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Firms? preadaptation and knowledge recombination in the face of an emerging core technology: an empirical study on photography industry

Luca Mongelli
LUISS University of Rome
Management
lmongelli@luiss.it

Abstract

In this paper we attempt to identify the main drivers for a firm?s success when it develops knowledge in an emerging core technology. To answer to this question we specifically deal with the case of discontinuous technological substitution in the photography industry, in which a radical shift from chemical to digital technology occurred. We referred to two main knowledge leveraging mechanisms, i.e. internal and external, and different kinds of technological domains, making a clear distention between core technology, i.e. the emerging domain, and complementary domains, i.e. industry-related vs. industry-unrelated domains.

In line with preadaptation theory, the main idea developed in the paper is that firms may both reap benefits from technological expertise in those domains which still characterize the ongoing industry paradigm and, in so doing, implement recombination processes among complementary domains. Accordingly with this interpretation the results confirmed our hypotheses: on the one hand, leveraging knowledge in the narrow emerging domain is more likely to have a limited effect on firms? technological performance; on the other hand, excessive crossing in unrelated domains, although slightly better than the previous case, is not the optimal solution as well. In line with our expectation the results showed that the best strategy is leveraging knowledge by crossing towards industry-related domains.

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Firm preadaptation and knowledge recombination in the face of an emerging core technology: an empirical study on the photography industry

1. INTRO

In many cases firms have to face discontinuous technological shifts characterized by the emergence of a new core technology. If we conceive a technological paradigm as a set of complementary and core technologies organized around a dominant design, all of these elements are supposed to evolve along technological trajectories for a period, and to shift to a new one when a new core technology emerges (Anderson and Tushman 1990, Utterback and Abernathy 1975, Utterback and Suarez 1993). When this shift occurs, the main firms' challenges concern the ability to innovate in the emerging technology and to deal with existing technological endowments. On this matter, researchers have begun to acknowledge the relevance of the dynamic processes by which firms manipulate and regenerate their knowledge (Cattani 2005, Eisenhardt and Martin 2000, Helfat et al. 2007, Teece et al. 1997).

However, the relationship between a firm's innovative performance in the emerging technology and the actual mechanisms through which they leverage and recombine the fruit of their past research is still open to debate in the current literature. The reason for this open discussion is that previous studies dealt with this topic through two distinct and apparently incompatible theoretical lines of research: local search theory (Ahuja and Lampert 2001, Leonard-Barton 1990, Levinthal and March 1993, Levitt and March 1988) and the literature on knowledge redeployment (Carroll et al. 1996, Helfat and Lieberman 2002, King and Tucci 2002, Klepper and Simons 2000, Miller et al. 2012)

Local search theory, although very influential in explaining why focusing on the neighborhood of a local domain is a natural tendency of organizations, has not explicitly considered, and in some cases even neglected, the positive role of prior research experience in the face of a

discontinuous technological shift. This stream of studies was very active in emphasizing the need for escaping from the well known learning traps (Levinthal and March 1993), such as competence traps (Levitt and March 1988), core rigidities (Leonard-Barton 1990), and familiarity, propinquity and maturity traps (Ahuja and Lampert 2001).

Literature on knowledge redeployment, although quite effective in supporting the positive effect of prior research experience, has been not entirely clear regarding the specification of the real mechanisms by which firms should exploit prior knowledge (Carroll et al. 1996, Helfat and Lieberman 2002, King and Tucci 2002, Klepper and Simons 2000). These studies focused on the concept of "similarity" between the type knowledge held by the firms and the type of knowledge needed in other contexts, to explain the actual advantage of transferring knowledge across domains (Helfat and Lieberman 2002). However, in case of technological knowledge, the definition of concept of similarity tends to remain unclear, raising the need for a more accurate specification of the technological domains that may provide valuable knowledge to leverage. In fact, when a discontinuous technological shift occurs, some research experience may have a detrimental effect on the ability to perform in an emerging domain (Leonard-Barton, 1992, Dougherty, 1995, Levitt and March, 1988), while other experience may "become a source of competitive advantage rather than a constraint" if carried out properly (p.564, Cattani, 2005).

In parallel with these two lines of research, the stream of studies on knowledge recombination faced the challenge of avoiding the local traps, deriving from exploitation of previously developed knowledge, by implementing exploration spanning across both technological and organizational boundaries. This stream of literature however, has yet to explicitly deal with the specificities stemming from an ongoing technological contest, which is supposed to present peculiar dynamics compared to established settings (Kogut and Zander 1992, Rosenkopf and Nerkar 2001).

In the light of this, in this study I build first on the empirical advances that have revealed the mechanisms of knowledge recombination in established contests (Rosenkopf and Nerkar 2001), to consider the implication of such mechanisms in an emerging technology; second, I build on

recent contributions that have dealt with the comparative logic of local search theory to literature on knowledge redeployment through the use of preadaptation theory (Cattani 2005). Thus the aim of this study is to address the following question: to what extent may recombination, which can take place from the use of preadaptation, successfully involve different technological domains in order to develop knowledge in the emerging core technology? What is the most effective scope of recombination?

I follow the Cattani (2005) preadaptation theory to explain the heterogeneity of firm performance in the face of an emerging technology. This theory makes a clear distinction between having preadaptation, according with the evolutionary perspective, and using preadaptation, as result of a proactive and deliberate choice on the part of the firm (Garud and Nayyar 1994). In this paper I consider prior experience in different types of technological domains as source of preadaptation which might turn out to be useful "when the firm uses it in a distinct application domain." (Cattani, page566). I thus extend this theory in two ways. First, I argue that preadaptation in different domains may be seen as a source to implement a process of knowledge recombination of which firms may try to take advantage to differing degrees and with different results. Second, building on recombination literature, I show that firms may implement a process of recombination by also taking advantage of the potential preadaptation deriving from other firms. When firms leverage knowledge from others, even in different domains, this is expected to boost their innovative performance (Laursen and Salter 2004, Miller et al. 2007, Rosenkopf and Nerkar 2001). Finally I make a clear contribution to recombination literature by investigating its mechanisms in an ongoing setting where, respect to an established setting, part of the implications deriving from the typologies of the domains involved may be challenged.

Empirically, I build on the stream of studies which investigate organizational search at the patent level and accounts for their impact by forward citations (Fleming and Sorenson 2004, Ghosh et al. 2013, Rosenkopf and Nerkar 2001). Thus, as Ghosh and al. (2013) have done, I tested our hypotheses in the photography industry, where technology substitution which

occurred between the previous chemical technology and the new digital technology, marked a discontinuous technological shift. Given the well-defined technological nature of the photography industry, I was able to clearly distinguish the characterizing technological domains involved in it. I could therefore reclassify patent subclasses in terms of technological domains, distinguishing between domains which are considered core, (chemical vs. digital), and complementary, i.e. industry-related (within the industry) vs. industry-unrelated (outside the industry)(Phene et al. 2006). In particular this study investigates the transition period between the two main core technologies, from the first application of digital to photography in the 1974, to its final establishment as the core of the new paradigm in the photography industry (2004).

The remainder of the paper is organized as follows. In the section 2, I review the literature of knowledge redeployment, grounding our research question on the discussion of preadaptation as a source of recombination. In section 3, I present the hypothesis, distinguishing between internal and external leveraging, and leveraging knowledge into different kinds of technological domains. In section 4, I describe the data and the empirical setting (the photography camera industry) in which I tested our hypotheses and discuss the methodology. Section 5 presents the empirical analysis and the results. Section 6 concludes and discusses the main research implications.

2. THEORY

2.1 knowledge redeployment

Many studies have extensively explored the relationship between firm prior experience, innovation, and performance. Miller and al. (2007) have recently observed the positive effect on innovation of the transferring and use of knowledge across different business divisions of diversified firms. More particularly, Helfat and Lieberman (2002) emphasize the significant match between the market entered and the firm's pre-entry resources and capabilities. According to the authors, a firm's entry, as well as its ability to survive and prosper longer may be explained by the "similarity" between pre-entry firm resources and those required by the target industry. On this point, extant literature provides this stream for a great deal of empirical

evidence . For instance, in the American automobile industry, Carroll et al. (1996) found that those firms entering from related industries are more likely to survive longer than those newly founded or coming from unrelated industries. In a longitudinal study of the television industry, Klepper and Simon indicated that firms with the most relevant experience, among those producing radios tended to enter earlier, survived longer, and had larger market shares than non-radio producers (Klepper and Simons 2000). Moreover, King and Tucci (2002) found that a firm's experience in previous existing markets, increases the probability of entry in the new disk-drive market niche and positively impact on their success. Further consistent results have been found in multiple case studies of the semiconductor industry by Holbrook et al. (2000). All of these contributions delved into the relationship between the heterogeneity in firm's prior experience and industry evolution by investigating the conditions enabling the fit between new market applications and knowledge developed. In some cases, literature also shows how the use of existing knowledge may lead to the emergence of new domains of application. For instance, Abernathy and Clark (1985), showed how already existing technologies developed by the firm can be also used to create new market niches. Building on an evolutionary perspective, Adner and Levinthal introduced the concept of "speciation" as that process through which the redeployment of existing knowledge across different domains generates new technological lineages and market opportunities (Adner and Levinthal 2002, Levinthal 1998).

