a first element from a new domain that has characteristics of generality similar to those of elements acquired from other domains. This aspect does not intervene in the theoretical discussion under an assumption that no external domain and no element from the domain is ex ante more suitable to be searched by the firm than other domains or elements. It might instead create empirical issues that will be accounted in the analysis by adding the necessary control variables that capture the firm's experience when initiating a sequential knowledge search in a domain.

with new general knowledge triggers internal mechanisms that enhance the firm's ability to work with other new knowledge.

A preceding element that is more general entails a higher number of interdependencies in its knowledge domain, thus offering a broader picture of the knowledge in the domain at the time of identifying a subsequent element of the sequential knowledge search. A higher generality of a preceding element also helps the firm to manipulate subsequent knowledge from the same domain.

Thus, from a searching firm's standpoint, internalizing a general knowledge element enhances the firm's absorptive capacity more than internalizing a specialist element by favoring the identification and application of subsequent elements from that domain.

Overall, when initiating a sequential knowledge search, to the extent that the generality of the first element of the sequence increases, the improved awareness of the interdependencies in the new domain enhances the firm's ability to understand, evaluate, and apply subsequent elements extracted from the same domain. In other words, the marginal absorptive capacity developed with a first element in the sequence increases with the level of generality of this element and has positive implications for the value of the inventions generated by applying subsequent elements.

H3: The higher the level of generality (specialization) of the first knowledge element acquired from an external knowledge domain, the higher (lower) the value of the invention a firm generates in its current domain of operation by applying subsequent knowledge elements acquired from the same external domain.

The indirect effect of the generality of a preceding element must also be considered in relation to the characteristics of the generality of the subsequent element that generates the invention.

Adding general knowledge on top of general knowledge creates redundancies between the preceding and the subsequent elements of a sequential knowledge search. These redundancies that make subsequent knowledge elements substitutable to preceding ones reduce the novelty that each subsequent element brings to the firm in terms of possible new combinations (Dibiaggio, Nasiriyar, & Nesta, 2014).

The novelty of knowledge is a crucial aspect to form new combinations of elements that entail a more significant value (Fleming, 2001). If two elements are redundant and substitutable, adding one on top of the other, brings limited inventive value to the searching firm.

On the other hand, adding less redundant specialist knowledge on top of general knowledge increases the complementarity between preceding and subsequent elements, and it brings more novelty to new combinations, thus enhancing the value of the resulting inventions (Dibiaggio et al., 2014).

Overall, not only the value of an invention generated by a subsequent element is greater when the first element of the sequential knowledge search is general, but even more so when the subsequent element is specialist and less redundant with the first.

H3a: The positive indirect effect of the level of generality of the first element on the value of the invention generated by subsequent elements decreases with the level of generality of the subsequent element.

DATA AND METHODS

To validate the proposed hypotheses, we look at the evolution of RIM (Blackberry) and its innovations in the mobile phone manufacturing industry. Due to its dynamic nature, the sector has a large availability of data linking knowledge search to innovation in a fairly concentrated period. This aspect allows us to track the entire history of firms innovating in this industry, and it diminishes the potential temporal concerns that arise from knowledge at different stages of maturity (Capaldo, Lavie, & Messeni Petruzzelli, 2017).

Moreover, in about 25 years, each firm operating in this sector initiated multiple sequential knowledge searches in several different knowledge domains to introduce new models of phones. This setting offers a reasonable variation in the data also at the level of an individual firm; an aspect particularly relevant as it allows us to focus our analysis on a single firm and contain the confounding effects that may arise in a multi-firm context while avoiding the loss of statistical power of our model.

Finally, RIM's orientation towards a single business strategy reduces the hardly trackable noise that arises from intra-firm knowledge spillovers (Rosenkopf & Nerkar, 2001) when assessing the value of inventions in multi-business firms.

Measures

From an operative standpoint, we derive the measures that represent our theoretical constructs using patents to identify knowledge elements and patent classes to identify knowledge domains.

From the USPTO database, we extract all the 8907 patents filed by RIM since its inception in 1993 to 2018. These patents represent RIM's inventions in the mobile phone domain.

Dependent variable, the value of an invention. We measure the value of an invention using the forward citations that each RIM's patent from 1993 to 2013 has received in the first five years after its application date.
Since the scientific value of an invention refers to its quality (Phene, Fladmoe-Lindquist, & Marsh, 2006), impact (Nerkar, 2003), and its contribution to further technological development (Albert, Avery, Narin, & McAllister, 1991; Sorenson, Rivkin, & Fleming, 2006; Trajtenberg, 1990), using forward citations seems particularly appropriate to measure this construct (i.e., Cattani, 2005; Singh, 2008).

To cope with the fact that older patents have more opportunities of being cited than younger ones, we restricted the time window to the five years after the focal patent's application date. A five-year period seems particularly interesting to understand a very dynamic industry such as mobile phones[17].

Independent variable, the place of an element in a sequential knowledge search. Backward citations, which are the patents cited by each RIM's patent, represent the knowledge elements that RIM has combined to generate an invention. When excluding the self-citation, which are RIM's backward citations to its own patents, the remaining set of backward citations represents the knowledge that RIM has searched outside its boundaries to innovate.

Since USPTO classifies each of the patents cited by RIM in CPC subgroups according to their technological characteristics, these subgroups can be used to identify the external knowledge domains that RIM has searched (i.e., Ahuja & Lampert, 2001; Duysters, Lavie, Sabidussi, & Stettner, 2019).

[17] The results are robust also considering a three and a seven years time window as well as considering the whole life of a patent and adding year fixed effects.

In a context where all the cited patents belonging to the same subgroup represent all the knowledge that RIM has extracted from an external domain, it is possible to rank in time when a patent from a subgroup has been cited by RIM. The application date of the patents by RIM that cite patents from a subgroup identifies the place of the cited patent in the sequential knowledge search in that subgroup.

In other words, if RIM's patent *p* at time *t* cites a non-RIM patent *z* from subgroup *i,* and RIM's patent *q* at time *t+1* cites a non-RIM patent *y* from subgroup *i*, patent *z* precedes patent *y* in RIM's sequential knowledge search in subgroup *i*.

Overall, RIM has a network of 581554 backward citations in 31978 subgroups from 1993 to 2018.

Independent variable, the generality of a knowledge element in a domain. Generality is usually measured following Trajtenberg, Henderson, & Jaffe (1997) and using forward citation to capture whether a patent is cited by subsequent patents that belong to a wide range of fields.

Despite its usefulness, this measure captures generality meant as the applicability of a knowledge element across domains. However, as correctly highlighted by Hall & Trajtenberg (2004), knowledge may be general across domains or within a domain; the former should receive more citations across fields, the latter within.

Since this paper focuses on generality within a domain, the measure proposed by Trajtenberg et al. (1997) may not fully capture the theoretical construct we are trying to measure.

Due to this limitation, we propose a new measure of generality based on the degree centrality of a patent in the network of backward citations that link this patent with other patents in the subgroup.

Scholars have shown that network measures can be applied in a patent context to capture different characteristics of knowledge (Carnabuci & Bruggeman, 2009; Yayavaram & Ahuja, 2008). In our framework, not only a measure based on the degree centrality captures the number of citations that a patent receives within a subgroup, and it is therefore conceptually aligned with the idea of generality developed in the paper, but it also accounts for the size of the subgroup.

To capture the degree centrality of each patent cited by RIM in its subgroup, we collected all the patents of each subgroup where a patent cited by RIM belongs. According to the network of backward citations of all the patents belonging to a subgroup, we computed the degree centrality of each patent cited by RIM at the time of RIM's citation.

In our data, centrality of cited patents goes from a minimum value of 0.00001 to a maximum value of 1; the mean value is 0.01101, with a standard deviation of 0.03304.

Control variables[18]: prior research has highlighted that several variables can affect the value of inventions and must be controlled for.

The age of the patent plays a role in identifying the number of citations that the patent can receive. On the one hand, an older patent benefits of more time for being cited; on the other hand, older knowledge is more likely to decay in value and become obsolete. Furthermore, different periods in a firm's history may experience more citing activity. Therefore, even though we partly coped with both effects and for right censoring by considering a five years window for forward citations, due to the potential effect of the

[18] Relatedness as control is not present in this version as still computing. It will be added to the final version.

age of a patent in this specific industry, we control for the number of years from the patent application date to 2013.

Since patents that cite more patents are more likely to receive more citations (Fleming, 2001), we control for the number of prior art meant as the number of citations made by a RIM's patent.

As time spread increases, recombinations may become more difficult yet fruitful (Nerkar, 2003). Thus, we control for the diversity of knowledge maturity as the standard deviation in the number of years elapsed since the filing date of patents cited by a RIM's patent (Katila, 2002).

Since search may follow different dimensions, we control for three main aspects. Firstly, the search span is measured as the number of different CPC main classes assigned to a patent by the USPTO (Capaldo & Messeni Petruzzelli, 2011; Fleming, 2001). Secondly, the search depth, meant in this case as the reuse of prior knowledge (Katila & Ahuja, 2002) is measured for each focal RIM's patent as the average number of times a patent was repeatedly cited during the past five years. Finally, the search scope (Katila & Ahuja, 2002) is measured for each RIM's patent as the share of citations that could not be found in the list of patents cited in the prior five years.

In addition to capturing aspects that may affect the value of an invention, controlling for the directions of search allows us to capture search behaviors that may affect a firm's choice to select a specific patent form a specific external domain. Indeed, since firms tend to follow paths in the selection of external knowledge, controlling for the familiarity that the searching firm has in terms of breadth, depth, and scope, with the prior art composing a combination of elements where the new elements from the sequential knowledge search are added, enables us to limit this endogeneity.

Moreover, since the USPTO assigns patents to multiple classes, it is possible that a patent occupying a certain place in the sequential knowledge search in a domain may as well occupy a higher rank in the firm's sequential knowledge search in a different domain (i.e., patent *p*, which is the first element acquired at time *t* from subgroup *i*, might also be the second acquired at time *t* from subgroup *j*). We control for this aspect introducing a dummy variable that captures whether the first element from a sequential knowledge search in a domain occupies a higher rank in the sequential knowledge search in a different domain. A similar dummy variable is constructed to identify those subsequent elements that occupy a higher rank in the sequential knowledge search in a different domain.

Following Sorenson et al. (2006), claiming that the complexity of the knowledge in an external domain may inhibit the firm's ability to integrate this knowledge in the firm's base, we control for the complexity of the knowledge in a domain by computing the network density of each subgroup of the patents cited by a RIM's patent. This subgroup level measure is computed at the application date of a RIM's patent that cites the patent in the subgroup.

In about 10% of the sequential knowledge searches in our sample, the subsequent element is the same as the preceding one (i.e. the first and second element in the sequence are the same). In this circumstance, the searching firm used the same element to generate subsequent sequential inventions. To avoid this confounding effect, whose consequences we did not consider conceptually, we include a dummy variable that captures when a subsequent element of a sequential knowledge search coincides with a preceding one.

Since patent information is recoded by USPTO starting in 1975, when adding the control variables that account for the application date of the patents cited by RIM, the lack of information for the cited patent older than 1975 makes us drop 92 backward citations from the sample.

Lastly, we include year dummies to account for effects resulting from specific years in the analysis.

Table 1 shows the correlation between the main variables included in our model.

Insert table 1 about here

Model

The overdispersed nature of our data evident in the coefficient of variation (standard deviation/mean) that equals 2.32, advocates for the use of a negative binomial instead of a Poisson model to properly estimate our nonnegative count dependent variable. The negative binomial model that corrects for such overdispersion is more suitable since it allows for greater variance (Gourieroux, Monfort, & Trognon, 1984; Hausman, Hall, & Griliches, 1984).

In a first model, we test our hypotheses and the validity of the controls considering only the first two elements of a sequential knowledge search. This limitation allows us to conduct a preliminary analysis to test our hypotheses in the initial section of a sequential knowledge search and obtain insights that are less affected by potential path dependences in the selection of the external elements used to innovate.

As a second step, we will propose an analysis that accounts for the first 11 elements of the sequence. This threshold is set by the first quartile of the element of the sequential knowledge searches in our sample[19].

Insert table 2 about here

RESULTS

Model 1 in table 2 tests the direct effect of the generality of a first element in the sequential knowledge search on the value of the invention of the first invention generated by this element.

The positive and significant coefficient of *Generality* (1.40, $p<0.01$) shows an average positive effect of generality on the value of innovation, which contradicts H1. Nonetheless, the negative and significant coefficient of *First patent X Generality* (-1.29, $p<0.01$) shows that this effect diminishes when the focal element is the first in a sequential knowledge search.

The negative coefficient of the interaction term is not statistically different from the positive coefficient of *Generality*. Overall, it appears that generality has an average positive effect on the value of innovation, but that this effect is not present at the initial stage of the sequential knowledge search when negative transfers are stronger.

Model 2 in table 2 tests the direct effect of the generality of a second element in the sequential knowledge search on the value of the invention generated by this element. Also in this case, the negative and significant coefficient of *Second patent X Generality*

[19] Median value is at the 37th element, which seems too far in the sequence to exclude other dominant effects different from those proposed in our theoretical model. Nonetheless, results are robust also at this threshold.

(-0.99, p<0.05) shows that the positive direct effect of *Generality* (1.36, p<0.01) on the value of innovation diminishes with respect to average when the focal element is the second in a sequential knowledge search. Again, we find support for the fact that the negative effects of generality are stronger at the initial stages of the sequential knowledge search.

Model 3 tests the previous results when jointly considering the direct effect of the generality of the first and second elements in the same model. The coefficients for *First patent X Generality* (-1.44, p<0.01) and *Second patent X Generality* (-1.23, p<0.05) remain consistent with the previous models, but the difference in magnitude between the two coefficients proposed in H2 is not supported. Although the negative effect of the generality of the second element (-1.23, p<0.05) seems slightly weaker than the negative direct effect of the generality of the first element (-1.44, p<0.01), a test to compare the magnitudes of the two coefficients shows that we cannot reject the equality hypothesis (Prob > chi2 = 0.58). Therefore, H2 is not supported.

Models 4 and 5 test the indirect effect of the generality of a first element on the value of the invention generated using the second element, the former excluding the direct effect of the first element, the latter including it.

The positive and significant coefficient of *Generality of first* in model 5 (1.25, p<0.01) shows that the generality of the first element has an average positive effect on the invention generated by the subsequent elements of the sequential knowledge search. This provides support for H3.

However, the negative and significant coefficient of *Second patent X Generality of first* (-1.05, p<0.05) cancels the indirect positive effect of the generality of the first element. Indeed, the sum of the positive coefficient of *Generality of first* and of the negative coefficient of *Second patent X Generality* is not statistically different from zero (Prob > chi2 = 0.47).

This aspect makes us suspicious about the fact that the positive indirect effect of the generality of the first element might not manifest immediately in the right subsequent element, but in elements that are located farther in the sequential knowledge search.

In a similar way, the negative and significant coefficient of *Generality X Generality of first* (-3.97, p<0.01) supports H3a that claims that the positive indirect effect of the generality of the first element is stronger when the subsequent elements are specialist. Once again though, the positive and significant coefficient of *Second patent X Generality X Generality of first* (4.35, p<0.01), shows that this effect of complementarity between the generality of the first element and the specialization of a subsequent element in positively affecting the value of an invention is not valid for the second element. Again, the sum of the coefficient of *Generality X Generality of first* and of *Second patent X Generality X Generality of first* is not statistically different from zero (Prob > chi2 = 0.86), and again, it appears that the positive effect of the complementarity manifests later in the sequence.

The results of the analysis of the direct and indirect effect of the first two elements in a sequential knowledge search provide partial support to the hypotheses proposed in this paper.