However redeploying knowledge across different settings is a firm's ability difficult to implement: "useful knowledge retrieval requires its modification to suit current needs. This might imply reinvention as new individuals interpret maintained knowledge in different ways" (Garud and Nayyar 1994, p. 377). Because of this, researchers have begun to acknowledge the relevance of the dynamic processes by which firms manipulate and regenerate their knowledge base (Cattani 2005, Eisenhardt and Martin 2000, Helfat et al. 2007, Teece et al. 1997). In this regard, a specific stream of literature has demonstrated that conducting or having access to previous research experience does not automatically imply the ability to dynamically use and leverage it for the development of new knowledge. Since the first studies in management,

scholars have recognized that firms with similar bases of resources can exploit them in different ways and with very different results (Penrose 1959). In the same fashion, more recent studies demonstrate that having access to a significant set of resources is quite a different thing from actually exploiting them fruitfully, and that the ability to take advantage of existing technological knowledge can differ radically among firms (Garud and Nayar, 1994; Cattani, 2005). According to Cattani, "having preadaptation, i.e. availability of relevant skills and knowledge is distinct from using preadaptation." (p. 567). The author shows that in the fiber optics industry, the more firms draw upon their technological preadaptation, the better the technological performance in the new domain of application. This means that related research experience is a pre-adaptation behavior to an ongoing landscape only when it actually results as a deliberate choice and not as a random coincidence coming from the contingent situations with which the firm had previously dealt.

2.2 Preadaptation as a source of recombination

Nevertheless, having and using preadaptation also regards knowledge in different types of domains other than in the specific emerging technology. As argued by Garud, in order to exploit new business opportunities firms have to focus on "reactivating maintained knowledge and coupling reactivated knowledge with other knowledge vectors" (p. 376). More particularly, when a new core technology emerges within an existing technological paradigm, it is supposed to affect the set of complementary technologies which had previously characterized the paradigm (Anderson and Tushman 1990, Utterback and Abernathy 1975, Utterback and Suarez 1993). When this occurs, the main firm's challenges concern not only the ability to innovate into the emerging technology per se but also to deal with those complementary domains of the existing paradigm which are likely to accompany the future paradigm. In cases like this indeed, such complementary domains can persist even after the establishment of the new technology. For example in the photography industry ,although the discontinuous shift from chemical to digital technology has been radical, it did not modify the baseline role of the complementary components: the role of optics is still to focus and carry light into the camera; similarly, the role

of the mechanical system continues to be the movement of the optics (Benner and Tripsas 2012, Ghosh et al. 2013). This means that firms may have some level of preadaptation on the emerging technology, as well as on "technologically proximate knowledge", defined by Phene et al as knowledge within-industry, or even on "technologically distant knowledge", from outside the industry (Brusoni et al. 2001, Cohen and Levinthal 1990, Patel and Pavitt 1997, Phene et al. 2006).

Extant studies further demonstrate that having preadaptation on different technological domains may become a potential source for recombination. Garud used the metaphor of pollen to explain how new knowledge creation derives from the interaction of knowledge vectors as stamen. In that sense, firms may proactively lead artificial-pollination by "choice of pollen, maintaining it over time and space, and its reactivation and synthesis to produce a hybrid." (p. 372). Thus recombination can actually be implemented by using preadaptation, namely through drawing upon the knowledge developed in different domains (Rosenkopf & Nerkar, 2001).

One aspect that current studies have yet to more deeply investigate is the specific challenge of developing knowledge in an emerging core technology through the implementation of knowledge recombination across different typologies of domains. Rosenkopf & Nerkar suggest that an interesting step in research, which has received relatively less attention to date, is "to address distinctions between developments in core components versus more peripheral components" (p. 304), by theoretically and empirically differentiating the role of knowledge recombination between core and complementary domains, and in the case of complementary components by distinguishing between industry-related domains (i.e. within-industry) and industry-unrelated domains (i.e. outside the industry)(Phene et al. 2006).

In light of this, I intend to expand the contribution coming from Cattani regarding the positive effect of having and using preadaptation in a new domain of application, to the case of a new technology which emerges as the new core within an existing industry. In doing so, I conceive the use of preadaptation as a main driver of recombination (Garud and Nayyar 1994, Rosenkopf and Nerkar 2001), raising the following question: to what extent can recombination, deriving

from the use of preadaptation, successfully involve other technological domains in order to develop knowledge in the emerging core technology? What is the right scope of recombination? In other words, what is not entirely clear within the literature, is the extent to which firms may exploit preadaptation through the process of knowledge recombination in industry-related and industry-unrelated domains, and how this may have different effects on firms' innovative performance.

3. HYPOTHESIS: RECOMBINATION WITHIN AND OUTSIDE THE ORGANIZATIONAL BOUNDARIES

Many authors have recognize knowledge recombination as main drive of innovation (Henderson and Cockburn 1994, Kogut and Zander 1992, Nelson and Winter 1982). Kogut and Zander (1992) argue that innovations stem from a "firm's combinative capabilities to generate new applications from existing knowledge" (p. 391) where *combinative capabilities* refers to the "capability of the firm to exploit its knowledge and the unexplored potential of the technology". Extant literature provides several consistent interpretations of the concept, making a clear distinction however between knowledge coming from inside firms' boundaries and knowledge coming from beyond them. For example Henderson and Cockburn (1994) refer to "architectural competence" as "the ability to access new knowledge from outside the boundaries of the organization and the ability to integrate knowledge flexibly across disciplinary [...] class boundaries within the organization". Similarly Rosenkopf and Nerkar define second-order competence as "the ability of a firm to create new knowledge through recombination of knowledge across […] both organizational and technological boundaries" (p. 289). Since many scholars have interpreted recombination in these terms (Miller et al. 2007, Nemet and Johnson 2012, Phene et al. 2006), accordingly I develop our hypothesis on the basis of this important distinction between internal and external sources of knowledge, and thus between internal and external leveraging.

3.1 Internal leveraging in the emerging domain

The relevance of internal leverage derives from the general prediction for which firms are supposed to be more capable of dealing with technological domains where they have prior research experience and knowledge that can be actually leveraged. However extant studies provided conflicting evidence regarding the relationship between firm innovation performance in the focal domain and the possibility to transfer knowledge across time through the process of knowledge leveraging (Cattani 2005, Garud and Nayyar 1994, Rosenkopf and Nerkar 2001). Rosenkopf and Nerkar empirically found that in the optical disk industry, firms implementing "local exploration", which implies building upon knowledge residing in the same technological domain within the firm, has negative effects on innovation's impact in the focal domain. On the contrary, Cattani found evidence to the contrary, internal knowledge leveraging of fiber optics technology being positively associated with a firm's innovative performance. Nevertheless, these apparently inconsistent results stem from the nature of setting under investigation. While the former, i.e. optical disk, has been used by the authors as a setting already established, fiber optics was investigated as a brand new one. In this case, firm's possibility to exploit prior research experience by using all the limited technical expertise already developed is quite more crucial. Indeed, referring to the existing knowledge is considerably preferable to exploring new technologies from scratch, especially because of the potential positive feedback from existing research experience (Levinthal and March 1993, March 1991). In this case in fact, either cognitive limits or fundamental uncertainty (March and Simon 1958, Nelson and Winter 1982) may lead inventors without experience to make two kinds of mistakes. On the one hand, they are likely to be faced with unfruitful combinations or dead ends that had appeared promising at first glance. On the other, initial negative results may prevent inventors from taking paths that might prove successful later on. Mutatis mutandis, the same logic can be applied in a setting where a new core technology emerges. Such a setting proves to be more similar to fiber optics as described by Cattani, compared to the established optical disk setting. Therefore, according to these arguments, in our baseline hypothesis I expect to find consistent results with Cattani findings:

Hypothesis 1: developing knowledge in an emerging core technology by the internal leveraging of knowledge in the same domains ***has a positive*** *impact on a firm's innovative performance.*

3.2 Internal recombination of knowledge in industry-related domains

Nevertheless, in the case of internal leveraging within the same emerging domain, I expect very limited contributions coming from the possibility to implement a recombination process, since the technological elements available are restricted to one specific domain (Fleming and Sorenson 2001). I expect recombination may produce a significant impact when firms decide to extend their research effort towards industry-related domains. Here, recombination may take place across a number of technological domains. So, thanks to the resulting heterogeneity, the variety in all the possible combinations among domains is expected to be higher than the single focus within the narrow emerging technology. As explained by Rosenkopf, "cognitive and social exhaustion will also constrain invention if inventors become locked into established thought patterns when they work with only a few components. With variety, the juxtaposition of disparate fields of thought or physical technology can trigger new associations and breakthroughs" (p. 1025). Many studies have empirically shown how local search without exploration may became a trap, thereby hampering a firm's innovation and performance (Helfat 1994, Miller et al. 2007, Phene et al. 2006, Stuart and Podolny 1996)