Whereas the focus on the first two elements of the sequence has enabled us to contain the complexity of the model and to explain the mechanisms in a stylized way, it might as well have led us to overlook the fact that the proposed mechanisms may manifest at later stages in a sequential knowledge search, as possibly indicated by these models.

Indeed, we proposed that the negative direct effect of generality diminishes immediately from the first to the second element of the sequence thanks to the increased familiarity of the searching firm with the external domain. However, it is reasonable to believe that it might take to a searching firm more than a single knowledge element to gain sufficient familiarity with the external domain as to disentangle the causal ambiguity the firm faces and limit the potential negative transfers and their harming effects.

Following this perspective, it is possible that the lack of support for H2 derives from the fact that familiarity is not strong enough when the second element is applied, but it could manifest at later stages of the sequential knowledge search. Should this be true, we could expect the magnitude of the negative direct effect of generality to diminish at later places in the sequential knowledge search, providing support to our second hypothesis, although with a slightly different nuance deriving from how and when this effect diminishes.

Similarly, one element could not suffice at substantially enhancing the searching firm's ability to internalize, understand, evaluate, and apply the knowledge in the external domain. Indeed, the improvement of the firm's domain-specific absorptive capacity might require more elements form that domain, and the indirect benefits of the generality of the first element might still be present but manifest farther in the sequential knowledge search when more elements from the same domain are acquired.

As Dibiaggio et al. (2014) show, redundancy of knowledge elements might be even beneficial in the first steps of the exploration of a new domain, as investing in elements that are functionally similar to other elements in the firm's knowledge base offer alternative options that support novel experimentation on the same combination. This perspective supports the idea that the benefits from complementarity between a preceding general element and a subsequent specialist element may manifest after the firm has become familiar with the new domain it is exploring.

To assess the validity of these claims, we propose in table 3 and 4[20] an analysis that considers the sequential knowledge search in each domain up to the eleventh element of the sequence. This analysis aims at capturing two aspects: the trend of the magnitude of the direct effect of generality and the trend of the positive indirect effect of the generality of the first element according to the generality of subsequent elements.

Insert table 3 about here

Model 7, OLS, and 8, negative binomial, in table 5 describe the trend of the magnitude of the negative direct effect of generality on the value of the invention. This trend is also depicted in figure 1, which graphs all the coefficients *nth X Generality*, in model 7 and their confidence intervals. These coefficients are negative and significant for the first seven elements in the sequence and become insignificant from the eighth element.

From the picture and the table, we notice that the direct effect of generality remains negative (less positive if we consider the difference with the coefficient of *Generality*) with a statistically equal magnitude when applying the first seven elements of a sequential knowledge search; from the eight element the effect of the place in the sequence disappears, and only the average one remains.

[20] For the sake of space, considering the many rows of the table, controls not shown, but are included in the model. Their coefficients are consistent with table 2.

This analysis provides support to H2, which claims that the negative direct effect of generality diminishes as the firm moves forth in the sequential knowledge search. However, it also highlights that this diminishing effect is not gradual, but manifests in a sudden after a certain threshold.

Insert table 4 about here

Model 11, OLS, and 12, negative binomial, in table 6 describe the trend of the magnitude of the indirect effect of the generality of the first element on the value of the inventions generated using the subsequent ten elements in the sequence, as well as the trend in the magnitude of the effect of complementarity between a general first element and more specialist subsequent elements.

We have seen in the previous models that the generality of the first element has an average positive indirect effect, as also confirmed by the statistically significant coefficient of *Generality of first* in model 11 (44.40, $p<0.01$) and model 12 (3.86, $p<0.01$). However, we also described that this positive indirect effect is discounted when the element is the second in the sequential search, and the total effect is basically inexistent at that stage of the sequence.

By looking at the coefficients *nth X Generality of first* in model 11, and to their graphical representation in figure 2, we capture that the discount on the positive indirect effect of the generality of the first element persists in the first seven elements of the sequence and disappears from the eight element.

Therefore, it seems that the positive indirect effect of the generality of the first element does not manifest when the firm applies the first seven elements in the sequence but emerges once the eight element is applied.
Again, it seems that the idea of a positive indirect effect of the generality of the first element is supported. However, this positive indirect effect manifests after the firm has progressed in the sequential search up to a certain threshold.

In a similar way, we have also found that, on average, the positive indirect effect of generality is stronger when the subsequent elements are specialist, as confirmed by the negative and significant coefficient *Generality X Generality of first* in model 11 (-104.89, $p<0.05$) and model 12 (-11.20, $p<0.05$). Nevertheless, this positive effect of complementarity between a general first element and a subsequent specialist element does not manifest in the first seven elements of the sequence as the significance of the coefficients of *nth X Generality X Generality* cancels the positive effect of the complementarity.

Figure 3 graphically depicts the discount of the positive effect of the complementarity at the different places of a sequential knowledge search.
Once again, the discount persists in the first seven elements of the sequence, but it disappears from the eight element, which identifies the step in the sequential knowledge search when the positive effect of adding a specialist knowledge element to a general first element manifests.

Overall, it seems that the effects that we proposed juxtaposing the first and the second individual elements in the sequential knowledge search manifest more concretely when considering a first bulk of elements and a second bulk of elements in the sequence. Indeed, although the proposed mechanisms seem supported, it appears that it takes a searching firm more than the first element alone to trigger the mechanisms of familiarity and absorptive capacity that relate the generality of knowledge to the value of an invention. In our case, the seventh element of the sequential knowledge search marks the threshold beyond which these mechanisms manifest.

Control function models

The models discussed above assume the choice of generality versus specialist knowledge by a searching firm to be exogenous.

Even though the added controls help to justify the validity of these models, the risk of endogeneity in the selection of an external knowledge element and its inherent generality remains. Indeed, the dynamics within RIM's R&D department that drive the selection of an external knowledge element over another remain unobservable.

To cope with this potential selection bias, we rely on the use of a control function, which offers a parsimonious way to account for endogeneity in linear and non-linear models (Wooldridge, 2015).

Control functions are variables that are estimated in a first stage (Heckman & Robb, 1985) thanks to the availability of instrumental variables that provide separate variation in the residuals, which are then used as a control in the second stage (Wooldridge, 2015). By adding an appropriate control function estimated in a first stage, the endogenous explanatory variable becomes appropriately exogenous in a second stage estimating equation.

A well-known example is the Heckman selection model, which represents a peculiar control function in the presence of non-randomly selected samples or truncated dependent variables.

This paper takes a more generic approach to control functions accounting for the continuous nature of generality.

The results of our negative binomial model with a control function to account for potential selection issues are described in model 6 of table 2, in model 9 (OLS) and 10 (NB) of table 3, and in model 13 (OLS) and 14 (NB) of table 4.

Before describing the results of these models, which are consistent with those of the previous ones and provide even support to H1, we describe the exogenous instrument used to estimate the control function in the first stage.

First stage: generality estimated in a difference in difference

The Leahy-Smith act changed the US patenting system from first to invent to first to file. Under a first to invent system, when an inventor conceives the invention and reduces it to practice (i.e. starts working on the invention), he or she sets the date of the invention as the date of conception. Thus, to the extent that the inventor can provide evidence of being the father of the invention, he or she would be entitled to patent the invention.

Under a first to file system, the granted right to a patent for an invention lies instead in the first person filing the application of that patent, regardless of the date of actual invention.

If a first to invent system allows inventors more time to adjust their invention before applying to a patent, as the paternity of the invention can be proved relying on reduction to practice, a first to file system calls for a swifter filing of the application. Consequently, under a first to file system, inventors have strong incentives to speed up the innovation process and be the first to file an application.

In the context of inventors adopting an element from an external domain, the time pressure would direct their choice to elements that are more specialist in nature and allow a swifter adoption. On the contrary, more general elements that require tailoring and manipulation of the knowledge they entail in order to fit the inventor’s specific needs may prove inefficient under a first to file system.

The change in the US legislation with the Leahy-Smith act, which was approved in 2011 and fully enforced in 2013, shifts the incentives of innovating firms toward the adoption of elements from new domains that are more specialized. Nevertheless, this search for more specialized elements is not expected to equally affect all the applications filed by RIM. Indeed, those applications pertaining to patent classes where competition on innovation is more intense, and the speed of filing an application becomes crucial to obtain paternity of an invention, are more subject to the effects of the new regulation with respect to applications in less competitive classes.
Whereas the paternity of those inventions filed in classes that are more dynamic might be assigned to competitors that work on similar inventions unless an application is swiftly filed, the paternity of those patents filed in classes that are less dynamic is less threatened, and speed in filing an application is less relevant. Therefore, whereas the choice of adopting more specialized external elements that enable a swifter application is preferred in dynamic classes under the new regulation, the incentive of adopting a more specialized external element remains low in less dynamic classes also under the Leahy-Smith act.

This context generates a setting for a difference in difference analysis where the generality of the acquired element is the dependent variable, the adoption of the Leahy-Smith act identifies the pre and post-shock, and the dynamism of the patent class creates the difference between treatment and control group on a continuous scale. RIM is expected to cite patents that show no difference in terms of generality when filing an application in different categories until 2012. After 2012, RIM is instead expected to cite patents less general when filing applications in those classes that show greater dynamism.

Using the number of patents filed in each of RIM's classes the year before each RIM's application to measure on a continuous scale the dynamism of each class where RIM files its patents, we adopt the following difference in difference model:

$$
\begin{aligned}
(A)\ & Generality\ of\ a\ cited\ patent_t \\
& = \alpha_0 + \alpha_1 Number\ of\ patents\ in\ the\ cited\ class_{t-1} \\
& + \alpha_2\ Number\ of\ patents\ in\ the\ cited\ class_{t-1} \times Post\ 2012 + \alpha_4 Post\ 2012 + Controls + e
\end{aligned}
$$

This model is empirically tested, and the results are provided in table 5, which shows the impact on the level of generality of cited patents when filing a patent application in classes with different levels of dynamism before and after 2012. We selected 2012 as the pre and post-treatment year, as the Leahy-Smith act was approved in September 2011 and, although the first to file system was fully enforced in March 2013, we expect firms to have started to align with the new requirements already in 2012.

Insert table 5 about here

From equation A we expect the coefficient α_2 to be negative and significant, as we find in table 5, which shows that the generality of the cited patent is indeed decreasing with the dynamism of the citing category after 2012[21].

To provide support to the validity of our shock, we test the parallel trend between the treatment and the control group before and after 2012. Table 6 shows that the dynamism of the class where RIM files its patents does not affect the level of generality of the cited patents until 2012, as all the coefficients that capture the interaction between dynamism of the filing category and the year of application for a patent are not significant.

After 2012, the coefficients capturing the same interaction become negative and significant, providing support to our perspective that after 2012 the level of dynamism of the class where a patent is filed negatively affects the level of generality of the patent cited.

Insert table 6 about here

Second stage: the residuals of the first stage as control

Computing the residuals of this first stage and adding them to model 5 in table 2, we obtain model 6, where the variable *Residuals* proxies for the factors in the error terms that are potentially correlated with generality and, thus, controls for the endogeneity

[21] The real coefficient is -0.0008, which might appear as a small magnitude. However, if weighted against the magnitude of generality it is possible to notice that this value is at about the 20th percentile of the distribution of generality. This supports the idea of a quite substantial impact of the interaction between the dynamism of the domain and the post 2012 on the generality of the elements extracted by RIM from an external domain.

inherent the unobserved motivations that may drive the selection of the external knowledge element.

In model 6, the coefficients of our variables of interest are consistent with those described in model 5. Moreover, the change in the sign of the coefficient of *Generality*, which goes from positive to negative (-173.18, $p<0.01$), supports also H1.

Indeed, it appears that, whereas the negative direct effect of generality in the case of the first and of the second element remains confirmed, the average positive effect of generality found in models 1 to 5 was just due to unobserved endogeneity. Therefore, under the new circumstances that highlight the real (negative) average effect of generality, H1 seems confirmed.

Similarly, models 9, 10, 13, and 14 in tables 3 and 4, offer results that are aligned with does described in the previous models, with the addition of support for an overall negative direct effect of generality on the value of an invention that decreases after few steps in the sequential knowledge search, and an overall positive indirect effect of the generality of the first element that manifests after few steps in the sequence as well as with the specialization of the subsequent elements.

DISCUSSION

This work introduces the concept of a sequential knowledge search to describe firms that progressively extract knowledge from an external domain and apply this knowledge to innovate in their domain of operation. In this context, it describes the direct and the indirect effect that different levels of generality of elements that occupy different places in the sequential knowledge search have on the value of the inventions that the searching firm generates.

It proposes that a more specialist knowledge element has a positive direct effect on the value of the invention generated by applying this knowledge, but that this positive effect decreases as the firm moves forth in the sequential knowledge search. Furthermore, it highlights that generality has a positive indirect effect on the inventions generated by applying subsequent knowledge elements, and that this positive indirect effect is stronger if the subsequent elements are specialists.

Overall, this work that specialist knowledge offers immediate benefits when a firm initiates a search in a new domain, but the return from specialist knowledge diminishes as the firm explores deeper in the domain. On the other hand, the benefits from general knowledge do not manifest immediately but enable the firm to generate better inventions at subsequent stages of the sequential knowledge search, and these benefits revamp the value of specialist knowledge acquired at later stages of the sequence.

In summary, subsequent specialized innovations from general knowledge seem relatively more valuable than subsequent specialized innovations from specialized knowledge.

This work contributes to the literature on knowledge search by introducing the idea of a sequence in the search process and paralleling it with the sequential innovations of a searching firm. At the same time, it bridges this literature with that on general versus specialist knowledge, which benefits from a study that considers the perspective of the firms that acquire the knowledge available in markets for technology and use it to innovate and compete in downstream product markets.

Lastly, it introduces a measure that captures generality within a domain and complements the more widely used measure of generality across domains.

Two main limitations appear evident. The first one concerns the average effect of generality on the value of inventions.

We found that generality has a positive average effect on invention, which offsets some of our findings, but we also found that this effect turns negative when controlling for the potential endogeneity deriving from possible selection biases.

This is a particularly important drawback as it is not clear whether the proposed effects of generality in a sequential knowledge search contribute to increasing an average negative effect or to diminishing a positive one.

Future research should better investigate the role of the average effect of the generality of knowledge on the value of inventions in order to capture the possible contingencies under which it is positive or negative and, thus, identify the circumstances that identify different nuances of our results.

To make an example, Teodoridis et al. (2019) have identified that general knowledge is more valuable in slower-paced knowledge domains, and specialist knowledge is more valuable in faster-evolving ones. Combining these findings with what has been proposed in this paper could offer interesting opportunities for future research.

The second main limitation of this paper is in the conclusions drawn from the analysis of the first elevent element of the sequence. In our example, it appears that the sevent element marks the threshold beyond which the direct benefits from specialist knowledge decay and the indirect benefits from general knowledge araise. However, this threshold may be firm or sector-specific, and further investigation to better understand the factors that might shift this threshold ahead or behind in the sequence are encouraged.

Despite these limitations, this work has started to scratch the surface of disentangling the relation between sequential knowledge search and sequential inventions and opens the door to engaging future research linking these two constructs.

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Table 1

Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Generality	1.000								
(2) Number prior art	0.062	1.000							
(3) Search span	0.013	0.327	1.000						
(4) Patent age	-0.072	0.021	0.061	1.000					
(5) Knowledge maturity d.	0.125	0.356	0.061	-0.337	1.000				
(6) Search depth	0.113	0.584	0.202	-0.324	0.397	1.000			
(7) Search scope	-0.051	-0.434	-0.201	0.227	-0.256	-0.512	1.000		
(8) Generality of first	0.382	-0.032	-0.024	0.035	-0.003	-0.045	0.097	1.000	
(9) Complexity	0.283	-0.001	-0.021	-0.019	0.072	0.044	-0.017	0.136	1.000

Table 2

Negative binomial

	(1) Value 5 years Coef./p	(2) Value 5 years Coef./p	(3) Value 5 years Coef./p	(4) Value 5 years Coef./p	(5) Value 5 years Coef./p	(6) Value 5 years Coef./p
Generality	1.40***	1.36***	1.58***	1.56***	1.56***	-173.18***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
First patent	0.09**		0.08*		0.06	0.07
	(0.04)		(0.09)		(0.19)	(0.15)
First patent X Generality	-1.29***		-1.44***		-0.76*	-0.85**
	(0.00)		(0.00)		(0.06)	(0.04)
Complexity	-2.07	-2.04	-2.05	-2.53**	-2.56**	-2.71***
	(0.13)	(0.15)	(0.14)	(0.02)	(0.02)	(0.01)
First and higher rank	0.25***	0.28***	0.31***	0.28***	0.30***	0.31***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Number prior art	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Search span	0.06***	0.06***	0.06***	0.06***	0.06***	0.06***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Patent age	0.12***	0.12***	0.12***	0.12***	0.12***	0.09***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Knowledge maturity div	0.08***	0.08***	0.08***	0.08***	0.08***	0.08***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Search depth	0.04***	0.04***	0.04***	0.04***	0.04***	0.04***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Search scope	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02
	(0.80)	(0.89)	(0.81)	(0.87)	(0.80)	(0.71)
Second patent		-0.03	-0.02	-0.02	-0.01	-0.02
		(0.42)	(0.66)	(0.61)	(0.80)	(0.70)
Second patent X Generality		-0.99**	-1.23**	-1.47**	-1.49**	-1.67***
		(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Second and higher rank		-0.09**	-0.07	-0.09**	-0.07	-0.07
		(0.04)	(0.14)	(0.04)	(0.13)	(0.14)
Second same as first		-0.03	-0.04	-0.03	-0.04	-0.04
		(0.47)	(0.44)	(0.47)	(0.44)	(0.37)
Generality first				1.28***	1.25***	1.14***
				(0.00)	(0.00)	(0.00)
Generality X Generality first				-4.49***	-3.97***	-3.97***
				(0.00)	(0.00)	(0.00)
Second patent X Generality first				-1.06**	-1.05**	-1.07**
				(0.03)	(0.03)	(0.03)
Second patent X Generality X Generality first				4.84***	4.35***	4.44***
				(0.00)	(0.00)	(0.00)
Control Function						174.93***
						(0.00)
Constant	-1.42***	-1.37***	-1.41***	-1.37***	-1.41***	0.84**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.05)
lnalpha	0.83***	0.83***	0.83***	0.83***	0.83***	0.83***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	514377	514377	514377	514377	514377	514377

Standard errors are robust and clustered at the level of the cited category.
* p<0.10, ** p<0.05, *** p<0.01

Table 3

OLS 7 and 9, NB 8 and 10

	(7)	(8)	(9)	(10)
	Value 5 years	Value 5 years	Value 5 years	Value 5 years
	Coef./p	Coef./p	Coef./p	Coef./p
Generality	19.08**	1.72**	-388.01***	-31.67**
	(0.03)	(0.04)	(0.00)	(0.02)
1st X Generality	-17.96**	-1.73**	-17.44*	-1.68**
	(0.05)	(0.04)	(0.05)	(0.05)
2nd X Generality	-19.66**	-1.70*	-19.12**	-1.67*
	(0.03)	(0.05)	(0.03)	(0.05)
3rd X Generality	-23.00**	-2.41***	-23.03**	-2.40***
	(0.01)	(0.01)	(0.01)	(0.01)
4th X Generality	-17.51**	-1.11	-17.33**	-1.08
	(0.03)	(0.18)	(0.03)	(0.19)
5th X Generality	-27.04***	-1.32	-26.89***	-1.29
	(0.00)	(0.15)	(0.00)	(0.16)
6th X Generality	-46.84***	-3.64***	-46.60***	-3.59***
	(0.00)	(0.00)	(0.00)	(0.00)
7th X Generality	-20.37**	-0.96	-20.15**	-0.90
	(0.02)	(0.40)	(0.02)	(0.43)
8th X Generality	-3.96	-0.39	-3.79	-0.34
	(0.68)	(0.75)	(0.69)	(0.78)
9th X Generality	-6.26	-1.41	-6.45	-1.39
	(0.52)	(0.24)	(0.50)	(0.25)
10th X Generality	-1.89	0.33	-1.96	0.42
	(0.90)	(0.85)	(0.89)	(0.82)
11th X Generality	-16.31	-0.23	-16.29	-0.18
	(0.20)	(0.87)	(0.20)	(0.90)
Control Function			407.18***	33.39**
			(0.00)	(0.01)
Constant	-5.06***	-0.77***	-2.48**	-0.56***
	(0.00)	(0.00)	(0.02)	(0.00)
/				
lnalpha		0.61***		0.61***
		(0.00)		(0.00)
year FE	Yes	Yes	Yes	Yes
sequence order FE	Yes	Yes	Yes	Yes
controls	Yes	Yes	Yes	Yes
R-squared	0.362		0.363	
N	149201	149201	149201	149201

Standard errors are robust and clustered at the level of the cited category.
* p<0.10, ** p<0.05, *** p<0.01

Table 4

OLS 11 and 13, NB 12 and 14

	(11) Value 5 years Coef./p	(12) Value 5 years Coef./p	(13) Value 5 years Coef./p	(14) Value 5 years Coef./p
Generality	13.62	1.19	-686.85***	-68.69***
	(0.20)	(0.38)	(0.00)	(0.00)
Generality of first	44.40***	3.86***	44.25***	3.82***
	(0.01)	(0.01)	(0.01)	(0.01)
Generality X Generality of first	-104.89**	-11.20**	-104.17**	-11.18**
	(0.02)	(0.02)	(0.02)	(0.02)
1st X Generality	-11.50	-0.62	-9.83	-0.53
	(0.44)	(0.68)	(0.50)	(0.72)
2nd X Generality	-14.62	-1.31	-13.04	-1.23
	(0.18)	(0.36)	(0.24)	(0.39)
3rd X Generality	-17.53	-1.50	-17.65	-1.51
	(0.12)	(0.31)	(0.12)	(0.30)
4th X Generality	-12.68	-0.27	-12.33	-0.27
	(0.22)	(0.84)	(0.23)	(0.84)
5th X Generality	-20.18*	-0.01	-19.45*	0.05
	(0.07)	(1.00)	(0.08)	(0.97)
6th X Generality	-39.99***	-1.92	-39.08***	-1.83
	(0.00)	(0.23)	(0.00)	(0.25)
7th X Generality	-14.05	0.39	-13.54	0.46
	(0.23)	(0.81)	(0.24)	(0.77)
8th X Generality	-1.10	-0.10	-0.80	0.01
	(0.92)	(0.95)	(0.94)	(1.00)
9th X Generality	6.30	-0.18	6.40	-0.13
	(0.68)	(0.92)	(0.68)	(0.94)
10th X Generality	26.98	2.62	26.86	2.79
	(0.18)	(0.26)	(0.18)	(0.24)
11th X Generality	-6.11	1.01	-6.07	1.05
	(0.68)	(0.60)	(0.68)	(0.59)
2nd X Generality of first	-46.56***	-3.91***	-45.93***	-3.85**
	(0.01)	(0.01)	(0.01)	(0.01)
3rd X Generality of first	-46.64***	-4.08**	-46.28***	-4.01**
	(0.01)	(0.01)	(0.01)	(0.01)
4th X Generality of first	-39.80***	-3.36**	-39.52**	-3.29**
	(0.01)	(0.02)	(0.01)	(0.02)
5th X Generality of first	-55.47***	-4.07***	-55.25***	-3.99***
	(0.00)	(0.01)	(0.00)	(0.01)
6th X Generality of first	-91.74***	-7.63***	-91.66***	-7.61***
	(0.00)	(0.00)	(0.00)	(0.00)
7th X Generality of first	-38.50**	-2.43	-38.06**	-2.32
	(0.02)	(0.16)	(0.02)	(0.19)
8th X Generality of first	-20.90	-1.80	-20.89	-1.74
	(0.21)	(0.26)	(0.21)	(0.28)
9th X Generality of first	-27.16*	-1.14	-27.22*	-1.09
	(0.09)	(0.51)	(0.09)	(0.53)
10th X Generality of first	-40.58**	-2.74	-40.51**	-2.68
	(0.04)	(0.10)	(0.04)	(0.11)
11th X Generality of first	-27.96	-1.63	-27.94	-1.59
	(0.17)	(0.45)	(0.17)	(0.46)
2nd X Generality X Generality of first	111.90**	11.73**	108.46**	11.49**
	(0.01)	(0.02)	(0.02)	(0.02)
3rd X Generality X Generality of first	106.99**	10.08**	106.06**	9.99**
	(0.02)	(0.04)	(0.02)	(0.04)

4th X Generality X Generality of first	96.37**	8.67*	95.28**	8.64*
	(0.03)	(0.07)	(0.03)	(0.07)
5th X Generality X Generality of first	122.77***	8.57*	120.48***	8.30*
	(0.01)	(0.07)	(0.01)	(0.07)
6th X Generality X Generality of first	200.88***	14.71**	198.68***	14.54**
	(0.00)	(0.01)	(0.00)	(0.01)
7th X Generality X Generality of first	91.19**	4.18	89.43*	3.99
	(0.05)	(0.44)	(0.05)	(0.46)
8th X Generality X Generality of first	64.30	7.21	63.92	7.04
	(0.16)	(0.15)	(0.16)	(0.16)
9th X Generality X Generality of first	36.85	-0.83	35.20	-1.06
	(0.43)	(0.87)	(0.44)	(0.84)
10th X Generality X Generality of first	14.86	-1.85	14.46	-2.14
	(0.79)	(0.81)	(0.80)	(0.78)
11th X Generality X Generality of first	43.70	-0.28	43.62	-0.11
	(0.40)	(0.97)	(0.40)	(0.99)
Control Function			700.63***	69.93***
			(0.00)	(0.00)
Constant	-4.68***	-0.83***	-0.23	-0.38**
	(0.00)	(0.00)	(0.86)	(0.02)
/				
lnalpha		0.59***		0.59***
		(0.00)		(0.00)
year FE	Yes	Yes	Yes	Yes
sequence order FE	Yes	Yes	Yes	Yes
controls	Yes	Yes	Yes	Yes
R-squared	0.334		0.334	
N	129769	129769	129769	129769

Standard errors are robust and clustered at the level of the cited category.
* p<0.10, ** p<0.05, *** p<0.01

Table 5

First stage control function

	(A) Generality Coef./p
Domain dynamism	0.000
	(0.27)
Post 2012	0.003***
	(0.00)
Post 2012 X Domain dynamism	-0.000**
	(0.02)
Complexity	0.991
	(0.12)
First and higher in rank	-0.002*
	(0.07)
Number prior art	0.000
	(0.27)
Search span	0.000**
	(0.04)
Patent age	0.000
	(.)
Second same as first	0.008***
	(0.00)
Second and higher in rank	0.004***
	(0.00)
Knowledge maturity div	0.001
	(0.11)
Search depth	0.000
	(0.69)
Search scope	-0.000
	(0.65)
Constant	0.004
	(0.13)
year FE	Yes
category FE	Yes
R-squared	0.196
N	581455

Standard errors are robust and clustered at the cited category level.
* p<0.10, ** p<0.05, *** p<0.01

Table 6

Parallel trend

	(B) Generality Coef./p
Domain dynamism	0.000066
	(0.39)
Treatment 2006	-0.000011
	(0.90)
Treatment 2007	0.000038
	(0.57)
Treatment 2008	0.000104
	(0.53)
Treatment 2009	-0.000083
	(0.28)
Treatment 2010	-0.000018
	(0.84)
Treatment 2011	-0.000055
	(0.25)
Treatment 2013	-0.000151*
	(0.08)
Treatment 2014	-0.000179**
	(0.03)
Treatment 2015	-0.000162***
	(0.00)
Treatment 2016	-0.000299***
	(0.00)
Constant	0.011646***
	(0.00)
year FE	Yes
cited category FE	Yes
R-squared	0.155
N	486531

Standard errors are robust and clustered at the cited category level.
* p<0.10, ** p<0.05, *** p<0.01