Furthermore, from an evolutionary perspective, a new technological paradigm emerges within an industry not only as a specific single domain, but also as the result of hybridizing different technologies in a common application context (Levinthal, 1998). Thus, narrowing the focus to one specific domain can mislead firms into confusing the emergence of a discontinuous core technology with a domain-specific innovation, leading them to develop inappropriate technological solutions (Henderson and Clark 1990). It is also important to note that when an old core technology is replaced by an emerging one, as in the case of the photography industry, problems related to the limited interactions between technologies may hinder proper

application of the new core (Henderson and Clark 1990, Henderson and Cockburn 1994). Thus, for a proper application, the new technology should be developed by crossing the boundaries of its own domain towards those industry-related domains with which the emerging technology is supposed to interact in the new industry paradigm. Hence I state that:

*Hypothesis 2a: developing knowledge in an emerging core technology by the internal leveraging of knowledge in industry-**related** domains **has a positive** impact on a firm's innovative performance.*

*Hypothesis 2b: developing knowledge in an emerging core technology by leveraging internal knowledge in industry-**related** domains has a **greater** effect than leveraging internal knowledge in the specific **emerging** domain.*

3.3 Internal recombination of knowledge in industry-unrelated domains

Recombination of knowledge in industry unrelated domains has been discussed in previous studies, even if with different perspective and interpretation. According to Rosenkopf and Nerkar (2001), exploring technologically distant knowledge available within the firm (i.e. internal boundary-spanning) has a negative impact on the future development in the same domain. As industries and technologies become mature, "continued exploration in one particular technological domain creates competence" that is "domain specific"(p. 192). In other words, the industry being well-established and the technological framework already set, such competencies tend to narrow down along a restricted technological trajectory. This implies that developing knowledge by recombining and building upon knowledge in unrelated domains may present an inefficient solution.

Nevertheless, here I can extend the distinctions made in the hypothesis 1, regarding the nature of the context under investigation and thus reverse some of the above arguments. In an ongoing context characterized by an emerging technology in fact, any path dependence process of knowledge accumulation is supposed to take place in the short term (Rosenkopf and Nerkar 2001). In such a case rather, increasing the scope of research may have several benefits. First, researchers may avoid the propinquity trap, defined by Ahuja as "propensity to search for

solutions in the neighborhood of existing solutions" (Ahuja and Lampert 2001, p. 528). Especially at the beginning, when the potential of a technology is not clear, searching extensively "for new solutions in the neighborhood of old solutions", implies that a broad set of potential solutions remains unexplored Second, recombination process can take advantage of a greater number of heterogenic elements to recombine(Fleming and Sorenson 2001). Thus, in this case, leveraging knowledge in an industry-unrelated domain is expected to positively impact on a firm's innovative performance. Accordingly:

> *Hypothesis 3a: developing knowledge in an emerging core technology by the internal leveraging of knowledge in industry-**related** domains **has positive** impacts on a firm's innovative performance.*

It is also true that moving outside the industry-related domains may also have other flipsides, mainly because of researchers' cognitive constraints (March and Simon 1958). The implementation of excessive "frenzies of experimentation"(Levinthal and March 1993), may reduce the expected positive effects of exploring and recombine heterogeneous streams of knowledge. As Fleming and Sorenson say: "the marginal benefit of variety probably decreases with the increasing number of components because inventors experience cognitive difficulty considering all the components and their potential relationships simultaneously" (p. 1025). Managing too many novelties stemming from an excessive level of exploration may cause information overloading, resulting as a source of confusion. Also Ahuja and Lampert argue that "the likelihood that the optimal or even a highly effective solution to a problem will be discovered diminishes as the range of problems addressed within a given set of competencies increases. Concurrently, the likelihood that some principles will be inappropriately applied rises as a constrained set of competencies is applied to several various technological problems" (p. 526). In particular in their analysis of the NBER's patents, Nemet and Johnson(2012) found that building on existing knowledge that is technologically close has a stronger effect than building on existing knowledge that is distant. Many further studies have enhanced our understanding of the relationship between recombining knowledge across industry-unrelated domains and a

firm's innovative performance and shed light on why and how this knowledge can be viewed as a heterogenic source for recombination but difficult to exploit beyond some level (Gruber et al. 2012, Miller et al. 2007, Phene et al. 2006)

Based on these considerations, the effect of recombination derived by leveraging knowledge in industry-unrelated domains is expected to be high. However I also expect the final impact on innovative performance to be lower than knowledge in industry-related domains for two reasons: first, because of the implication on inventors' cognitive constraints (Levinthal and March, 1993); second, because this kind of recombination will not take advantage of the positive effects of leveraging knowledge in domains which are supposed to characterize the new industry paradigm (Henderson and Clark 1990, Henderson and Cockburn 1994). At the same time, I expect a higher impact than leveraging knowledge in the narrow emerging domain thanks to the additional, albeit reduced, effect deriving from recombination. Thus I hypothesize that:

> *Hypothesis 3b: developing knowledge in an emerging core technology with high level of complementarity in industry-**UNrelated** domains has a **lower** effect on a firm's innovative performance, than complementarity in industry-**related**, but a **higher** effect than leveraging internal knowledge in the specific **emerging** domain.*

3.4 External leverage and recombination of knowledge

I have focused so far on internal leveraging, namely a firm's ability to take advantage of its own previous research experience. However, while a firm's "preadaptation" implies a specific focus on internal resources, it does not prevent it from accessing external sources of knowledge. Previous studies have extensively investigated the firm's use of external knowledge sources as an additional source for new ideas, focusing for example on the implication in terms of absorptive capacity (Laursen and Salter 2004) and exploration (Miller et al. 2007, Rosenkopf and Nerkar 2001). It is important to remember that dispersed knowledge, especially in emergent technology environments, is not so easy to identify and transfer inside the organizational boundaries, even by active firms in possession of adequate absorptive capacity.

In that sense, the ability by which firms dynamically look outside the boundaries of their own organization (Helfat et al., 2007; Rosenkopf and Nerkar, 2001) has been recognized as critical for a firm's success. This is because an excessively internal focus may stifle the development of knowledge in a new technology due to limited cognition schemas and the "familiarity trap"(Levinthal and March, 1993; Cohen and Levinthal, 1990; Ahuja and Lampert, 2001).

However, in order to reap the benefits of a positive impact from external source of knowledge, firms have first to scan the external environment, filtering and assessing the existing knowledge so as to guide future development (Pandza and Holt, 2007). Second firms, have to build on the identified knowledge to develop new knowledge. Regarding this last point, Rosenkopf found that firms actually implementing research activity across organization boundaries increase their innovative performance (Rosenkopf and Nerkar, 2001), precisely thanks to the recombination among complementary sources of knowledge (Rosenkopf and Nerkar, 2001; Kogut and Zander, 1992; Iansiti and Clark, 1994; Fleming and Sorenson, 2001). Accordingly, when firms are actually able to implement a recombination process by leveraging knowledge across organizational boundaries, the expected contribution to the firm's innovative performance is positive and even higher than internal leveraging.

Thus for all of three cases described herein (i.e. levering in the same domain, in industry-related domains, and in industry-unrelated domains), I expect building on external sources of knowledge to boost a firm's innovative performance by increasing the level of recombination. Therefore, I state that:

> *Hypothesis 4: The effect on a firm's innovative performance of* ***leveraging external*** *knowledge respectively in the emerging, industry-related and industry-unrelated domains is always* ***higher*** *than the respective case of* ***leveraging internal*** *knowledge.*

4. EMPIRICAL SETTINGS

To test our hypotheses, I investigate the evolution of the photography industry. There are several reasons for this choice. First, the photography industry has undergone a discontinuous technology substitution between hitherto disparate domains of knowledge, from chemical to

digital. For two centuries, chemical technology strongly affected the technological paradigm of the photography industry. Nevertheless, in 2004, digital camera sales surpassed those of chemical-based cameras. Today, cameras based on chemical technology account for less than 1% of total world revenues (DATAMONITOR, 2009), and digital technologies have become the new core technology. The decision to ground our empirical settings in the photography industry also stems from its specific nature, in which it is possible to clearly distinguish between the different embedded technological domains. Finally, despite the novelty of digital technology, this industry is mature enough to provide useful data for the purposes of this research.

4.1. Technological domains of the photography industry

As Ghosh et al. (2013) explain, the photography technologies usually have been developed around two main aspects. The first concerns the whole set of mechanisms that characterize the overall product's functionality: the optical system, the mechanical and electrical systems, the LCD screen and the external tools (e.g., flash). The second aspect concerns the for image-capturing technology, which can be seen as the core element of the overall system. From the beginning, photographic cameras relied on chemical technologies. In this technology, the photographic image is generated from an interaction between the silver halide of the film and light waves. The introduction of digital technologies triggered a revolution in several aspects of the imaging field, including image capturing and its related storage, manipulation, and display. Despite the fact that the first digital imaging technologies emerged during the 1970s, and the first digital camera prototype was unveiled by Sony in 1981 with the pioneering Mavica, the real commercial advent of the digital camera occurred only in the second half of the 1990s. The CCD (charge-coupled devices), the main digital technology, has gradually replaced traditional film-based photography (Benner and Tushman, 2002; Tripsas and Gavetti, 2000) because of its capacity to convert light images into binary data. More recently, a new generation of sensors, the CMOS (Combined Metal Oxide Semiconductor), has been replacing the CCD due to its superior performance in terms of cost and energy consumption.

As opposed to classical chemical pictures, digital format pictures are treated as electronic data: storage, transmission and the elaboration processes occur electronically. However this change did not modify the main role of the camera's optical, mechanical, and electrical systems, or the external tools such as the flash. The role of optics is still to focus and carry light into the camera. Similarly, the role of the mechanical system continues to be the movement of the optics. However, new problems related specifically to the use of digital technology did arise, requiring brand new solutions. Two instances of such problems are the elaboration of the image by the processor and its storage in specific memory devices. The microprocessor chip controls the digital camera's operations by managing the whole product architecture and converting the numeric data coming from the sensor into a digital format image. The storage device generally is a removable media storage card or micro drive, which replaces the film roll found in the chemical-based camera. While these components were not originally considered photographic components, they have affected the success of the digital camera as their specific applications have, over time, been developed for photographic use. Finally, the LCD technology has been applied to the camera in order to provide users with a preview of the pictures.

4.2. Research Design

In the photography setting, the described components tend to form coherent and circumscribed technological domains. So in order to measure the knowledge firms developed within such domains, I used patents (Hall et al., 2001). While patents are not able to measure all the knowledge held by firms, researchers have increasingly employed them as indicators of the technological knowledge in the firms(Hall et al. 2001, Patel and Pavitt 1997, Stuart and Podolny 1996), especially in contexts like the photography industry, where firms tend to use patents to protect their technological endowment (Benner and Tushman 2002, Ghosh et al. 2013, Oriani and Sobrero 2008, Srinivasan et al. 2007). Moreover, since the Patent Office usually grants only those patents that prove to be useful and non-obvious and provide a substantial contribution to the relative technological class, they can be seen as a manifestation of the knowledge flow developed by firms.

Patents also reveal other important information about the technological domain that they are likely to involve. The granting process (see USPTO Granting Guide, as well as other patent institutions) requires that every patent have one, and only one, principal mandatory classification. This is known as "Original Classification" (OR), and concerns the subject matters for which a patent voluntarily or involuntarily makes claims (claimed or unclaimed invention information). This first classification is composed of the combination of one class and, within it, a more specific subclass. For example "exposure control system responsive to focal length" is classified as Original Classification in the 396/63 (class/subclass). In general each class may contain several hundreds of subclasses. However not all of them have the same importance since they are hierarchically ordered in technological domains by different levels of indent. In particular mainline-subclasses are those subclasses within each class that, having an "indent level" of zero, provide the main subject matters of the class (USPTO Guide, Dec. 2009). In general there are only a few for each class but they are quite useful to group all the other subclasses in consistent technological domains. In fact, all other subclasses within the class with an indent level higher than zero are subordinated to them. In this paper I used mainline-subclasses for implementing a reclassification process within the technological classes provided by previous studies on photography industry (see section Method).

4.3. Method

In order to track a firm's knowledge through patents, it was necessary to select which domains related to the photographic technologies were relevant for the overall industry paradigm, and then link each of them to the more appropriate patent classes. In our sample I focused on patents granted within the 12 patent classes that previous literature had considered relevant for the photography industry(Benner and Tushman 2002, Srinivasan et al. 2007)[1].

It is important to specify that the decision to consider all these patent classes, rather than just the specific photography class (396), stems from the particular nature of technological

[1]The patent classes are: radiant energy (250); computer graphics processing, operator interface processing, and selective visual display systems (345); television (348); photocopying (355); optics: measure and testing (356); optics: systems (including communication and elements) (359); dynamic magnetic information storage or retrieval (360); image analysis (382); television signal processing for dynamic recording or reproducing (386); photography (396); stock material or miscellaneous articles (428); and radiation imagery chemistry: process, composition, or product (430).

knowledge. Technologies in general are not always clearly provided for in any one class and may develop in more than one class simultaneously (USPTO Guide, Dec. 2009). Even if classes are "mutually exclusive" and the subject matter of one class does not overlap that of another, technologies (such as the digital technology which initially had no clear definition) may have different effects in several technological classes. Because of technological nature of these issues, I was supported by two specialists from "Centro Nazionale delle Ricerche" (CNR)[2] and "National Institute of Optics" (INO)[3],who helped us to carry out the analysis along two fundamental steps. The first was aimed at identifying the technological domains as described above. I identified the following: digital sensor, processor, digital storage, optics, mechanics, electronics, lcd, external equipment, and chemical film. The first three domains—i.e. the digital sensor, processor, and digital storage—were considered to be substantial parts of the emerging technology domain since they specifically and exclusively accounted for the application of digital-based technology in the photography industry. Optics, mechanics, electronics, lcd, and external equipment were considered industry-related domains since they refer to those sets of technologies used in both the previous and the new industry paradigm. All the other technological classes listed in the collected patents not belonging to any classes mentioned before were considered industry-unrelated domains. Finally, the chemical domain and the corresponding classes were referenced as substituted old core technology. In the second step, I reclassify all the mainline-subclasses (and consequently all their subordinate subclasses) listed in the 12 patent classes suggested by extant studies in this field (Benner and Tushman 2002, Srinivasan et al. 2007) according to the technological domain identified in the previous step. Only the mainline-subclasses having a direct connection with the selected digital technologies-related domains were reclassified as emerging domains, or industry-related domain when related to optics, mechanics, electronics, lcd, and external equipment. All others were simply considered industry-unrelated domains.

2The CNR is the most important Italian research center

3The INO is an independent research institute which has been working in the field of Optics for over ninety years

4.4 Sample

The sample was drawn from the segment of firms having entered digital technology with a minimum level of patent activities along the transition period of industry to the new paradigm. Consistently with the intention to capture only non-episodic or non-casual firm efforts in this field, I set this minimum threshold to an average patent activity within the digital class equal to 10 patents per year. Information on patent data was collected from the U.S. Patent and Trademark Office for patents granted until December 2013. However the focal sample of digital patents takes into account only the transition period of industry to the new paradigm, namely from 1974 to 2004. Moreover, consistent with previous contributions in the field (Cattani 2005, Hall et al. 2001), in our dataset I considered patents on the basis of their submission date to the USPTO and not the granting date. This is because the granting process entails a certain amount of time for assessing the potential patent (USPTO Granting Guide), making the submission date a more accurate indicator of the moment in which new knowledge was developed than the actual granting date. The relevant information obtained from the USPTO was: Patent Number, Assignee Name, Assignee State, Issue Date, Application Date, Current US Original Classification, Current US Cross References Classification, and Other References and Claims. In the end, I collected 45912 digital patents from 1974 to 2004, granted to155 firms.

4.5. Dependent variable and model specification

In this paper, I build on the stream of literature which investigates organizational search at the patent level and accounts for their impact by forward citations (Fleming and Sorenson 2004, Ghosh et al. 2013, Rosenkopf and Nerkar 2001). I thus estimate the value of innovative company performance in the emerging domains by using citations that digital patents received from patents granted by other organizations. I excluded future self-citations in order to highlight those patents that actually contributed to the creation of useful knowledge in the emerging technological domain.