Figure 1

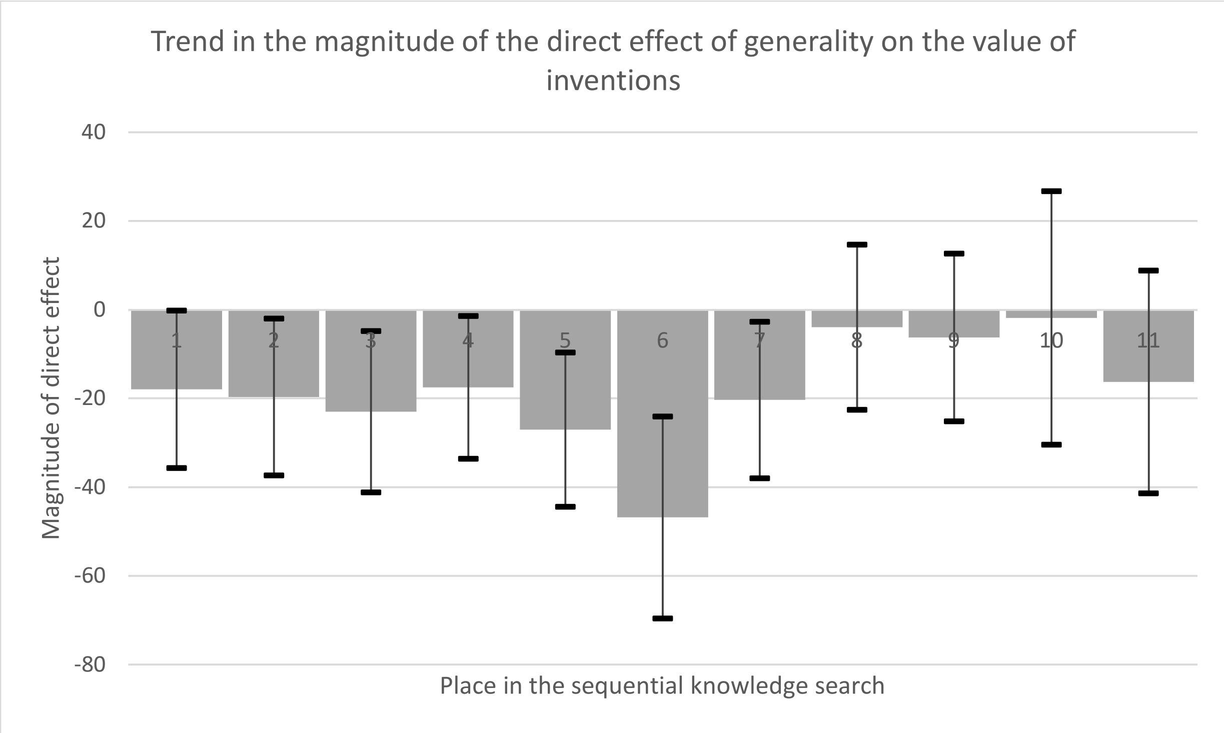


Figure 2

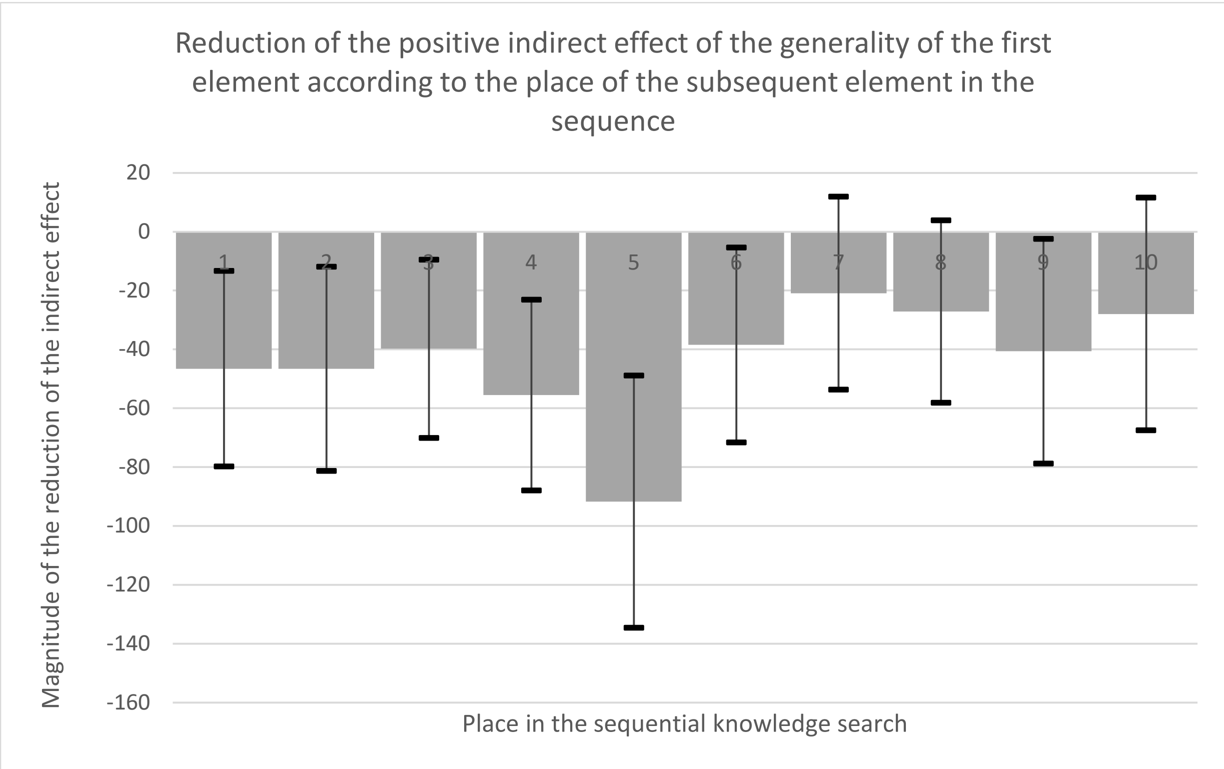
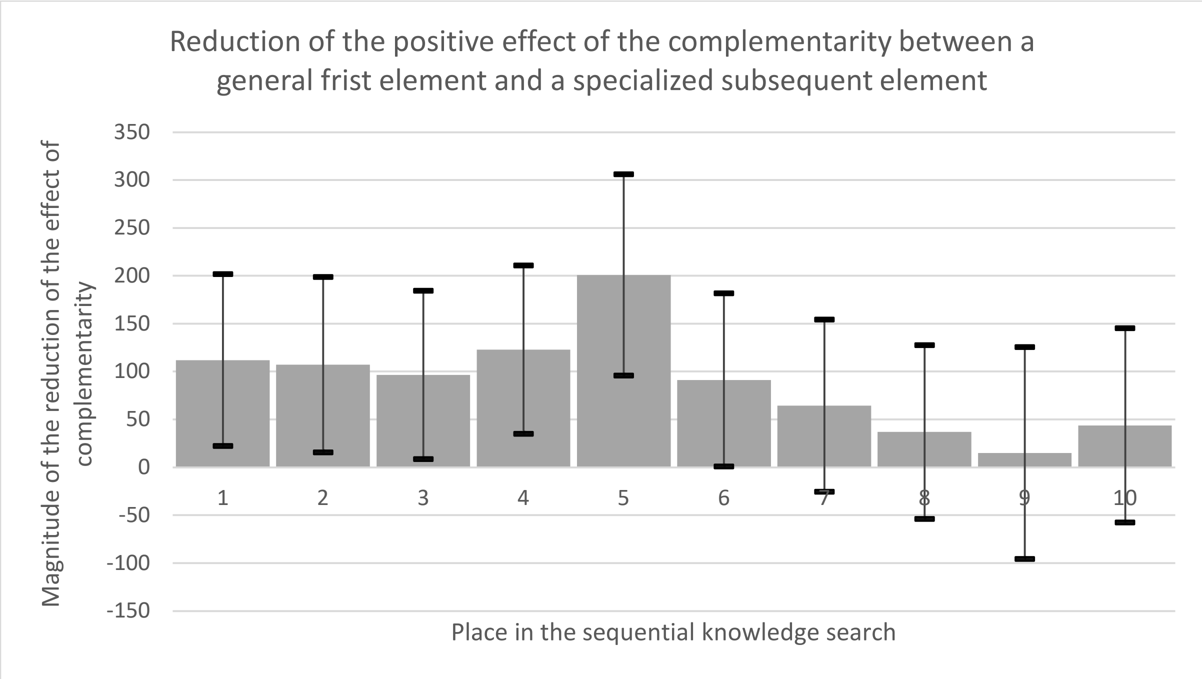


Figure 3



Reduction of the positive effect of the complementarity between a general frist element and a specialized subsequent element
Magnitude of the reduction of the effect of complementarity
350
300
250
200
150
100
50
0
-50
-100
-150
1
2
3
4
5
6
7
8
9
10
Place in the sequential knowledge search

CHAPTER 3

Knowledge reconfiguration, implication of different modes on quality of innovation.

with Dovev Lavie, Bocconi University

Resource reconfiguration refers to firms adding, removing, and recombining or redeploying their resource stocks (Karim & Capron, 2016; Karim & Mitchell, 2004). The resource reconfiguration activity is needed for pursuing various strategies such as growth (Capron, Dussauge, & Mitchell, 1998; Galunic & Rodan, 1998; Helfat & Eisenhardt, 2004; Karim, 2006; Karim & Mitchell, 2000; Stettner & Lavie, 2014), retrenchment (Anand & Singh, 1997; Bergh, 1997; Capron, Mitchell, & Swaminathan, 2001; Karim, 2006; Kaul, 2012), or internationalization (Chakrabarti, Vidal, & Mitchell, 2011; Koza, Tallman, & Ataay, 2011), but the success of reconfiguration efforts is often difficult to predict.

Research on the consequences of resource reconfiguration has traditionally considered reconfiguration of businesses across product markets of multi business firms (Karim, 2009; Sakhartov & Folta, 2014, 2015), which explains firms' exit from declining product markets or entry to emerging markets (Anand & Singh, 1997; Dothan & Lavie, 2016; Karim & Capron, 2016). Yet, this research does not directly measure resource reconfiguration, which is more difficult to observe.

Despite having highlighted different modes for reconfiguring resources, past research falls short of evaluating the corresponding outcomes.
These shortcomings prevent scholars from properly assessing the success of resource reconfiguration activities and suggesting preferred reconfiguration modes.

Moreover, resources do not necessarily overlap with product markets. It is possible to have established and emerging resource domains within a single product market, as in the case of emerging technologies that challenge or improve an industry's dominant design. A theory of resource reconfiguration should be also applicable to single-business firms.

Needed is a theory and a method that allow for comparing the implications of each reconfiguration mode within a given firm.

This study sets to overcome these shortcomings and contribute by providing a framework that highlights the implications of reconfiguration at the resource level and compares the outcomes of different reconfiguration modes.

It focuses on knowledge as resource of interest, while identifying corresponding modes for reconfiguring it and assessing their outcomes.

There are at least three main reasons why knowledge is a suitable resource to investigate on the implications of different modes for reconfiguring resources.

Firstly, knowledge is a critical asset in most industries and at the base of the performance of innovating firms.

Secondly, scholars have developed reliable measures for knowledge, which allow for a refined identification of reconfiguration modes and their implications at the resource level.

Thirdly, it is possible to study reconfiguration of knowledge within and across product markets, while considering both established and emerging knowledge domains.

The underlying research questions that this paper wants to address are: (a) what are the modes of knowledge reconfiguration, and (b) how does reconfiguration of knowledge (within and across domains) using these different modes affect the quality of innovation in an emerging knowledge domain that the firm has entered?

To answer these research questions, we start by explaining the relation between knowledge reconfiguration and innovation. We then identify different modes for reconfiguring knowledge across an established and an emerging knowledge domain and within the latter. In a third step, we analyse the impact of each mode, or combination of modes, for reconfiguring knowledge on the quality of innovation generated in the emerging knowledge domain.

CONCEPTUAL FRAMEWORK

Knowledge reconfiguration and innovation in an emerging domain

Innovation emerges via combinations of knowledge elements that were previously unconnected or by developing novel ways of combining elements that were previously connected (Fleming, 2001; Nahapiet & Ghoshal, 1998; Schumpeter, 1934). Hence, innovation in the emerging domain is a consequence of new knowledge generated in this domain. Such knowledge can be created via addition of knowledge elements from other domains that enable new combinations, and/or via recombination of elements in the emerging domain associating elements previously unconnected or developing new ways of combining previously associated elements.

Taking the perspective of firms operating in an established knowledge domain who import elements from an emerging knowledge domain to innovate in the former, scholars have shown that relatedness between the two domains plays a major role in defining the quality of the innovation generated (Rosenkopf & Nerkar, 2001). Although this paper takes the opposite perspective, that of firms operating in an established knowledge domain who export elements in an emerging knowledge domain to innovate in the latter, relatedness between the two domains still plays a major role in defining the quality of innovation.

Our arguments develop on the role of relatedness between the established and the emerging domain to claim that different modes for reconfiguring knowledge from the established to the emerging domain generate different implications for the quality of innovation, depending on the relatedness between the two domains.

We consider knowledge reconfiguration in a scenario with only an established and an emerging knowledge domain. Therefore, when a knowledge element is reconfigured across knowledge domains, it can be added to the emerging domain from a single established domain only. We exclude from our framework the possibility of knowledge elements added to the emerging domain from other external domains that are different from the focal one. This boundary condition allows us to contain the complexity and effectively describe the mechanisms related to knowledge reconfiguration. Although we acknowledge that a scenario with more than two domains represents an interesting opportunity to extend this work, limiting the analysis to one established and one emerging domain does not undermine the main thesis, as our framework explains the basic situation common to all reconfiguration contexts, independently of the number of established domains under consideration.

Furthermore, to properly isolate the mechanisms, and to set aside questions concerning the amount of knowledge reconfigured, we consider a single knowledge element that is reconfigured using different modes of reconfiguration.

We also acknowledge that knowledge reconfiguration from the established to the emerging domain might have a rebound effect on quality of innovation also in the established domain but, since our interest is in the quality of innovation in the emerging domain, we consider this effect as a potential extension for future work and we limit our analysis to the implications of reconfiguration of elements in the emerging domain.

Modes for reconfiguring knowledge

Before delving into the relation between modes for reconfiguring knowledge and the quality of innovation in the emerging domain, we must define the different modes that firms can adopt when reconfiguring knowledge to innovate in the emerging domain.

Reconfiguration across domains

Resources are categorized as scale-free, when their value is not reduced as a result of the sheer magnitude of operations over which they are applied, and not scale-free when their value is instead reduced as a result of the sheer magnitude of operations over which they are applied (Levinthal & Wu, 2010).

Given the nature of knowledge as a scale-free resource, there are in fact two modes for reconfiguring a knowledge element across domains: a knowledge element is *co-deployed* when it is shared and applied in both the established and emerging domains; a knowledge element is instead *transferred* from the established to the emerging domain when it is removed from the established domain and added to the emerging one.

It must be highlighted that, in the case of resources which are not scale-free, there will be no distinction between co-deployment and transfer, wherein addition to the emerging domain means removing from the established domain.

The relevant difference between scale-free and not scale-free resources, makes the framework of knowledge recombination we propose, more general than frameworks that adopt other resources that are not scale-free in nature.

Reconfiguration within the emerging domain

Since innovation emerges via combinations of knowledge elements that were previously unconnected or by developing novel ways of combining elements that were previously connected, not only innovating firms can reconfigure knowledge from the established to the emerging domain, but they can also change existing combinations of knowledge elements within the emerging domain.

Knowledge is reconfigured within the emerging domain when a knowledge element is *recombined* with other elements internal to that domain in combinations that are different from pre-existing ones.

At a given point in time, a knowledge element belonging to the emerging domain is combined with other elements in its domain. Recombination occurs when these combinations are changed, and the focal element becomes part of novel and previously untested combinations with other elements of its domain.

A second mode of reconfiguration within the emerging domain manifests when a new combination is formed by *discarding* an element that was previously part of a combination of elements.

Discarding does not generate new combinations by shuffling elements in new ways, but by eliminating one or more elements from a pre-existing combination.

Reconfiguration across and within

Implications of reconfiguration within a domain have been extensively studied in the literature and different implications of each mode on the quality of innovation have been identified.

Nevertheless, knowledge reconfiguration within and across domains may manifest simultaneously, and little has been said about the consequences of reconfiguring within an emerging domain when a knowledge element is also transferred or co-deployed from an established domain.

Thus, our focus goes on a transferred or co-deployed element that joins a new combination of elements originated by recombination or replaces an element that has been discarded from an existing combination, in the emerging domain. In our analysis, we briefly summarize the consequences of recombining or discarding elements from the emerging domain that have been highlighted in prior work, to then delve into the understudied implications for quality of innovation in the emerging domain when recombination and discarding in the emerging domain involve an element that is transferred or co-deployed from the established domain.

We proceed to compare modes for reconfiguring knowledge by juxtaposing their implications for the quality of innovation in the emerging domain in the following manners:

- Co-deployment versus transfer in the case of reconfiguration across domains. In both cases, elements from the established domain are added to pre-existing combinations of elements from the emerging domain.
- Co-deployment with recombination versus transfer with recombination in the case of knowledge recombined across and within domains. In these cases, elements from the established domain are added via transfer or co-deployment to new combinations in the emerging domain that differ from pre-existing ones.
- Co-deployment and replacement versus transfer and replacement in the case of knowledge recombined across and within domains. In these cases, the transferred or co-deployed element replaces in a specific pre-existing combination an element that has been discarded from the emerging domain.

Reconfiguration across domains: comparing implications of co-deployment and transfer

When a knowledge element from the established domain is reconfigured in the emerging domain, it is added to pre-existing combinations of other knowledge elements already present in that domain.

While this is the case for both transfer and co-deployment, there is a difference between these two modes with respect to the role of the reconfigured element in the established domain.

Whereas transfer implies that the element is no longer used in the established domain, in co-deployment the element remains in the established domain in which it is used following the co-deployment.

This difference has implications for absorptive capacity, synergies, and negative transfer that affect the quality of innovation in the emerging domain, contingent on the relatedness between the established knowledge domain and the emerging knowledge domain

The effect of knowledge relatedness on the quality of innovation in the case of co-deployment

The role of absorptive capacity

When a firm co-deploys a knowledge element from the established domain in the emerging domain, it can leverage its absorptive capacity (Cohen & Levinthal, 1990), which is the ability to internalize, understand, evaluate, and apply the knowledge across related domains, in order to identify the combinations in the emerging domain where the co-deployed element would be most effective.

The greater the relatedness between the established and emerging knowledge domain, the more straightforward is the application of the experience that the firm accumulated in its established domain with the knowledge element, and the more relevant this application to the emerging domain.

The relatedness between the domains enables in fact the co-deploying firm to identify and pursue valuable knowledge combinations involving the knowledge element in the emerging domain based on its absorptive capacity.

However, beyond a certain threshold of relatedness, although the application of the accumulated knowhow becomes straightforward, it would not materially extend the frontier of the knowledge domain nor allow for innovative new combinations, which limits novelty in the emerging domain.

Therefore, the quality of innovation in the emerging domain will increase with the relatedness of the knowledge domains up to a point beyond which it will decline.

The role of synergies

Co-deployment of knowledge elements furnishes synergies from economies of scope and positive spillover. Specifically, to the extent that the same knowledge is implemented in both domains simultaneously, the firm can leverage some complementary resources more efficiently (Montgomery & Hariharan, 1991; Silverman, 1999; Singh & Montgomery, 1987; Villalonga, 2004). For example, when products are tested in both domains, these tests may uncover aspects that would be otherwise overlooked if the product was tested only in one domain (i.e. whereas testing a carbon inserts on skis highlights resistance to torsion, on snowboard it highlights reactivity to flexion. Feedback from skis helps to improve the application of carbon inserts to reduce torsion in snowboarding, which are most likely unnoticed when carbon inserts are tested only on snowboards). Moreover, the fact that the knowledge element has been used in the established domain enhances its reliability in use in the emerging domain as well as the market's receptivity to that element in the emerging domain, so that positive spillover is expected.

The aforementioned synergies increase with the level of relatedness between the established and emerging knowledge domain, since the ability to share design, testing, and other activities across domains, depends on the similarity between them. To the extent that the domains are dissimilar, they would require separate design, testing, and other independent work.

Similarly, relatedness enables employees and other stakeholders to draw analogies and apply experience across domains, but as the knowledge domains become less related, it is less possible to assume reliability or expect successful outcomes based on the application of the knowledge element in the established domain.

Overall, the economies of scope and positive spillover from the co-deployment of the knowledge element will increase with the relatedness of the knowledge domains. The synergies arising from co-deployment enable the firm to pursue more prospective knowledge combinations in the emerging domain and gain more value from the use of the shared knowledge elements, so that the quality of innovation increases with the relatedness between the knowledge domains.

The role of negative transfer learning

The notion of negative transfer relates to the misapplication of knowhow and routines developed in the established domain when introduced to the emerging domain (Novick, 1988).

Negative transfer declines with the level of relatedness between the knowledge domains. However, as relatedness increases beyond a certain threshold, negative transfer increases as well because it becomes difficult to identify meaningful differences between the domains, and the firm would be less likely to implement necessary adjustments in the emerging domain (Zahavi & Lavie, 2013).

In the case of co-deployment, negative transfer is expected to be prevalent because the firm would face challenges in developing inconsistent routines and dislodging from the inertial pressure of applying these routines in the established domain.

The inertial pressure would limit the firm’s ability to modify the learned routines and make adjustments in the emerging domain, which become more necessary at lower levels of relatedness. Furthermore, the inertial pressure makes it more challenging for the firm to identify the need for adjustments at very high levels of relatedness.

The higher the relatedness between the knowledge domains, the weaker the need to make such adjustments and the more effective is the application of the routines that have been developed in the established domain, so that negative transfer is diminished with relatedness up to a point.

Beyond a certain threshold, the need for adjustments is smaller but, due to the superficial similarities that the two domains share, it is less likely that the firm would recognize such need and make adjustments.

Negative transfer undermines the quality of innovation at both low and high levels of relatedness given that at high levels of relatedness the need for adjustment is overlooked so that established routines are applied inappropriately, while at low levels of relatedness it prevents effective adjustment of these routines, which remain suboptimal

Therefore, the greater the relatedness between the knowledge domains, the higher the quality of innovation up to a point beyond which it declines.

The effect of knowledge relatedness on the quality of innovation in the case of transfer

The role of absorptive capacity

When knowledge is transferred and the firm reconfiguring firm discontinues its application in the established domain, some of the accumulated knowhow is lost, because the knowledge is not fully codified, and its tacit aspects are difficult to retain when the knowledge is no longer applied.

The firm may rebuild its absorptive capacity in the emerging domain, depending on the extent of relatedness to the established domain, but the value of the rebuilt absorptive capacity will not have immediate implications for the quality of innovation.

In the case of transfer, the rebuilt absorptive capacity is expected to be limited compared to co-deployment, given that the differences between the emerging and established domain support a broader scope for knowledge development compared to the narrower scope of knowledge in the case of transfer.

It has been described that the absorptive capacity developed by the firm across domains in the case of co-deployment will be maximal at intermediate levels of relatedness. In the case of transfer, there is no reason to believe that the application of the firm's absorptive capacity in the emerging domain would change besides the dumping of its value given memory loss at any level of relatedness.

The greater the relatedness between the established and emerging knowledge domains, the more straightforward the application of the experience that the firm accumulated in the established domain with the knowledge element, and the more relevant this application to the emerging domain, only that not all of that accumulated knowledge will be transferred.

The relatedness between the domains enables the firm to identify and pursue valuable knowledge combinations involving the knowledge element in the emerging domain based on the firm's absorptive capacity, but some valuable combinations will be overlooked as a result of non-transferred knowhow.

Furthermore, to the extent that the relatedness reaches beyond a certain threshold, the applied knowledge will not materially extend the frontier of the knowledge domain or allow for innovative new combinations, which limits novelty in the emerging domain.

Therefore, the quality of innovation in the emerging domain will increase with the relatedness of the knowledge domains up to a point beyond which it will decline, with the level of quality being lower than that achieved via co-deployment.

The role of synergies

The synergies available in the case of co-deployment will not be available in the case of transfer since the firm limits its focus to the emerging domain and there is no simultaneous application of the element in both domains. Thus, the firm cannot achieve economies of scope or enjoy positive spillover from the established domain to the emerging domain.

The role of negative transfer learning

Unlike the case of co-deployment where the continuous application of the knowledge element in the established domain reinforces existing routines and practices, in the case of knowledge transfer, the firm can dislodge more easily from the learned practices and more effectively make adjustments that are needed in the emerging domain.

Discontinued application of the knowledge element in the established domain relieves the firm from the implicit or explicit comparison across domains, and enables it to identify the need for adjustments irrespective of the relatedness to the established domain.

However, some negative transfer may still occur since resources and activities transferred to the emerging domain in connection with the knowledge element have a carryover effect. For example, individuals that have worked in the established domain and now work in the emerging domain may retain the cognitive scheme used in the established domain, even though it has been discontinued. Nevertheless, the effect of negative transfer learning is expected to be mitigated following the discontinued application in the established domain.

Overall, negative transfer may still occur, but its effect will be limited compared to the case of co-deployment. Moreover, in transfer, negative transfer learning is mostly related to the difficulty of dislodging from learned practices, whereas in co-deployment it is mostly related to the failure to recognize the need for change.

As relatedness increases, negative transfer is mitigated given more straightforward adjustments to the emerging knowledge domain, but beyond a certain threshold, the inability to discern the nuanced differences between the emerging and the established domain, especially since application in the established domain is discontinued (and hence the reference point is unclear), increases misapplication of knowledge in the emerging domain.

Since negative transfer has negative implications for the quality of innovation, as relatedness increases, the quality of innovation will first increase and then decline, but to a lesser extent than the case of co-deployment.

Comparing the net effect of the proposed mechanisms in the case of co-deployment and transfer

The case of co-deployment

When an element is co-deployed, absorptive capacity describes an inverted U-shaped relation between relatedness and the quality of innovation, synergies make quality of innovation increase with relatedness, and negative transfer describes an inverted U-shaped relation between relatedness and the quality of innovation.

The net effect of the proposed mechanisms allows us to formulate:

> *H1a: when a knowledge element is codeployed across an established knowledge domain and an emerging knowledge domain, an inverted U-shaped relationship prevails between relatedness of these knowledge domains and the quality of innovation in the emerging domain.*

The case of transfer

When an element is transferred, absorptive capacity describes an inverted U-shaped relation between relatedness and the quality of innovation, synergies are not present, and negative transfer describes an inverted U-shaped relation between relatedness and the quality of innovation.

The net effect of the proposed mechanisms allows us to formulate:

H1b: when a knowledge element is transferred from an established domain to an emerging domain, an inverted U-shaped relationship prevails between relatedness of these knowledge domains and the quality of innovation in the emerging domain.

Comparing co-deployment and transfer

When comparing the effects of transfer and co-deployment on the quality of innovation in the emerging domain, we must consider how the proposed mechanisms behave at different levels of relatedness.

When relatedness is low, co-deployment better leverages absorptive capacity compared to transfer, and thus leads to better quality of innovation in the emerging domain; synergies that manifest with co-deployment are minimal and there is no substantial difference in how transfer and co-deployment impact the quality of innovation through synergies; transfer invokes less negative transfer learning, which also positively affects the quality of innovation.

Overall, at low levels of relatedness, synergies are not relevant for the distinction between co-deployment and transfer in affecting the quality of innovation; in terms of absorptive capacity, co-deployment is preferred to transfer as it generates superior quality; in terms of negative transfer learning, transfer is preferred to co-deployment as it entails less negative effect on quality. Comparing these mechanisms, we cannot assess which dominates, so that we cannot draw any specific conclusions about the relative advantages of transfer versus co-deployment at this range of relatedness.

When relatedness increases to moderate levels, co-deployment is still superior to transfer with respect to leveraging absorptive capacity; synergies, which manifest only in case of co-deployment, increase with relatedness, and so do the benefits of co-deployment over transfer for the quality of innovation; negative transfer learning is minimal in both reconfiguration modes, but transfer still generates less negative transfer learning, with positive implications for the quality of innovation.

Overall, co-deployment is still superior to transfer in terms of absorptive capacity, but the opposite is true in terms of negative transfer learning. Nevertheless, synergies that manifest with co-deployment become more evident as relatedness increases. This makes co-deployment increasingly superior to transfer.

When relatedness increases to high levels, co-deployment remains superior in leveraging absorptive capacity and enhancing the quality of innovation; synergies continue to increase the benefits of co-deployment; negative transfer learning is still lower for transfer than for co-deployment.

Overall, co-deployment is still superior to transfer in terms of absorptive capacity, but the opposite is true in terms of negative transfer learning. Nevertheless, the benefits generated by synergies in the case of co-deployment but not transfer, keep increasing with relatedness, and thus increase the superiority of co-deployment over transfer.

In sum, at any level of relatedness, co-deployment is superior to transfer for improving the quality of innovation through absorptive capacity, although transfer is superior to co-deployment in mitigating negative transfer learning. Whereas conclusions cannot be drawn from the conflicting effects of absorptive capacity and negative transfer, synergies, which manifest only in the case of co-deployment, and are beneficial for the quality of innovation, increase with relatedness, and so do the benefits of co-deployment versus transfer for the quality of innovation in the emerging domain.

H2: When an element is reconfigured across an established and an emerging knowledge domain, the relative innovation quality advantage (disadvantage) of co-deployment of the element compared to a transfer, increases (decreases) with the relatedness of knowledge between domains.

Reconfiguration with the emerging domain: recombination

Recombining knowledge elements in a domain in a way that involves previously untested combinations, has positive implications for the quality of innovation as it provides new opportunities for innovation beyond those previously available to the firm in the emerging domain.

New combinations in the emerging domain can be achieved in two ways: recombining elements belonging to the emerging domain, or recombining elements belonging to the emerging domain with at least one element that has been transferred or co-deployed from the established domain.

The first case has been widely studied in the literature, mostly in terms of how frequently knowledge is recombined, which has shown that recombination of elements belonging to the emerging domain improves the quality of innovation as it enhances novelty, while reducing the likelihood of error, making the outcome more predictable, and highlighting the most valuable elements in different combinations (Fleming, 2001). Nevertheless, excessive recombination might have negative consequences. Building on the same knowledge elements has diminishing returns as novelty introduced by new combinations of the same elements tends to be exhausted with recombination while generating rigidities that limit the firm's ability to spot new opportunities to innovate (Kim & Kogut, 1996; Leonard-Barton, 1992). Thus, the quality of innovation grows with the frequency of recombination up to a point wherein it exhausts novelty and rigidities manifest, causing a decline in the quality of innovation.

Prior research has highlighted how adding knowledge from an external domain generates new combinations that are unavailable using internal knowledge. Nevertheless, it has been assumed that the firm has not operated in that external domain, with almost no attention paid to that the case of a firm infusing knowledge from an established domain in which it operates into an emerging domain.

We consider the implications of recombining knowledge in the emerging domain when elements are added from the established domain. We then proceed to compare the outcome of recombination following co-deployment versus transfer.

The effect of relatedness on innovation quality in the case of recombination in the emerging domain with a co-deployed or transferred element

The role of recombinative capability

When a firm recombines a knowledge element that was co-deployed or transferred from the established domain with knowledge elements already belonging to the emerging domain, the firm's absorptive capacity plays a limited role, since the knowledge combination is new to the firm, and its implications are unknown.

Nevertheless, the firm can still leverage the recombinative capability (the knowhow how to recombine knowledge elements) that it has developed in the established domain to recombine elements in the emerging domain. That recombinative capability evolves with experience and may have some carryover from the established domain to the emerging domain.

The greater the relatedness between the established and the emerging domain, the more applicable is the knowhow and the recombination techniques learned in the established domain to seek and implement new combinations in the emerging domain. Thus, relatedness between the two domains enables the firm to generate previously untried combinations in the emerging domain by leveraging the recombinative capability developed in the established domain.

The new combinations involving knowledge elements from the established domain with knowledge elements from the emerging domain contribute to the quality of innovation in the emerging domain since they provide opportunities for innovation that go beyond those previously available to the firm in the emerging domain.

Therefore, the quality of innovation in the emerging domain is expected to increase with the relatedness of the knowledge domains. As discussed in detail later, the extent of this increase is expected to be higher for co-deployment than for transfer.

The role of expanding knowledge scope

When a knowledge element is added to the emerging domain from the established domain via co-deployment or transfer, it expands the scope of knowledge in the emerging domain and generates more possible combinations that can be used for innovation in the emerging domain.

When relatedness is low, the knowledge that is brought in the emerging domain by transferring or co-deploying an element from the established domain is quite distinct from the knowledge already present in the emerging domain, this leads to a substantial expansion of the scope of knowledge in the emerging domain and allows for more novelty that can be used for innovation. In turn, the higher the relatedness, the more similar becomes the transferred/co-deployed element to knowledge already present in the emerging domain.

Thus, although the number of knowledge elements increases in the emerging domain due to the addition of the transferred/co-deployed element, and so does the number of possible combinations, the diversity in terms of content of knowledge available in the emerging domain that can be tried in new combinations in the emerging domain diminishes with relatedness. The variety of knowledge elements that can be used in combinations to innovate in the emerging domain diminishes with relatedness between the two domains.

Therefore, the quality of innovation associated with knowledge scope in the emerging domain is expected to decrease with the relatedness of the knowledge domains, irrespective of whether the element was introduced via transfer or co-deployment.

The role of negative transfer of recombinative capability

When knowledge is recombined within the emerging domain, the firm applies its recombinative capability which has been developed in the established domain. Thus, although the firm does not misapply knowledge elements in the emerging domain, it may misapply recombination routines, to the extent that the required routines differ between the established and the emerging domains.

At low levels of relatedness, wherein knowledge elements in the established domain differ substantially from elements in the emerging domain, recombination routines learned in the established domain must be substantially adjusted in order to be properly applied in the emerging domain. Such adjustments are likely to be difficult to implement due to inertia, which leaves room for negative transfer of the firm's recombinative capability.