I did not use patent count in the emerging domain since the value of the patents is an aspect for which patent count does not constitute a good proxy (Griliches et al. 1987, Hall 2000, Scherer

1980). Although the propensity to patent may differ among firms, not all patented inventions result in future technological development (Hall and Ham-Ziedonis 2001, Hall et al. 2001), since many of them have marginal actual relevance and do not reflect any truly original and incremental implication. Particularly in R&D-intensive industries like the photography industry, the number of forward-citations that a patent receives is an accurate measure of innovative performance, affording a closer estimation of the actual value of the focal patents (Griliches 1981, Trajtenberg 1990a, b). In this context, forward citations prove that: "the cited patents opened the way to a technologically successful line of innovation. Thus, if citations keep coming, it must be that the innovation originating in the cited patent had indeed proven to be valuable" (Trajtenberg 1990a, p. 174). Several other studies also have investigated the positive relation between patent citations and the firm's market value (Hall 2000, Hall et al. 2001, Shane and Klock 1997), as well as other performance indicators like company sales and profits (Narin et al. 2001). However it is accepted that patents more frequently cited by subsequent patents tend to be the most valuable for firms (Harhoff et al. 1999). In our sample, I collected future citations of digital patents in the sample until December 2013. I then organized patents in a panel structure based on the filing year. Since patents filed in earlier years were able to be cited for a longer period, I also set a panel of sliding windows with three different scopes: 5 years, 7 years, and 10 years. This allowed us to implement several robustness checks with homogeneous comparison over time, since the windows captured different potential interpretations of the patent life cycle (Trajtenberg 1990a, b). Regarding the model specification, our dependent variable can only take non-negative integer values. Accordingly the recommended models are the Poisson and the Negative Binomial Specification (Hausman et al., 1984). However, because of presence of over-dispersion, as is the case of our data, the variance tends to be greater than the mean. So I chose the negative binomial specification and applied it to a more prudent panel with fixed effect in order to control for all fixed unobserved effects. In the fixed effect, I controlled for the firm id, patent year, and digital id (sensor, processor, and storage)[4-5]. Finally in order to compare the

[4] I estimate the model before in SAS, using GENMOD PROC through which it is possible to account for more than two fixed effect

magnitude of the effect as theorized in the hypothesis, I computed the incident rate ratio of estimation (IRR, Table 3), and successfully tested the inequality of the coefficients using a Wald-test (I reject the null hypothesis where the coefficients are equal).

4.6. Independent variables

- *Leveraging internal and external knowledge in the emerging domain.* In order to test Hypotheses about leveraging into the emerging domain, I created the "int_lev_emerging_dom" and "est_lev_emerging_dom", which capture, respectively, the concept of leveraging internal and external knowledge in the emerging domain. The former measures the number of self backward citations to patents classified as digital, divided by the number of backward citations. The latter corresponds to the number of citations to external patents classified as digital, divided by the number of backward citations.

- Leveraging internal and external knowledge in industry-related domains. In order to test Hypotheses about leveraging into the related domains, I created the "int_lev_ind_related_dom" and "est_lev_ind_related_dom", which capture respectively the concept of leveraging internal and external knowledge within the industry-related domains. The former calculates the number of self backward citations to patents classified as industry-related domains, divided by the number of backward citations. The latter calculates the number of citations to external patents classified as industry-related domains, divided by the number of backward citations.

- Leveraging internal and external knowledge in industry-unrelated domains. In order to test Hypotheses about leveraging into the industry-unrelated domains, I created "int_lev_ind_Unrelated_dom" and "est_lev_ind_related_dom" which capture, respectively, the concept of leveraging internal and external knowledge in the industry-unrelated domains. With the former, I calculated the number of self backward citations to patents classified as industry-unrelated domains, divided by the number of backward citations. With the latter, I calculate the number of citations to external patents classified as industry-unrelated domains, divided by the

dimensions, and then STATA with NBEREG, where the fixed effect was captured by using dummies. Because the two computations yielded almost identical results, I only report estimates from STATA

[5] As suggested in previous studies (Sørenson and Stuart 2000), I controlled for the differences in the propensity to patent across digital technological fields by using the digitialid (the identification id for the digital fields) in the fixed effect.

number of backward citations.

TABLE 1: Correlations

4.7. Control variables

- *Research Experience in industry-related* and *–unrelated domains* are derived from the number of patents granted by firms in the previous five years in the industry-related domains and industry-unrelated domains, respectively. They account for the extent to which firms invested, researched, and actually produced knowledge in those research domains, namely their R&D effort. These two controls are quite relevant in our theoretical framework, since they allowed us to account for the differences among firms in terms of previous experience. Setting sliding windows of five years made it possible to render the real dynamics of how firms define their research strategy over time.

- *Average Digital Patent Impact* is a ratio between the total number of forward citations received by digital patents filed in a specific year and the number of digital patents filed in the same year. This variable accounts for the seniority of the patent, where on average older patents are more frequently cited than younger patents mainly because their seniority increase the likelihood of citations for a longer period (Cattani 2005).

- *Log claims* is a patent level variable, this calculates the logarithm of the total number of technological claims for each patent. It accounts for the extent of technological contributions that the patent is likely to bring and which previous studies have shown to be relevant for the future success of the patent(Merges and Nelson, 1994, Hall et al., 2005,Novelli 2015)

- *Average Back Lag* is a patent level variable that measures the average age of cited patents. It accounts for the extent to which the focal patents have built on old knowledge. Extant literature in fact provides evidence for which the value of older patents is doomed to decay over time (Oriani and Sobrero 2008). Thus building on older patents may negatively impact on patent forward citations (Rosenkopf and Nerkar 2001).

- *Other References* is patent level variable, this refers to the number of scientific references cited by the patent. Science has been recognized as a main driver in the development of new knowledge (Brusoni et al., 2005; Fleming and Sorenson, 2004;).

- *Number of inventors* is a patent level variable that measures the number of people on the team of inventors of the focal patent. A greater number of inventors is considered to better contribute to the final output.

- Time to Grant is a patent level variable that measures the lapse of time between the

TABLE 2: Models and Reuslts

TABLE 3: Incident Rate Ratio (IRR)

5. RESULTS

In order to detect differences that may occur in the interpretation of the actual patent's lifecycle, I tested our model several times, setting the dependent variables (forward citations) with different time windows as explained above (namely 5, 7, and 10 years). Setting different time windows obviously affected the number of forward citations in the final sample. In the case of a 5-year time window for example, since the final year in our sample is the 2004, I considered forward citation until 2009, excluding citation after that year. In fact, setting a 5-year time window makes 2009 the last the year to be included. For time windows of 7 and 9 years, I considered forward citations until 2011 and 2013 respectively. Nevertheless, after several robustness checks, I found that the choice of the time windows did not affect the results. Therefore, in the end I decided to use no time windows but rather the overall forward citation available until December 2014. However in order to account for the difference in terms of patent life cycle (patents granted in 1990 will have a different citation life cycle from those granted in 2010), I decided to control for the average patent impact of digital patents granted by the firms in the sample each year of observation (Cattani 2005).

In order to make explicit the real effect of the mechanisms discussed before, in the Table 2 I developed our analysis in 5 definitive models: in Model 1 I consider only the control variables; in the Model 2 I consider the impact of internal and external knowledge leveraging and the

control variables; in Model 3, which is our main model for the hypotheses testing, I opened up the leveraging, distinguishing between the different technological domains; in the Model 4 with tested the main regressors with the constant[6]; in the Model 5 I perform the same with an alternative model specification. In the same table I further run two more models in order to perform part of our robustness check. All the implemented analyses are fairly consistent in terms of the results obtained. In fact, all theoretical and control variables that proved significant in a certain model remained significant in all the others, thus providing robust support for the hypotheses tested. Also the correlation table reveals relatively low correlation values between all the variables examined (see Table 1). I found only two exceptions. The first regards the variable "*experience in the emerging domain*", which proves to be correlated with "*experience in the emerging domain*" (with a value of approximately 0.75). Because of this, in our model I use only the latter, which has the advantage of showing a lower correlation with experience in industry-related domains. The second variable is the "*Average Digital Patent Impact*", which proves to be correlated with the time variable *"Year"* (-0.62). This is not unexpected, since the forward citation is expected to increase over time. However even when I removed this variable from the analysis, the results were confirmed.

Looking at the Model 3 (Table 2), the results show that the baseline hypothesis 1 is verified, internal leveraging knowledge being in the same emerging domain positively associated with innovative performance. This confirms the prediction coming from preadaptation theory which basically makes a distinction between having and using preadaptation in the emerging domain (Cattani). In line with our theory, results show that internal leveraging of knowledge in industry-related domains is first positively associated with innovative performance, providing supports for Hypothesis 2a. Second the respective IRR (Table 3) is higher than leveraging in the same domain (1.490 vs. 2.335), giving support to the HP-2b. I also found support for Hypotheses 3a and 3b, since the leveraging knowledge in industry-UNrelated domain is

[6] All the leveraging variables are ratios which sum is expected to equals 1. Therefore to avoid multicollinearity, in the analysis I dropped the constant. So in the Model 4 I also test the constant by dropping, however, one of the leveraging variables. The analysis shows that even with the constant the results are totally consisted with those coming from the main Model 3.

positively associated with innovative performance, and the magnitude of impact lower (IRR: 1.976) than industry-related domain but higher than leveraging knowledge in the same domain (Table 3). Finally with Hypothesis 7— fully verified—I tested whether leveraging external knowledge may produce some value added coming from the combination of external sources of knowledge. In the same hypothesis I also tested whether the effect of leveraging external knowledge follows the same theoretical pattern of results as that I hypothesized for internal leveraging, especially for the magnitude effects of the three typologies of knowledge. All the respective IRR (Table 3) are higher than those of internal leveraging and respectively they maintain the same proportion in terms of magnitude effects (2.769 for leveraging external knowledge in industry-related domains, 2.275 and 1.962 respectively for leveraging external knowledge in industry-UNrelated domains and in the emerging domain).