As the relatedness between the established and emerging domains increases, recombination routines that were developed in the established domain become more relevant for the emerging domain, and the need for adjustments is reduced. Thus, even if inertial pressures limit sufficient adjustment, as relatedness increases, negative transfer of the recombinative capability diminishes.

When the two domains are related beyond a certain threshold, although the need for adjustment of recombination routines is minimal, it is more difficult for the firm to recognize the nuanced differences between the established and emerging domains, and hence the need for adjusting the recombination routines. This leads to an increase in negative transfer of the recombinative capability.

Therefore, the negative transfer of recombinative capability undermines the quality of innovation at low and high levels of relatedness. At low levels it inhibits the firm’s ability to implement the adjustments, whereas at high levels it prevents the firm from recognizing necessary adjustments. In both cases, the application of recombinative capability learned in the established domain becomes suboptimal in the emerging domain.

Because the recombinative capability supports the firm’s ability to generate valuable knowledge combinations in the emerging domain, the quality of innovation will first increase with relatedness as the negative transfer of recombinative capability diminishes, up to a threshold level beyond which it will decline with the increase in negative transfer of recombinative capability. This suggests an inverted U-shaped association between knowledge relatedness and the quality of innovation as a function of negative transfer.

Negative transfer is expected to be stronger for co-deployment than for transfer at low levels of relatedness and become more similar as relatedness increases, as discussed in detail later.

The role of synergies from combinations

Co-deployment of a knowledge element creates synergies due to its simultaneous application in the established and emerging domains. These synergies arise not only due to the use of the co-deployed element in both domains, but also due to availability of new combinations involving that element in the emerging domain which echo combinations in the established domain.

Replicating combinations across domains generates synergies form exchange of knowhow and feedback across domains.

To the extent that the same combination is implemented in both domains simultaneously, the firm can rely on the feedback concerning the adoption of the combination in the established domain to enhance the performance of that same combination in the emerging domain. Leveraging such feedback offers a more comprehensive perspective on the application of the combination, and enhances the reliability of its application, which produces a positive effect on the quality of innovation in the emerging domain.

In the example of applying knowledge on how a carbon insert affects snowboards when simultaneously being used on skis, the insert can be combined with different woods of different sizes and fiberglass that can be oriented in different directions and in a different number of layers with settings that are somehow standard in the manufacturing of snowboard. In applying the carbon insert to a snowboard, the reconfiguring firm applies its knowledge concerning the carbon insert, its knowledge concerning wood, and its knowledge concerning fiberglass, to alter the standard combinations of wood and fiberglass in order to find the optimal combination when carbon is added. The outcome of a new combination involving a new carbon insert, a new kind of wood, and a new setting of fiberglass layers, is greatly uncertain and requires several trials in order to find the optimal mix. Nevertheless, if the same carbon insert is simultaneously tested also in skis in combination with different woods and different layers of fiberglass, not only the firm can leverage feedback coming from tests on skis to reduce the trials required to find the optimal mix in snowboard, but it can also obtain a better snowboard by studying the nuanced different results learned when testing the combination in both domains. A test in a single domain would lead to overlooking aspects that become evident only in simultaneous tests in the other domain.

For these synergies to manifest, it is necessary that the elements involved in a new combination be available in both the established and the emerging domains. The likelihood of finding a similar element in both domains that can lead to synergies from combinations increases with the relatedness between the established and the emerging domains. To the extent that the domains are dissimilar, it is unlikely to observe combinations involving the co-deployed element in both the established and emerging domains.

As relatedness increases, so do synergies arising from the exchange of feedback across domains with positive implications for the quality of innovation, which increases with relatedness. This effect is idiosyncratic of co-deployment, as transfer does not allow for simultaneous application of the same combination across domains.

Comparing the net effect of the proposed mechanisms with recombination in the case of co-deployment and transfer

The case of co-deployment

When the element recombined in the emerging domain has been co-deployed from the established domain, quality of innovation: increases with relatedness due to improved applicability of recombinative capability; decreases with relatedness due to diminishing expansion of knowledge scope in the emerging domain; first increases, and then decreases with relatedness due to negative transfer of recombinative capability (inverted U-shaped association); increases with relatedness due to synergies from combinations.

Overall, in the case of co-deployment, the quality of innovation first increases with relatedness due to the increasing positive effects of leveraging the recombinative capability, growing synergies from combinations and reduced negative transfer of recombinative capability. As the level of relatedness continues to increase, although the positive effects of recombinative capability and synergies keep growing, they are contrasted by the impeding effects of negative transfer of recombinative capability and the diminishing effect of expansion in knowledge scope that declines with relatedness.

Because negative transfer of the recombinative capability reduces the benefits of applying the recombinative capability but is unlikely to completely offset them, the net effect of these mechanisms is likely to exhibit a positive effect on innovation quality or a positive effect that diminishes with relatedness of the knowledge domains (r-shape).

Similarly, the decrease in expansion of knowledge scope only limits the synergies resulting from the application of combinations across domains following the co-deployed element. Thus, the effect of synergies that increase with relatedness net the diminishing expansion in knowledge scope, suggest that the quality of innovation related to these synergies and knowledge scope will increase with relatedness, or at least, increase at a diminishing rate with relatedness.

Therefore, assuming that the effects of negative transfer of recombinative capability and expansion of knowledge scope only diminish the dominant positive effects of recombinative capability and synergies, but do not offset them, the quality of innovation in the emerging domain is expected to increase at a diminishing rate with the relatedness of knowledge domains.

H3a: when a knowledge element is co-deployed from an established knowledge domain and recombined in an emerging knowledge domain, the quality of innovation in the emerging domain increases with relatedness of the knowledge domains at a decreasing marginal rate (r-shaped effect).

The case of transfer

When the element recombined in the emerging domain has been transferred from the established domain, quality of innovation: increases with relatedness due to improved applicability of recombinative capability; decreases with relatedness due to diminishing scope of knowledge in the emerging domain; first increases, and then decreases with relatedness due to negative transfer of recombinative capability (inverted U-shaped association), it is not affected by synergies.

In the case of transfer, the quality of innovation first increases with relatedness due to the increasing positive effect of recombinative capability and diminishing negative transfer of recombinative capability.

As relatedness further increases, although the positive effect of recombinative capability keeps increasing, it is contrasted by the effects of negative transfer and diminishing expansion of knowledge scope.

As in the case of codeployment, the effect of recombinative capability is expected to dominate that of negative transfer, but since synergies are not present to contrast the effect of decreasing expansion of knowledge scope, the net effect can become detrimental for the quality of innovation beyond a certain level of relatedness.

H3b: when a knowledge element is transferred from an established knowledge domain and recombined in an emerging knowledge domain, an inverted U-shaped relationship prevails between relatedness of these knowledge domains and the quality of innovation in the emerging domain.

Comparing co-deployment and transfer

Although the firm leverages its recomibinative capability in both transfer and codeployment, since transfer involves discontinuing the use of the knowledge element in the established domain, part of the knowhow that the firm has accumulated in the established domain about recombining this element is lost with transfer. This relative disadvantage of transfer becomes stronger as relatedness increases due to the greater applicability of the recombination capability across domains. Therefore, with increasing relatedness, the quality of innovation due to application of recombinative capability increases more for co-deployment than for transfer.

With respect to expanding the knowledge scope, no difference is expected for transfer versus co-deployment.

Negative transfer of the recombinative capability manifests with both transfer and co-deployment. However, unlike the case of co-deployment, the discontinued application of the knowledge element in the established domain following transfer partly relieves the firm from the inertial pressure when adjusting its capability, so misapplication of routines is expected to be stronger in the case of co-deployment. Hence, at low levels of relatedness, the decline in innovation quality due to negative transfer will be lower for transfer than for co-deployment.

Synergies from combinations and their positive implications for innovation quality manifest only in the case of co-deployment.

Overall, although negative transfer manifests more strongly in co-deployment than in transfer at low levels of relatedness, assuming that the impeding effect of negative transfers only weakens the positive effect of recombinative capability (which dominates), then co-deployment is expected to be superior to transfer at low levels of relatedness

Co-deployment becomes even more superior to transfer at higher levels of relatedness due to recombinative capability and synergies.

Hence, the advantage of co-deployment over transfer is expected to increase with relatedness.

H4a: When a knowledge element is reconfigured across domains and recombined in the emerging domain, the quality of innovation in the emerging domain is likely to be better following co-deployment than following transfer at any level of relatedness of the knowledge domains.

H4b: When a knowledge element is reconfigured across domains and recombined in the emerging domain, the difference in the quality of innovation in the emerging domain generated following co-deployment versus transfer, increases with relatedness of the knowledge domains.

Reconfiguration with the emerging domain: discarding

Discarding generates new combinations by subtracting an element from pre-existing combinations in the emerging domain, without reconfiguring the other elements that compose the combination.

When discarding is implemented without recombination, it can improve the quality of innovation to the extent that the discarded element was detrimental to the combination, thus improving the overall quality of the innovation. An example is antivibration plates adopted in snowboarding, which are still used in the so called "hard" boards used in slalom competitions but have been dismissed in "soft" boards used in the more acrobatic disciplines. However, the discarding of an element can also undermine the quality of innovation, to the extent that the discarded element is essential for the value of the combination. An example can be found in the Stradivarius violin. Violin makers were unable to recreate the violin as it was produced by the original innovator about four centuries ago, because of one knowledge element that was discarded, namely the protective lacquer whose formula was not documented and forgotten. This single element that is missing undermined the quality of innovation.

Nevertheless, of interest here are the implications of discarding an element from the emerging domain and replacing it with an element that has been either transferred or co-deployed from the established domain. To keep the example of antivibration systems in snowboarding, plates have been replaced in “soft” boards by new shapes of the edges (i.e. magne traction technology), whose concept originates from ice skating. Again, replacing an element in the emerging domain can either enhance or reduce the value of a combination, depending whether the reconfigured element is more or less valuable to the combination than the discarded element.

We first consider the general implications for the quality of innovation in the emerging domain of replacing a discarded element in a pre-existing combination with an element from the established domain. We then compare these implications to those for transfer versus co-deployment.

The effect of relatedness on innovation quality in the case of replacing an element in the emerging domain with a co-deployed or transferred element from the established domain

The role of absorptive capacity

When an element co-deployed or transferred from the established domain replaces an element discarded from a pre-existing combination in the emerging domain, the firm must understand the functionality of both elements as well as the extent and implications of their substitution. in order to properly replace the element in the emerging domain.

The greater the relatedness between the established and emerging knowledge domains, the more straightforward the replacing of the element in the emerging domain and the more likely that the substitution will be successful. Additionally, the greater the relatedness between domains, the better the firm’s ability to identify a knowledge element in the established domain that can properly replace the element discarded from the emerging domain.

Therefore, the quality of innovation in the emerging domain is expected to increase with the relatedness of the knowledge domains. Absorptive capacity manifests in both transfer and co-deployment, but to a greater extent in co-deployment, as discussed later.

The role of novelty

When an element is discarded from a combination in the emerging domain and replaced with a transferred/co-deployed element from the established domain, it can potentially enhance the novelty of the combination, and hence improve the quality of innovation in the emerging domain.

As the relatedness between the established and emerging domains increases, so does the similarity of discarded and replacing elements. Hence, relatedness decreases the novelty of the combination following the replacement by the transferred/co-deployed element, which undermines the quality of innovation.

Therefore, there is a negative association between relatedness of the knowledge domains and the quality of innovation as a result of reduced novelty. This implication is expected to be similar in both transfer and co-deployment, since the novelty of the resulting combination following the replacement is irrespective of the mode of reconfiguration that led to such replacement.

The role of negative transfer learning

Negative transfer learning declines with the level of relatedness between the established and the emerging domain, up to a point where relatedness inhibits the firm's ability to identify meaningful differences between the domains, making the firm less likely to implement necessary adjustments in the emerging domain.

When an element is transferred/co-deployed from the established domain in order to replace an element in the emerging domain, the firm can consider the pre-existing combination as a reference to compare against the revised combination with the replaced element in order to identify differences between the application of the transfer/co-deployed element across domains and highlight necessary adjustments.

At low levels of relatedness, relying on the comparison of combinations across domains to identify differences between domains is fairly straightforward. This helps the firm to spot the necessary adjustments when adopting the transferred/co-deployed element in the emerging domain. On the other hand, inertial pressure makes implementing these adjustments extremely difficult, generating high negative transfer learning.

As relatedness increases, less adjustment is needed to optimize the application of a transferred/co-deployed element in the emerging domain. Thus, negative transfer learning decreases with relatedness.

Nevertheless, as relatedness increases beyond a certain threshold, identifying meaningful differences between the two domains becomes more difficult, and although fewer adjustments are required when transferring/co-deploying an element, firms are less likely to spot the necessary adjustments, which are therefore overlooked and not implemented.

Thus, negative transfer learning decreases with relatedness up to the point where it increases again.

Negative transfer learning undermines the quality of innovation at low and high levels of relatedness as necessary adjustments are difficult to implement at low levels of relatedness and they are overlooked at high levels of relatedness, making the application of a transferred/co-deployed element suboptimal.

Therefore, the quality of innovation increases with relatedness up to the point beyond which it declines following the replacement of a knowledge element in the emerging domain.

This association holds for both transfer and co-deployment, although negative transfer is expected to be stronger in the case of co-deployment at low levels of relatedness, as discussed in detail in a later session.

The role of synergies from combinations

When an element from the established domain replaces an element in a combination featured in the emerging domain, it substitutes knowledge that has been repeatedly used and applied in the emerging domain while introducing knowledge that is foreign to this context. Hence, the reliability of using the transferred/co-deployed element is likely to be lower than that of the element that was replaced. Even if the replacing element is superior to the discarded one, it might take some time until the replacing element can be used reliably in combination with other elements in the emerging domain.

Nevertheless, the more the replacing element is applied, the greater its reliability. With repeated use, the firm learns how to effectively apply that element in combination with other elements.

When the replacing element has been co-deployed in the emerging domain, it continues to be applied also in the established domain. The continued application in both domains enhances the firm's understanding of how to combine that element effectively with other elements in a combination while improving its reliable use ang generating synergies.

To illustrate, in 2001 Volant, a ski manufacturer, introduced the concept of “rocker” as a substitute of the more traditional “camber” construction. Rocker inverts the profile of skis to make them more manoeuvrable. Few years later, the knowledge related to rocker construction and its benefits on manoeuvrability, started to be adopted also in snowboarding. One of the leaders of this change was K2, which manufactures both skis and boards. Although the first applications of rocker constructions have been promising for boards dedicated to specific uses, the traditional camber remained the dominant design for several years. In fact, although rockered boards were more manoeuvrable, they also lost much of their reactivity and stability. Thanks to the continued application and improvement of the rocker construction on skis, where more sophistication is required to obtain highly performing tools, K2 improve the reliability of the concept of rocker by adjusted it and applying it to specific parts of the ski in order to leverage on the benefit of improved manoeuvrability, while maintaining reactivity and stability. These revealing findings on the knowledge of rocker construction have then been applied with some adjustments to snowboard, enhancing the reliability of the concept of rocker in this domain, up to the point that nowadays, almost each snowboard model has a rocker construction and camber has basically disappeared.

The greater the relatedness between the knowledge domains, the more relevant the feedback received from the application of the element in the established domain and the greater the potential synergies and reliability enhancements for the replacing element in the emerging domain.

Potential synergies, useful feedback and enhanced reliability of applying the replacing element in combinations across domains contributes to the quality of innovation in the emerging domain.

Therefore, the quality of innovation in the emerging domain increases with relatedness in the case of co-deployment. These benefits, however, are unavailable when the knowledge element is transferred and its application in the established domain is discontinued.