Regarding the controls, the most interesting elements concern two variables: "research experience in industry-related domains" and "research experience industry-unrelated domains". As per our expectation, the former is quite significant, with a positive coefficient. The latter is still significant, but the coefficient is surprisingly negative. This result may be due to the priority in resource allocation, meaning that in the face of discontinuous technological shift regarding the core technology, scattering research activities across too many domains not directly involved in the evolution of the industry paradigm may impede the research in the emerging domain and to some extent hamper the full development of new knowledge. (Levinthal and March, 1993; Ahuja and Lampert, 2001).

Robustness check. I finally tested the robustness of the results obtained against an alternative model specifications. First of all, I found that the dependent variable is characterized by a substantial number of zeros (11.35% of the patents in our population has zero forward citations) which may bias our results. This would normally be modeled with the zero-inflation version of the model specification. However this proved impossible to run due to difficulties in convergence in the log-likely estimation function. To investigate this further, I ran truncated negative binomials with truncation in the zeros. This estimate provided confirmatory analysis

consistent with the initial model (TABLE XXX). This indicates that any biased attributed to the excessive number of zeros is small enough to confirm our analysis. Hence I provide evidence suggesting that I can consider these estimates reliable. I further recognized that the large number of observations in the dependent variable may raise a large-sample bias. I thus checked our results using a reduced sample size through the bootstrap technique to the negative binomial regression of the model 3 (Greene 2008: 596; Wooldridge 2002: 378). The bootstrap technique, randomly sets a series of subsamples with replacement from the full sample. It implies: first, the construction of several subsamples defined by a number of observations which is significantly lower than the full sample; second, a regression on each subsample is performed; third, the significance of the resulting statistic is assessed in terms of their distribution along all the samples. In order to fix a representative number of references for the sub-sample size, I looked at the study from Gosh et al. (Ghosh et al. 2013, p. 7), which has the characteristic of having performed a patent level analysis in the same industry. According to the number of their final sample, I set the bootstrapping with a series of subsamples (2000 in our case) with 6500 observations. The results of this analysis show that all the coefficients still remain significant even if some of them with level slightly lower than before (TABLES 4). The only exception concerns the control variable "experience in industry-related domains" which is not significant any more. In conclusion I can state that the impact of large-sample bias on our hypothesis is marginal and our earlier findings are confirmed.

6. DISCUSSION AND CONCLUSION

In this paper I attempt to identify the main drivers for a firm's success when it develops knowledge in an emerging technology. I specifically deal with the case of discontinuous technological substitution in the photography industry, where a radical shift from chemical to digital technology occurred. Quite often, when a new core technology emerges (the digital), this may to lead to the reconfiguration of an entire industry paradigm. This implies that some previous technologies are doomed to disappear (chemical), but others may continue their trajectories within the new paradigm (i.e. optic, mechanical, and electronics).

In order to development of knowledge in the emerging technology, firms may implement research strategies aimed at establishing technological exploration across different domains. Thus, the main focus of this paper is to realize how far the research strategy should look for fruitful cross-domain opportunity in order to positively impact on a firm's innovative performance.

To answer this question I referred to two main leveraging mechanisms, e.g. internal and external (Miller et al. 2007, Nemet and Johnson 2012, Phene et al. 2006, Rosenkopf and Nerkar 2001), and different kinds of technological domains where leveraging knowledge, making a clear distinction between core technology -- the emerging domain, and complementary domains -- industry-related vs. industry-unrelated domains (Phene et al., 2006).

In line with preadaptation theory, the main idea developed in the paper is that firms may reap benefits from technological expertise in those domains which still characterize the ongoing industry paradigm and, in so doing, implement recombination processes among complementary domains. Accordingly, the results confirmed our hypotheses: on the one hand, leveraging knowledge in the narrow emerging domain is more likely to have a limited effect on firm's technological performance; on the other, excessive crossing in unrelated domains, although slightly better than in the previous case, is not the optimal solution as well. In line with our expectations, the results showed that the best strategy is leveraging knowledge by crossing towards industry-related domains. Furthermore, the dynamic ability to extend the scope of leveraging beyond the organizational boundary also proves to positively enhance overall performance, since it is expected to increase the variety of possible solutions.

This study contributes to the existing literature in several fashions. First, previous studies on knowledge redeployment have provided extensive evidence supporting the positive relationship between a firm's prior experience, innovation, and performance (Carroll et al. 1996, Helfat and Lieberman 2002, King and Tucci 2002, Klepper and Simons 2000). However these contributions have been substantially neglected by local search literature when the case of investigation regards a firm's ability to innovate in the face of a discontinues technological

shift (Leonard-Barton, 1990; Levinthal & March, 1993; Levitt & March, 1988). Further gaps in the literature emerged from the misspecification of the concept of "similarity", which should regard the type of knowledge held by the firms, to explain the actual firm advantage of transferring knowledge across domains (Helfat and Lieberman 2002). Building on recombination literature, I addressed this gap by arguing that it is possible to avoid the local traps deriving from the exploitation of existing knowledge by spanning exploration across technological and organizational boundaries and providing evidence in this regard (Kogut and Zander 1992, Rosenkopf and Nerkar 2001). I also contribute to this discussion by making a clear distinction between the types of knowledge that may be actually leveraged and so becomes a source of competitive advantage, rather than a constraint. Second, I provide a clarification of apparently inconsistent results deriving from leveraging knowledge in a specific technological domain (Cattani 2005, Rosenkopf and Nerkar 2001). In particular our study deals with a mixed scenario, looking at an emerging core technology, as in the case of Cattani's study, but within an established setting, as in the case of Rosenkopf and Nerkar's study. The results provide evidence that confirms the predictions coming from preadaptation theory, whose application can thus be extended. Third, I also extended this theory by looking at the concept of "*having*" preadaptation in different technological domains (i.e. not only in the emerging technology) as the base for a proactive recombination process. Such interpretation is consistent with the idea of "*artificial-pollinations"* coming from Garud & Nayyar, through which knowledge reactivation and synthesis in new forms allows "pollinators to overcome myopic selection pressures of natural environments by transferring desired pollen across time and space"(Garud and Nayyar 1994, p. 372). In that sense our study proves to be useful in defining the boundary conditions and explaining the mechanisms by which such processes can take place in facing the emergence of a new core technology.

The findings of this study may also have other implications, in particular, regarding our understanding of how incumbents and new entrants may differently perform in the face of technological discontinuity (Carroll et al. 1996, Christensen and Rosenbloom 1995, Helfat and

Lieberman 2002). From the theory I developed, it may be derived that the so called "*de novo firms*", as defined by Carroll et al.(1996), cannot exploit any previous research experience whether in the emerging technology or in other technological domains. They can still try to leverage knowledge from other firms. However, what makes it difficult for them to positively benefit from external source of knowledge is their limited absorptive capacity, in terms of ability to scan the external environment, filter and judge available knowledge (Cohen and Levinthal 1990, Pandza and Holt 2007). In the same fashion, *"de alio firms"* which may have potential source of preadaptation, but deliberately choose not to use it, are expected to be at a disadvantage compared to those which use their preadaptation.

A second important implication of our study is that the best preadaptation that firms can exploit does not derive from the emerging core technology per se, which on the contrary may restrict the possible externalities. Indeed, the only focus on the new technology tends to: first lock the firm to a specific technology regime; second it may limit the firm's possibility to both implement recombination processes and to establish this emerging technology among the other technologies which can concur to characterize the final paradigm. Rather, the preadaptation that best supports firms' innovative performance in the emerging domain comes from industry-related domains. This evidence has both managerial and theoretical implications. From the managerial standpoint, either when the new technology fails in establishing itself as the new core, or in the case where firms had not previously invested in it, knowledge developed in related technologies always proves to be relatively valuable. In fact, a firm's effort in complementary domains creates the further advantage of being less dependent on the success of the potential new technology. Theoretically speaking, this evidence seems to challenge the main contribution coming from existing literature on radical innovation, where some scholars consider previous technological effort as dysfunctional for dealing with a new core technology (Dougherty 1995, Leonard-Barton 1992, Levitt and March 1988), for example, due to the presence of the architectural competences developed by the organization to manage the old

core technology (Henderson and Clark 1990) and the related managerial cognitive schemas (Tripsas and Gavetti 2000).

Finally our findings may also contribute to the "ambidexterity" literature. Indeed through this strategy of leveraging knowledge in industry-related domains, firms are also able to reconcile two theoretically apparently divergent activities: exploration i.e. the pursuit of new knowledge and of things that might be discovered; and exploitation, i.e. the use and development of things already known. In fact, "an organization that engages exclusively in exploration will ordinarily suffer from the fact that it never gains the returns of its knowledge; an organization that engages exclusively in exploitation will ordinarily suffer from obsolescence" (Levinthal and March, 1993: p. 105). Here, exploration and exploration are combined in what the literature defines as "ambidexterity" (O'Reilly and Tushman, 2004, Tushman and O'Reilly, 1996), since exploration in the emerging domain is carried out consistently with the exploitation of knowledge in those domains which prove to still be functional for the new technological paradigm of the industry.