The role of recombinative capability

Replacing an element in the emerging domain with an element from the established domain requires reliance on recombinative capability in the emerging domain, as the recombination involves not only the addition of an element from the established domain, but also selecting the right element to replace, discarding of that element from the pre-existing combination, transplanting the replacing element, and ensuring its effective interplay with the other elements in the combination.

The firm's ability to adopt recombinative techniques learned in the established domain to identify, replace, and properly transplant an element in the emerging domain, increases with the relatedness of the knowledge domains.

Thus, the quality of innovation, which benefits from an improved applicability of the firm's recombinative capability, increases with relatedness as well. Although this effect is present in the case of both transfer and co-deployment, it is stronger with the latter, as discussed later.

The role of expanding knowledge scope

There is no expansion of the knowledge scope if an element in the emerging domain is replaced with a co-deployed/transferred element from the established domain, as the number of possible combinations remains unchanged and the replacing element is added to a specific combination that involved the discarded element.

Since one element is added and another is discarded there is no change in the number of possible combinations in the emerging domain.

Thus, the quality of innovation is not affected by expanding the knowledge scope following discarding a knowledge element

The role of negative transfer of recombinative capability

Replacing a knowledge element requires the firm to leverage its recombinative capability. Nevertheless, to the extent that the required routines differ between the established and the emerging domains, the recombinative capability developed in the established domain may be misapplied in the emerging domain.

At low levels of relatedness, not only the ability to apply in the emerging domain recombinative techniques learned in the established domain is lower, but even when the firm can apply a recombinative technique across domains, due to the differences between the domains, this technique is also more likely to require important adjustments. Such adjustments are likely to be difficult to implement due to inertia, which leaves room for negative transfer of the firm's recombinative capability.

As the relatedness between the established and emerging domains increases, not only recombination routines that were developed in the established domain become more relevant for the emerging domain, but also the need for adjustments is reduced due to the increased similarity between the two domains. Thus, even if inertial pressures may still restrict adjustment, as relatedness increases, negative transfer of the recombinative capability diminishes.

When the two domains are related beyond a certain threshold, although the need for adjustment of recombination routines is minimal, it is more difficult for the firm to recognize the nuanced differences between the established and emerging domains, and hence the need for adjusting the recombination routines. This leads to an increase in negative transfer of the recombinative capability.

Therefore, the negative transfer of recombinative capability undermines the quality of innovation at low and high levels of relatedness. At low levels it inhibits the firm's ability to implement the adjustments, whereas at high levels it prevents the firm from recognizing necessary adjustments. In both cases, the application of recombinative capability learned in the established domain becomes suboptimal in the emerging domain.

Because the recombinative capability supports the firm's ability to select the right element to replace, discard an element from a pre-existing combination, transplant the replacing element, and maintain its interdependencies with the other elements in the combination, the quality of innovation will first increase with relatedness as the negative transfer of recombinative capability diminishes, up to a threshold level beyond which it will decline with the increase in negative transfer of recombinative capability. This suggests an inverted U-shaped association between knowledge relatedness and the quality of innovation as a function of negative transfer. Negative transfer is expected to be stronger for co-deployment than for transfer at low levels of relatedness, as discussed in detail later.

Comparing the net effect of the proposed mechanisms with replacement in the case of co-deployment and transfer

The case of co-deployment

When an element is co-deployed from the established domain to the emerging domain, quality of innovation in the emerging domain: increases with relatedness due to improved absorptive capacity; decreases with relatedness due to a decrease in novelty; takes an inverted U-shape with relatedness due to negative transfer learning; increases with relatedness due to applicability of recombinative capability; is not affected by the expansion of knowledge scope; takes an inverted U-shape due to negative transfer of recombinative capability.

It is reasonable to assume that the positive effect of recombinative capability dominates the discounting effect of negative transfer, but the negative effect of novelty still counters the positive effects of absorptive capacity and synergies. The expected net effect is thus an inverted U-shaped association between the quality of innovation and the relatedness of knowledge domains.

> *H5a: When a knowledge element is co-deployed across an established knowledge domain and an emerging knowledge domain to replace a discarded element in the latter, an inverted U-shaped relationship prevails between relatedness of these knowledge domains and the quality of innovation in the emerging domain.*

The case of co-deployment

When an element is transferred from the established domain to the emerging domain, quality of innovation in the emerging domain: increases with relatedness due to improved absorptive capacity; decreases with relatedness due to decreasing novelty; takes an inverted U-shape relation with relatedness due to negative transfer learning; is not affected by synergies; increases with relatedness due to improved applicability of recombinative capability; is not affected by the expansion of knowledge scope; takes an inverted U-shape relation with relatedness due to negative transfer of recombinative capability.

The net effect of these mechanisms makes quality of innovation increase with relatedness up to a certain threshold, beyond which, the quality of innovation decreases with relatedness.

H5b: When a knowledge element is transferred from an established knowledge domain to replace a discarded element in an emerging domain, an inverted U-shaped relationship prevails between relatedness of these knowledge domains and the quality of innovation in the emerging domain.

Comparing co-deployment and transfer

Since the relation between quality of innovation in the emerging domain and relatedness takes the same shape when the element is transferred or co-deployed to replace a discarded element in the emerging domain, it becomes utmost interesting to compare the effects of the two mechanisms that a firm can adopt to reconfigure its knowledge across domains.

The discontinued application of the transferred element in the established domain implies a partial loss of accumulated absorptive capacity in the case of transfer at any level of relatedness. Therefore, when replacing an element in the emerging domain, absorptive capacity increases the quality of innovation to a greater extent via co-deployment than via transfer, at any level of relatedness.

Novelty impacts the quality of innovation to the same extent via transfer or co-deployment, at any level of relatedness.

The discontinued application of the transferred element facilitates the dislodging from routines learned in the established domain. This makes it easier to overcome negative transfer learning and make the adjustments needed to properly replace the element in the emerging domain. However, this advantage of transfer over co-deployment diminishes with relatedness, as the necessary adjustments become marginal and overlooked differences less consequential. Hence, as relatedness between the knowledge domains increases, the differential in the magnitude of negative transfer learning between knowledge transfer and co-deployment diminishes. Thus, due to negative transfer learning, transfer generates quality superior to co-deployment at low levels of relatedness, but as relatedness increases, the quality differences between the two modes diminish.

Synergies, do not manifest in the case of transfer, but they make the quality of innovation increase with relatedness in the case of co-deployment

Recombinative capability, makes the quality of innovation increase with relatedness, in both modes, but the gain in quality is expected to be stronger in the case of co-deployment, due to the discontinued application of the transferred element in the established domain, that entails a partial loss of knowhow that the firm has accumulated prior to the reconfiguration. This disadvantage of transfer relative to co-deployment becomes stronger as relatedness increases, due to the more effective application of the firm's recombination capability across domains.

The expansion of knowledge scope is irrelevant for both transfer and co-deployment.

Negative transfer of the recombinative capability manifests in both transfer and co-deployment. However, unlike the case of co-deployment, the discontinued application of the knowledge element in the established domain following transfer partly relieves the firm from the inertial pressure when adjusting this capability, so misapplication of routines is more likely in the case of co-deployment. Hence, at low levels of relatedness, the decline in innovation quality due to negative transfer of recombinative capability is expected to be lower for transfer than for co-deployment.

Overall, the net effect of these mechanisms in the case of co-deployment versus transfer results from the fact that: in terms of absorptive capacity, co-deployment increases the quality of innovation more than transfer at any level of relatedness; in terms of negative transfer learning, transfer improves the quality of innovation more than co-deployment at low levels of relatedness, but this quality advantage diminishes as relatedness increases; synergies enhance the quality of innovation as relatedness increases in the case of co-deployment but not transfer; recombinative capability makes the quality of innovation increase with relatedness in the case of co-deployment more than in the case of transfer; negative transfer of recombinative capability discounts the quality of innovation less with transfer than with co-deployment, yet this advantage diminishes with relatedness.

Taken together these mechanisms highlight that co-deployment is superior to transfer at high levels of relatedness due to better absorptive capacity recombinative capability, and synergies.

Although negative transfer of recombinative capability is stronger for co-deployment than for transfer at low levels of relatedness, assuming that the discounting effect of negative transfer does not completely offset the positive effect of the recombinative capability, co-deployment is expected to be superior to transfer also at low levels of relatedness.

Furthermore, the relative advantage of co-deployment over transfer is expected to increase with relatedness.

H6a: When a knowledge element is reconfigured across domains to replace an element in the emerging domain, the quality of innovation in the emerging domain is likely to be better following co-deployment than following transfer at any level of relatedness of the knowledge domains.

H6b: When a knowledge element is reconfigured across domains to replace an element in the emerging domain, the difference in the quality of innovation in the emerging domain generated following co-deployment versus transfer, increases with relatedness of the knowledge domains.

METHODS[22]

Research Setting and Sample

In the mid-1990s, snowboarding confirmed its image as a legitimate outdoor activity and attracted firms from different industry sectors. Innovation in the snowboard domain surged during the years 1994-2009, as evident by the number of snowboard patents filed during this period.

Accordingly, during these years, the snowboard industry represented an emerging knowledge domain for several firms which have traditionally operated in various industry sectors, including skiing, surfing, chemicals, mountain biking, and fishing. These firms innovated and patented in snowboarding by transferring or co-deploying knowledge from their established knowledge domains.

To identify firms that innovated in this emerging knowledge domain, we rely on patent data extracted from the Orbis IP database. This source is particularly suitable for our setting as it covers all the patent offices where firms innovating in the snowboard industry have the incentive to protect their inventions: North America, Europe, and Asia (mainly China and Japan). The need to acquire data from all these offices arises from applications of patents that are not necessarily filed across all the patent offices but are restricted to specific ones. Indeed, focusing on sources from specific geographies (i.e. USPTO or EPO) would overlook important patents that have been filed in other geographies and provide an incomplete picture of a firm's patenting activity.

Taking the standpoint of a firm that enters the snowboarding knowledge domain, the firm's patents filed in that domain represent the innovations of interest for assessing their quality. These patents may cite the firm's previous patents from non-

[22] This section is incomplete and might not be fully precise. At the current stage it only offers a direction for the intended research design. Improvements to the model and preliminary results will be available in the future.

snowboard domains and thus represent knowledge elements that the firm reconfigures from its established domains and introduces into the emerging snowboard domain.

IPC patent classes represent knowledge domains. A firm patent classified as snowboard by the IPC system represent its innovation in this emerging domain for which we want to assess the quality. That same firm's patents not classified as snowboard by IPC, but cited by firm snowboard patents represent the firm's knowledge elements originating from different established domains that were either transferred or co-deployed in the snowboard domain.

Snowboard patents are assigned to two IPC classes: snowboard binding patents A63C10 (pertaining to the devices that link a rider's foot to the board) and snowboard patents A63C5 (meant as the very board that slides on the snow) which are classified in the IPC class together with ski boards. Therefore, whereas patents in the A63C10 class are unequivocally related to the snowboard domain, those belonging to the A63C5 class can be either ski or snowboard patents.

In order to isolate snowboard patents from ski patents within the A63C5 class, we rely on textual analysis of the description of each patent in this class and use Doc2vec algorithm to compute the similarity score between a patent description and each of the patents filed up to that patent's application date by five dedicated snowboard firms, namely Burton, F2, Sims, Nitro, and Flow, that never entered the skiing domain and have a patenting history focused exclusively on snowboarding. Indeed, since snowboard represented the new wave against the status quo embedded in skiing, until very recent times, skiers and snowboarders have been frowning upon each other. The stigma that snowboard manufacturers received from their users when entering the ski domain has been a strong deterrent for these five firms to diversify into skiing. In an interview for Fortune magazine published in the

April 2007 issue, Jack Burton, founder, owner, and CEO of Burton Snowboards, declared that his company would not follow the diversification path taken by ski manufacturers and would instead remain focused on producing snowboards. Interestingly enough, until very recent years, Burton snowboard was hiring only snowboarders among its human capital.

Moreover, whereas the snowboard sector has been growing until about 2010, the skiing industry had reached its maturity in the 1990s. Therefore the economic incentive that pushed ski manufacturers to enter the snowboard domain was not present in snowboard manufacturers already operating in the growing industry. Overall, these five pure snowboard companies never diversified into skiing and their innovations patented in the A63C5 class clearly identify snowboard patents within this class. Thus, their patents represent an ideal benchmark to identify via text similarity other snowboard patents in this class belonging to other firms that are not pure snowboard companies.

After computing the maximum similarity of each patent in A63C5 with each of the patents in the benchmark, we set 0.8 as the similarity threshold that separates snowboard and ski patents within A63C5 class. Those patents with a similarity score higher than 0.8 are identified as snowboard patents and belong to the emerging domain; those with a score lower than this threshold are instead ski patents and belong to an established domain. Taking the maximum similarity instead of the average is relevant in this context. Indeed the benchmark snowboard patents are quite different across each other as they refer to diverse aspects of boards that span from the design to the chemical components of the base. Since we are rather interested in grasping whether a patent is similar to any of the patents in the benchmark independently on how similar it is on average to all of them, the maximum similarity score seems to be the most suitable for the purpose.

The 0.8 threshold to separate snowboard from ski patents is set according to two criteria: firstly, when sorting from the highest to the lowest similarity score, we noticed that, whereas the score decreases gradually from 1 to 0.81, it leaps from 0.81 to 0.69, to decrease again gradually from 0.69 to 0.06. This leap in the similarity score identifies a unique net boundary (spline function) within IPC class A63C5. The plot of the similarity scores of the 6516 patents present in the class A63C5 is visible in figure 1. From this graph, it is possible to appreciate that the values pertaining to a similarity score between 0.68 and 0.8 are not populated by any patents in this class, confirming the evident separation between the ski and snowboard patents. Secondly, to validate that this boundary and the 0.8 threshold indeed separate ski and snowboard patents within this class, we showed the texts and images of those patents with similarity scores around 0.81 and 0.69 to three industry experts (former snowboard athletes that cooperated with snowboard manufacturers in the years between 1998 and 2003). By looking at the proposed documents, there was agreement on identifying the patents with a similarity score greater than 0.8 as snowboard ones and those with a similarity score smaller or equal to 0.69 as non-snowboard ones.

This approach identified 264[23] snowboard patents by 87 firms that filed from a minimum of 1 to a maximum of 42 patents in the snowboard domain. Among these firms, 58 have only one snowboard patent. Since it is hard to imagine a firm with only one patent in a domain to be a firm that actively wants to enter the domain to

[23] We actually identified 529 snowboard patents, however, half of them were filed by unclassified independent individual inventors. It is important to notice that these independent inventors are not inventors that worked for firm patenting in snowboarding. Indeed, inventors working for companies have been identified and their patents assigned to the firm they worked for (i.e. JF Pelchat, founder of Now Snowboards has two patents filed under his name. These patents have been assigned to Now Snowboards). Thus, the unclassified inventors that we discarded are independent actors that do not systematically innovate in the snowboard domain and that do not have an active role when considering firms reconfiguring knowledge from an established domain to enter and innovate in snowboard.

innovate, we focus our attention on those 29 firms that have filed 2 or more snowboard patents[24]. The entire patenting activity of these 29 firms generates a pool of 238484 patents filed in different IPC classes. The most focused firm has a patenting history in 2 IPC classes only, the most diversified one in 6681 classes.

Insert figure 1 about here

IPC classes are considered at the level of the "group" (i.e. A63C5). This categorization, which is a compromise between the "subclass" level (i.e. A63C) and the "subgroup" level (i.e. A63C5/09), ensures that the identified domains are inherently different in terms of their knowledge while maintaining enough variation in terms of the number of classes as well as patents per class filed by each firm. Indeed, whereas different subgroups belonging to the same group tend to contain knowledge from the same domain (i.e. A63C10/02 comprises the patents related to the straps of snowboard bindings and A63C10/14 patents pertaining to the base of a snowboard binding), individual subclasses often contain knowledge from multiple domains (i.e. subclass A63B includes swimming aids in the A63B31 group and mountaineering gear in the A63B29 one). Therefore, subgroups straddle a single knowledge domain on the one hand, while subclasses comprise multiple domains on the other. In this setting, the group level appears to be the one that best matches our theoretical setting.

At the chosen level of categorization, we have an average of 3.86 patents per class and an average of 417 classes per firm[25].

[24] This selection criteria will be controlled for using a two stage approach that captures the likelihood of firms to engage in a patenting activity of two or more patents in the snowboard domain.
[25] Following our selection criteria, even though we can confidently exclude the use of subgroups to categorize knowledge domains, it may appear that having a firms spanning more than 400 domains on average is too much. For this reason, we do not completely exclude the subclasses level from our analysis, but test it in a robustness check.

Measures

Dependent variable, the quality of an innovation. We measure the value of an invention using the forward citations that each focal snowboard patent receives by other snowboard patents from any firm in the first five years after its application date. Since the scientific value of an invention refers to its quality (Phene, Fladmoe-Lindquist, & Marsh, 2006), impact (Nerkar, 2003), and its contribution to further technological development (Albert, Avery, Narin, & McAllister, 1991; Sorenson, Rivkin, & Fleming, 2006; Trajtenberg, 1990), using forward citations seems particularly appropriate to measure this construct (i.e., Cattani, 2005; Singh, 2008).

However, since we are interested in capturing the quality of innovation within the emerging domain, we restrict the forward citations to those made by other snowboard patents. Moreover, being interested in assessing the overall quality of the innovation in the domain, we consider forward citations by all the firms operating in the snowboard domain, including self citations of the firm of the focal patent.

To cope with the fact that older patents have more opportunities of being cited than younger ones, we restricted the time window to five years after the focal patent's application date[26].

Finally, since the patenting activity in snowboarding has not been regular in time with the same number of patents filed each year and some time windows have been more prolific than others, we standardize the measure dividing by the number of snowboard patents filed in the period for which we count the number of forward citations.

Independent variable, relatedness between knowledge domains. Maintaining the perspective of the firm applying for the focal snowboard patent at time *t*, we identify

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[26] As robustness test we consider different time windows (3, 7, and 10 years) as well as the entire life of the patent including a fixed effect that captures its year of application.

the established and the emerging domain by considering the firm's stock of non-snowboard and snowboard patents respectively up to time *t*. The time component allows us to capture evolution of the firm's knowledge stock in both domain and account for the fact that the relatedness between the established and the emerging domain might change from when the firm files for a focal snowboard patent and the subsequent one.

Relatedness itself is measured using the text similarity between the firm's stock of non-snowboad patents and its stock of snowboard patents. For each firm *a*'s non-snowboard patent *j* filed up to time *t*, we use Doc2vec to compute the text similarity to each firm a's snowboard patent *k* up to time *t*. The similarity score of each non-snowboard patent *j* is the average of its simialirty score with each snowboard patent *k*. However, since relatedness is at the domain level, we average again the similarity scores of all the non-snowboard patents *j* up to time *t* to find the final similarity score that represents the relatedness between the domains at the moment when the firm files the application for the focal snowboad patent[27].

Moderating variable, co-deployment of knowledge. Before measuring co-deployment, we must identify which firm's knowledge behind an innovation in the emerging domain by the same firm was reconfigured from the established domain.

As previously discussed, we consider a firm's snowboard patents to be the innovations in the emerging domain that can be generated via co-deployment or transfer by the focal firm. Each snowboard patent filed by the focal firm relies on prior knowledge that is embedded in the patent and represented by the citations that the patent makes to previous patents. Thus, for each firm *a*'s focal snowboard patent, we

[27] As robustness check we use the measured proposed by Jaffe (1986).

consider its set of backward citations and isolate those that refer to previous firm *a*'s patents filed in any class that is non-snowboard.

Even though this step allows us to identify firm *a*'s knowledge from the established domain that the firm has used to generate a focal innovation in the emerging domain, we still have to clarify whether the knowledge was co-deployed or transferred.

To be identified as co-deployed, each selected backward citation must satisfy two criteria. First, it must have been cited by firm *a* in one or more snowboard patents before the focal snowboard patent object of the analysis. This first criterium allows us to distinguish between established knowledge that was purposely applied by the firm to enter the emerging domain from established knowledge that was used in the emerging domain in a less intentional way (i.e. knowledge applied to a patent that has been filed in the snowboard class because of its possible applications in this domain, despite the firm's lack of interest in actively entering the snowboard industry). Second, it must have been cited by firm *a* in one or more non-snowboard patents in the time window between firm *a*'s first snowboard patent making the focal citation and the focal snowboard patent making the same citation. This second criterium allows us to capture whether the knowledge was continuously used in the established domain while applied in the emerging one and to tease out the crucial difference between co-deployment and transfer.

Thus a firm *a*'s backward citation *Ci* made by firm *a*'s focal snowboard patent *p* filed at time *t* represents co-deployed knowledge if it was cited by at least an older firm *a*'s snowboard patent *k* filed at *t0* (with *t0* being earlier than *t*) and by at least an older firm *a*'s non-snowboard patent *j* filed at *t1* (with *t1* being later than the filing date of the oldest snowboard patent *k* citing *Ci* and earlier than *t*).

Moreover, since the focal snowboard patent *p* may make multiple citations to firm *a*'s non-snowboard patents, the proposed criteria apply to all frim *a*'s backward citations made by the focal snowboard patent *p*.

Thus, accounting for all the backward citations embedded in the focal patent, the amount of co-deployed knowledge in a focal snowboard patent *p* filed at time *t* can be measured as:

$$Cod_{p,t} = \sum_{i} \frac{C_{i,p,t} C_{i,k \neq p,t0} \sum_{j} C_{i,j,t1}}{\sum_{k} C_{i,k \neq p,t0}}$$

$C_{i,p,t}$ represents firm *a*'s non-snowboard citation *Ci* by the focal snowboard patent *p* at time *t*; $C_{i,k \neq p,t0}$ represents the same backward citation *Ci*, but when made by other firm *a*'s snowboard patents *k* with application date preceding *p*'s application date; $C_{i,j,t1}$ represents the same backward citation, but when made by firm *a*'s non-snowboard patents *j* in the time interval from the application date of the first snowboard patent *k* making the citation to the application date of *p*.

Overall, the numerator of the fraction satisfies the above-mentioned criteria, and the summation in *i* accounts for all the firm *a*'s backward citations in the focal snowboard patent that satisfy the criteria. Moreover, the summation in *j* accounts for the fact that the more *Ci* is continuously used in the established domain in the time interval the higher will be the level of co-deployment brought by *Ci* to the focal snowboard patent *p*.

By contrast, since the number of times a focal citation *Ci* is cited by other snowboard or patents filed by firm *a* in the time interval may affect the impact that the citation has on the focal snowboard patent for reasons that are not related to its continuous use in the established domain, we discount for this effect in the measure of co-deployment by dividing for the number of times *Ci* was cited by firm *a*'s snowboard patents *k* in the time interval, as described by the denominator of the fraction and the summations in *k*.

Moderating variable, transfer of knowledge. To measure transfer we reason along the same lines as for co-deployment, with the main difference between the two constructs residing in the fact that, whereas co-codeployed knowledge is continuously used in the established domain, the application of transferred knowledge in the established domain disappears.

Accordingly we still want to consider whether a citation *Ci* by the focal snowboard patent *p* filed at time *t* is also cited by other snowboard patents *k* filed before *t* and discount the effect of the sum of the citations by all *k* patents, however, to capture transfer we also have to discount for how many times *Ci* is cited by non-snowboard patents *j* in the time interval from the application date of the first snowbard patent *k* citing *Ci* and the time *t*.

Also in this case we want to account for all the citations *Ci* made by the focal patent. Overall, the level of the of transferred knowledge in a focal snowboard patent *p* filed at time *t* can be measured as:

$$Trans_{p,t} = \sum_i \frac{C_{i,p,t} C_{i,k \neq p,t0}}{\sum_k C_{i,k \neq p,t0} + \sum_j C_{i,j,t1}}$$

Moderating variable, recombination. In order to identify the level of recombination in the emerging domain, we rely on co-citations of patents within the snowboard domain.

We consider a focal snowboard patent's set of backward citations excluding those capturing transfer or co-deployment and compare the remaining set of citations with all the sets of backward citations behind each pre-existing snowboard patent by the focal firm. This highlights the novelty of a combination of cited patents in the snowboard domain with respect to pre-existing combinations of cited patents in the same domain.

We rely on the angular separation between combinations of cited patents and we compare the cosine similarity between the combination of backward citations of the focal snowboard patent (excluding transferred or co-deployed elements) and the set of backward citations of each snowboard patent by the focal firm available at the moment of filing the application for the focal patent.

The maximum value among the resulting cosine similarities for the focal patent gives us the level of similarity of the combination of backward citations behind the focal patent with pre-existing combinations. The level of novelty, which represents the level of recombination, is the opposite of this similarity and is calculated taking the complement of this measure (one minus similarity)[28].

Moderating variable, replacement. In order identify the level of replacement, we consider instead the just mentioned similarity score and we highlight how similar the combination of patents, excluding the transferred/co-deployed element, cited by the focal snowboard patents is to combinations previously cited by other snowboard patents.

Similarity should not be one, as at least one element must have changed, but it should be in the high part of the distribution.

Control variables. Characteristics of the established domain different from relatedness might affect the number of citations received by a patent. For this reason, we introduce a fixed effect that captures the CPC subgroup of the transferred/co-deployed patents.

[28] This measure and possible alternatives based on text similarity between care currently under development.

Since we are comparing citations of patents filed at different times and forward citations can follow waves of innovation that exploit specific categories in specific years, we add a fixed effect that captures the year of application of the focal patent.

Since the value of knowledge might decay in time, we also control for the granting date of the co-deployed/transferred patent.

Since a patent that entails more knowledge might be more appealing for future citations, the number of backward citations might have an effect on the number of forward citations received by the focal patent. Thus, we include the number of backward citations in the controls.

Next steps

This paper is not yet complete and at the current stage it offers an idea of the direction that our current research is pursuing. Although data collection has been completed, we are finalizing the concpetualization and the construction of the measures focusing on two main aspects: factoring the effect of time in the measures, and screening the literature to identify existing measures that capture constructs similar to those that we propose in this paper. This should allow us to ground our measures in accepted standards, while capturing constructs that have not yet been directly measured in the literature.

DISCUSSION

Innovating firms frequently enter emerging knowledge domains, may these be new product/markets or new technologies that affect the product/markets where the firms operate.

Although in order to enter an emerging knowledge domain, firms reconfigure their resource base, knowledge in particular, the consequences of different modes for reconfiguring resources on quality of innovation have been overlooked by scholars involved in the study of resource reconfiguration.

This paper considers the possible modes that firms can adopt when reconfiguring the knowledge they have acquired in their established domain in order to enter an emerging domain, and compares, according to the relatedness between the two domains, the effect of each mode on quality of innovation in the emerging domain.

It first identifies that the relation between relatedness and quality of innovation is not linear, but it mostly shows that, when reconfiguration across the two domains is associate within reconfiguration also within the emerging domain, co-deployment generates superior quality with respect to transfer, and that the superiority from co-deployment increases with the relatedness between the two domains.

This aspect is of utmost relevance, as scholars involved in the study of inter-temporal resource redeployment, a concept similar to transfer, have highlighted the benefits of moving resources back and forth across domains when they become more related and the cost of reconfiguration across domains drops. By analyzing benefits instead of costs, we show not only that the efficacy of inter-temporal reconfiguration increases only up to a certain threshold of relatedness, but also that intra-temporal reconfiguration, a concept similar to co-deployment, leads to an overall greater quality of innovation with respect to inter-temporal reconfiguration.
Looking at benefits from reconfiguration, our findings suggest that intra-temporal reconfiguration (co-deployment), might be preferred to inter-temporal reconfiguration (transfer).

Not only this paper raises questions on how to interpret established findings in the literature and advocates for further investigations on the consequences of different modes for reconfiguring resource that analyze pros and cons of each mode, but it also offers to practitioners more insights on what they should expect when choosing a reconfiguring mode over the other. The resulting overview on the implications of each reconfiguring mode facilitates decisions of managers that plan to enter emerging domains.

Finally, to our knowledge, this paper is the first one attempting to measure in details the concepts of co-deployment and transfer that have populated the literature on resource reconfiguration, but have not yet been properly measured at the level of an individual resource.

In addition to its current incompleteness, this paper is limited in scope, in the sense that it does not account for possible implications that the proposed reconfiguration modes have on quality of innovation in the established domain, which might be affected by a "rebound" effect of the knowledge that is transferred/co-deployed into the emerging domain. Furthermore, it does not identify contingencies where the proposed effects increase or decrease in magnitude. We acknowledge these limitations and are currently coping with some of them (i.e. completing the measures and the analysis) while leaving others as opportunities for future research projects.

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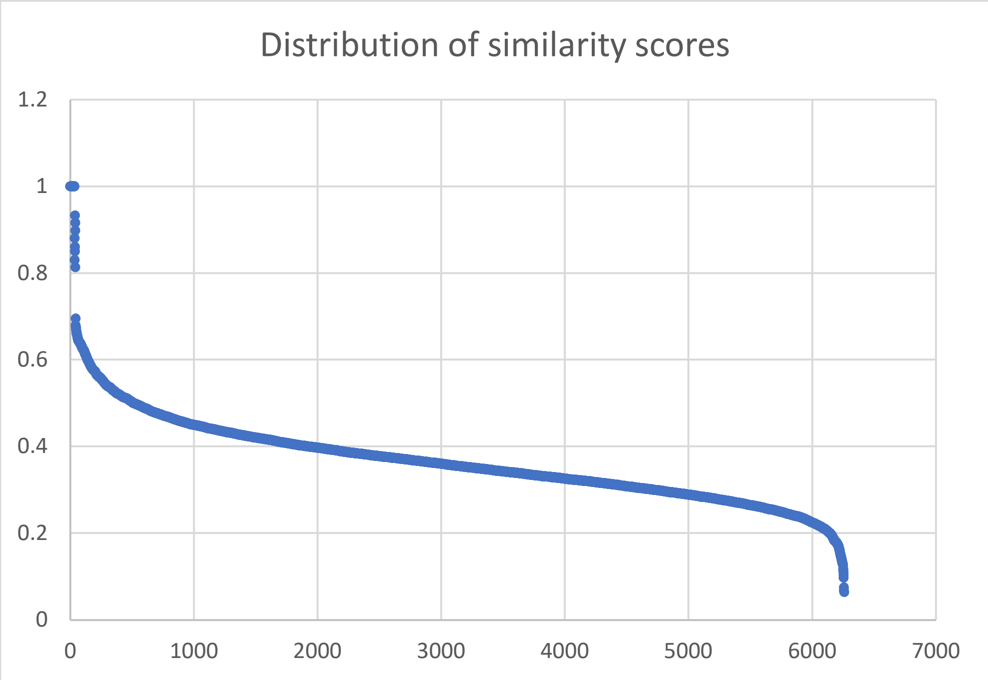
Figure 1


Distribution of similarity scores
1.2
1
0.8
0.6
0.4
0.2
0
0
1000
2000
3000
4000
5000
6000
7000