A further line of research should however investigate the existence of some organizational contingencies which may affect the firm's ability to perform knowledge leveraging. In particular, and this is the main limitation of this study, what is lacking in literature is a general theory able to identify the real effects of previous technological choices on the possibility to implement leveraging strategy. In this regard, work has be done to explain the relationship between technological search and decomposability in knowledge structures, in order to account for the malleability of knowledge-base (Yayavaram and Ahuja 2008). However a further step should consider the impact of technological choices, in particular in terms of interdependence between specific typologies of technological domains, e.g. core vs. complementary.

REFERENCES

Adner, R., D. A. Levinthal. 2002. The emergence of emerging technologies. *Calif. Manage. Rev.* 45(1) 50–66.

Ahuja, G., C. M. Lampert. 2001. Entrepreneurship in the large corporation: a longitudinal study of how established firms create breakthrough inventions. *Strateg. Manag. J.* 22.

Anderson, P., M. L. Tushman. 1990. Technological Discontinuities and Dominant Designs: A Cyciical Model of Technological Change. *Adm. Sci. Quarteriy* 35 604–633.

Benner, M. J., M. Tripsas. 2012. The Influence Of Prior Industry Affiliation On Framing In Nascent Industries: The Evolution Of Digital Cameras. *Strateg. Manag. J.* 33 277–302.

Benner, M. J., M. L. Tushman. 2002. Process management and technological innovation: A longitudinal study of the photography and paint indus- tries. *Adm. Sci. Quarteriy* 47.

Brusoni, S., A. Prencipe, K. Pavitt. 2001. Knowledge specialization, organizational coupling, and the boundaries of the firm: why do firms know more than they make?

Carroll, G. R., L. Bigelow, M. D. Seidel, L. Tsai.. 1996. The fates of de novo and de alio producers in the

Cattani, G. 2005. Preadaptation, Firm Heterogeneity, and Technological Performance: A Study on the Evolution of Fiber Optics, 1970–1995. *Organ. Sci.* 16(6).

Christensen, C. M., R. Rosenbloom. 1995. Explaining the attacker's advantage: technological paradigms, organizational dynamics, and the value network. *Res. Policy* 24.

Cohen, W. M., D. A. Levinthal. 1990. Absorptive capacity: A new perspective on learning and innovation. *Adm. Sci. Q.*

Dougherty, D. 1995. Managing Your Core Incompetencies for Corporate Venturing. *Entrep. theory prectice* Spring .

Eisenhardt, K., J. Martin. 2000. Dynamic capabilities: what are they? *Strateg. Manag. J.* Special Is(21).

Fleming, L., O. Sorenson. 2001. Technology as a complex adaptive system: evidence from patent data. *Res. Policy* 30.

Fleming, L., O. Sorenson. 2004. Science as a map in technological search. *Strateg. Manag. J.* 25.

Garud, R., P. Nayyar. 1994. Trasformative capacity: continual structuring by intertemporal tachnoogy transfer. *Strateg. Manag. J.* 15.

Ghosh, A., X. Martin, J. M. Pennings, F. C. Wezel. 2013. Ambition Is Nothing Without Focus : Compensating for Negative Transfer of Experience in R & D.

Griliches, Z. 1981. Market value, R&D, and patents. *Econ. Lett.* 7 183–187.

Gruber, M., D. Harhoff, K. Hoisl. 2012. Knowledge Recombination Across Technological Boundaries: Scientists vs. Engineers. *Manage. Sci.*

Hall, B. H., R. Ham-Ziedonis. 2001. The patent paradox revisited: An empirical study of patenting in the US semiconductor industry, 1979–1995. *RAND J. Econ.* 32(1) 101–128.

Hall, Jaffe, Trajtenberg. 2001. The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools. *Natl. Bur. Econ. Res. Cambridge, Mass., USA.*

Harhoff, D., F. Narin, F. M. Scherer, K. Vopel. 1999. Citation frequency and the value of patented inventions. *Rev. Econ. Stat.* 81(3) 511–515.

Helfat, C. 1994. Evolutionary trajectories in petrolium firm R&D. *Manage. Sci.* 40(12).

Helfat, C., S. Finkelstein, W. Mitchell, M. A. Peteraf, H. Singh, D. J. Teece, S. G. Winter. 2007. Dynamic Capabilities: Understanding Strategic Change in Organizations. *Blackwell*.

Helfat, Lieberman. 2002. The birth of capabilities: market entry and the importaqnce of pre-history. *Indust. Corp. Chang.*
Henderson, R., K. Clark. 1990. Architectural Innovation: The Reconfiguration of Existing Product Technologies and the failure of Established Firms. *Adm. Sci. Q.* 35.
Henderson, R., I. Cockburn. 1994. Measuring competence? Exploring firm effect in pharmaceutical research. *Strateg. Manag. J.* 15.
Holbrook, D., W. M. Cohen, D. a. Hounshell, S. Klepper. 2000. The nature, sources, and consequences of
King, A., C. L. Tucci. 2002. Incumbent entry into new market niches: The role of experience and managerial choice in the creation of dynamic capabilities. *Manage. Sci.* 48(2) .
Klepper, S., K. L. Simons. 2000. Dominance by birthright: Entry of prior radio producers and competitive ramifications in the US television receiver industry. *Strateg. Manag. J.* 21 997–1016.
Kogut, B., U. Zander. 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. *Organ. Sci.* 3.
Laursen, K., A. Salter. 2004. Searching high and low: What types of firms use universities as a source of innovation? *Res. Policy* 33 1201–1215.
Leonard-Barton, D. 1990. A dual methodology for case studies: Synergistic use of a longitudinal single site with replicated multiple sites. *Organ. Sci.* 1(3) 248–266.
Leonard-Barton, D. 1992. Core capabilities and core rigidities: a paradox in managing new product development. *Strateg. Manag. J.* 13.
Levinthal, D. 1998. The Slow Pace of Rapid Technological Change: Gradualism and Punctuation in Technological Change. *Ind. Corp. Chang.* 7(2).
Levinthal, D. A., J. G. March. 1993. The myopia of learning. *Strateg. Manag. J.* 14 .
Levitt, B., J. G. March. 1988. Organizational learning. *Annu. Rev. Soc.* 14.
March, J. G. 1991. Exploration and exploitation in organizational learning. *Organ. Sci.* 2(1) 71–87.
March, J. G., H. A. Simon. 1958. Organization. Oxford, En.
Miller, D. J., M. J. Fern, L. B. Cardinal, J. Douglas. 2007. The Use of Knowledge for Technological Innovation within Diversified Firms. 50(2) 308–326.
Miller, T. L., M. G. Grimes, J. S. McMullen, T. J. Vogus. 2012. Venturing for others with heart and head: how compassion encourages social entrepreneurship. *Acad. Manag. Rev.* 37(4) 616–640.
Narin, F., P. Thomas, A. Breitzman. 2001. Using patent indicators to predict stock portfolio performance.
Nelson, R. R., S. G. Winter. 1982. An Evolutionary Theory of Economic Change. *Chang. Cambridge, MA Belkn. Press Harvard Univ.*
Nemet, G. F., E. Johnson. 2012. Do important inventions benefit from knowledge originating in other technological domains? *Res. Policy* 41(1) 190–200.
Novelli, E. 2015. An examination of the antecedents and implications of patent scope. *Res. Policy* 44(2) 493–507.
Oriani, R., M. Sobrero. 2008. UNCERTAINTY AND THE MARKET VALUATION OF R&D WITHIN A REAL OPTIONS LOGIC. *Strateg. Manag. J.* 29(4).
Pandza, K., R. Holt. 2007. Absorptive and transformative capacities in nanotechnology innovation systems. *J. Eng. Technol. Manag.* 24 347–365.
Patel, P., K. Pavitt. 1997. The technological competencies of the world' s largest firms" complex and path-dependent, but not much variety. *Res. Policy*.
Penrose, E. 1959. The Theory of the Growth of the Firm. *London, Oxford Univ. Press.*
Phene, A., K. Fladmoe-Lindquist, L. Marsh. 2006. Breakthrough innovations in the U.S. biotechnology industry: The effects of technological space and geographic origin. *Strateg. Manag. J.* 27(April 2003) 369–388.
Rosenkopf, L., A. Nerkar. 2001. Beyond local search: boundary-spanning, exploration, and impact in the optical disk industry. *Strateg. Manag. J.* 306(March 1999) 287–306.
Scherer, F. M. 1980. *Industrial market structure and economic performance.* Boston: Houghton Mifflin.
Shane, H., M. Klock. 1997. The relation between patent citations and Tobin's Q in the semiconductor industry. *Rev. Quant. Financ. Account.* 9(2).
Sørenson, J. B., T. E. Stuart. 2000. Aging, Obsolesence, and Organizational Innovation. *Adm. Sci. Q.* 45(1) 81–112.
Srinivasan, R., P. Haunschild, R. Grewal. 2007. Vicarious Learning in New Product Introductions . *Manage. Sci.*
Stuart, T. E., J. M. Podolny. 1996. Local search and the evolution of technological capabilities . *Strateg. Manag. J.*
Teece, D., G. Pisano, A. Shuen. 1997. Dynamic Capabilities and Strategic Management. *Strateg. Manag. J.*

Trajtenberg, M. 1990a. A penny for your quotes: Patent citations and the value of innovations. *RAND J. Econ.* 21(1).
Trajtenberg, M. 1990b. *Economic Analysis of Product Innovation.* Harvard University Press, Cambridge, MA.
Tripsas, M., G. Gavetti. 2000. Capabilies, cognition and inertia: evidance from digital imaging. *Strateg. Manag. J.*
Utterback, Suarez. 1993. Innovation, competition, and industry structure. *Res. Policy*.
Yayavaram, S., G. Ahuja. 2008. Decomposability in Knowledge Structures and Its Impact on the Usefulness of Inventions and Knowledge-base Malleability. *Adm. Sci. Q.* 53(2).

Table 1: Correlation Table

		1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.
1.	patent_year	1																
2.	firmid	-0.09*	1															
3.	digitalid	0.04*	0.01*	1														
4.	claims	0.22*	0.03*	-0.03*	1													
5.	avg_back_lag	-0.02*	0.03*	-0.12*	-0.03*	1												
6.	other_ref	0.10*	-0.02*	0.02*	0.12*	0.02*	1											
7.	log_n_inv	0.11*	-0.04*	0.04*	0.06*	-0.00	0.06*	1										
8.	digital_avg_pat_impact	-0.63*	-0.01	-0.01*	-0.14*	-0.05*	-0.03*	-0.09*	1									
9.	experience_emerging_dom	0.34*	-0.16*	0.12*	0.06*	-0.05*	-0.03*	0.09*	-0.17*	1								
10.	experience_ind_related_dom	0.23*	-0.17*	-0.07*	0.06*	-0.01*	-0.05*	-0.02*	-0.10*	0.63*	1							
11.	experience_ind_UNrelated_dom	0.36*	-0.19*	0.03*	0.08*	-0.02*	0.01*	0.08*	-0.26*	0.75*	0.48*	1						
12.	int_lev_emerging_dom	-0.02*	-0.04*	-0.02*	-0.00	-0.10*	-0.03*	0.02*	0.03*	0.16*	0.10*	0.09*	1					
13.	int_lev_ind_related_dom	-0.01*	-0.02*	-0.10*	0.01*	-0.03*	-0.02*	-0.00*	0.03*	0.03*	0.17*	0.00	0.02*	1				
14.	int_lev_ind_UNrelated_dom	0.03*	-0.03*	-0.05*	0.02*	-0.05*	0.02*	0.02*	0.00	0.10*	0.09*	0.10*	0.02*	0.02*	1			
15.	est_lev_emerging_dom	-0.04*	0.05*	0.21*	-0.04*	-0.03*	-0.04*	-0.01*	0.03*	-0.06*	-0.1344*	-0.08*	-0.25*	-0.19*	-0.25*	1		
16.	est_lev_ind_related_dom	0.01	-0.03*	-0.20*	0.02*	0.05*	0.02*	-0.04*	0.00	-0.05*	0.0747*	-0.01*	-0.15*	0.07*	-0.08*	-0.38*	1	
17.	est_lev_ind_UNrelated_dom	0.04*	0.01	-0.08*	0.04*	0.09*	0.05*	0.00	-0.06*	-0.04*	-0.0404*	0.01*	-0.25*	-0.11*	-0.01*	-0.56*	-0.16*	1

Table 2: Main Models

Variables	model_1 only controls	model_2 leveraging vars	model_3 full model	model_4 test cons	model_5 truncated
claims	0.0116***	0.0115***	0.0114***	0.0112***	0.00903***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
avg_back_lag	-0.0247***	-0.0269***	-0.0275***	-0.0282***	-0.0266***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
other_ref	0.0163***	0.0162***	0.0158***	0.0157***	0.00978***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log_n_inv	0.152***	0.157***	0.157***	0.154***	0.179***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)
digital_avg_pat_impact	0.0830***	0.0733***	0.0727***	0.0583***	0.0733***
	(0.009)	(0.007)	(0.007)	(0.006)	(0.007)
experience_ind_related_dom	0.0000991*	0.000123**	0.000103**	0.000120**	0.000163***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
experience_ind_UNrelated_dom	-0.0000320***	-0.0000320***	-0.0000299***	-0.0000289***	-0.0000261***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
internal_leveraging		0.486***			
		(0.083)			
external_leveraging		0.741***			
		(0.081)			
int_lev_emerging_dom			0.399***		0.373***
			(0.086)		(0.088)
int_lev_ind_related_dom			0.848***	0.484***	0.678***
			(0.108)	(0.083)	(0.113)
int_lev_ind_UNrelated_dom			0.682***	0.321***	0.562***
			(0.097)	(0.068)	(0.103)
ext_lev_emerging_dom			0.674***	0.309***	0.539***
			(0.080)	(0.037)	(0.082)
ext_lev_ind_related_dom			1.019***	0.645***	0.927***
			(0.084)	(0.043)	(0.088)
ext_lev_ind_UNrelated_dom			0.822***	0.447***	0.707***
			(0.083)	(0.038)	(0.084)
_cons				1.915***	
				(0.308)	
N	45912	45912	45912	45912	40746
Log pseudolikelihood	-146153.6	-146025.67	-145895.32	-145862.71	-284788.96

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 3: IRR Model

forw_other_cit	Incident Rate Ratio (IRR) IRR	Robust Std. Err.	z	P>|z|	% Conf. Interval]	
claims	1.011421	.0005032	22.82	0.000	1.010435	1.012407
avg_back_lag	.9728934	.0017321	-15.44	0.000	.9695044	.9762942
other_ref	1.01593	.0010217	15.71	0.000	1.013929	1.017934
log_n_inv	1.170497	.0116878	15.77	0.000	1.147812	1.19363
digital_avg_pat_impact	1.075366	.0077039	10.14	0.000	1.060372	1.090572
experience_ind_related_dom	1.000103	.0000395	2.62	0.009	1.000026	1.000181
experience_ind_unrelated_dom	.9999701	4.28e-06	-6.98	0.000	.9999617	.9999785
int_lev_emerging_dom	1.490578	.1282069	4.64	0.000	1.259335	1.764281
int_lev_ind_related_dom	2.335515	.2521233	7.86	0.000	1.89014	2.885835
int_lev_ind_unrelated_dom	1.976964	.1918761	7.02	0.000	1.634499	2.391184
ext_lev_emerging_dom	1.962289	.1560183	8.48	0.000	1.679134	2.293193
ext_lev_ind_related_dom	2.769335	.2325632	12.13	0.000	2.349056	3.264809
ext_lev_ind_unrelated_dom	2.275899	.1886972	9.92	0.000	1.934546	2.677485
N	45912					
Log pseudolikelihood	-145895.32					

Table 4: Bootstrapping analysis

forw_other_cit	Boostrap (size=6500, reps=2000) Coef.	Robust Std. Err.	z	P>|z|	% Conf. Interval]	
claims	.011356	.0012276	9.25	0.000	.0089499	.0137621
avg_back_lag	-.0274808	.004256	-6.46	0.000	-.0358223	-.0191392
other_ref	.0158041	.0025557	6.18	0.000	.010795	.0208132
log_n_inv	.1574286	.0290645	5.42	0.000	.1004633	.214394
digital_avg_pat_impact	.072661	.0147623	4.92	0.000	.0437274	.1015945
experience_ind_related_dom	.0001033	.0000771	1.34	0.180	-.0000479	.0002545
experience_ind_unrelated_dom	-.0000299	.0000137	-2.18	0.029	-.0000568	-3.08e-06
int_lev_emerging_dom	.3991637	.1826558	2.19	0.029	.0411649	.7571625
int_lev_ind_related_dom	.8482325	.3033484	2.80	0.005	.2536806	1.442785
int_lev_ind_unrelated_dom	.6815626	.2424071	2.81	0.005	.2064533	1.156672
ext_lev_emerging_dom	.6741118	.1807395	3.73	0.000	.3198688	1.028355
ext_lev_ind_related_dom	1.018607	.187222	5.44	0.000	.651659	1.385556
ext_lev_ind_unrelated_dom	.8223752	.1786883	4.60	0.000	.4721526	1.172598
N	45912					
Log pseudolikelihood	-145895.32					