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Searching in the Dark: Exploring the Technological Search Process during the Business Cycle and in the Pharmaceutical Industry

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Non è vero che l’uomo insegue la verità: è la verità che insegue l’uomo.

Robert Musil

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Chapter 1

General Introduction

1.1 Search, Innovation and Growth

Technological change is considered a driving force of long-term economic growth and societal progress. Advancements in several domains have contributed to the outward shift of the production-possibility frontier paving the way to economic development. In particular, technological change occurs when new or improved technologies are introduced into the existing repertoire of knowledge. The polymerase chain reaction, for example, is considered an indispensable technique useful for the diagnosis of genetic diseases and for the study of specific segments of DNA. The laser, another key achievement of the twentieth century, has been defined as an ubiquitous invention given its wide application in scientific and industrial development (eye surgery, fiber-optic communication, bar code readers, cancer treatment to mention few). In health care, biopharmaceutical drugs - using biological rather than chemical synthesis- are increasingly improving treatment in a range of diagnostic areas. Other famous inventions like the personal computer, GPS, blockchain algorithms, MOOCs (Massive Open Online Courses), autonomous cars, defibrillators, Google's Page Rank algorithm, and the 3D printer illustrate how drastic improvements in technology can open up new markets, inspire a range of applications and, in doing so, increase both social and economic welfare.

Given the importance of technological change, scholars have focused on the understanding of the locus and mechanisms of the inventive process. Arthur (2007) notes that a novel technology, like those mentioned above, "*seems to materialize out of nothing, but it emerges always from a cumulation of previous components and functionality already in place*" (p. 284). In a similar vein, other scholar have identified the recombination of existing or of new technologies as the "fil rouge" in the development of inventions

(Schumpeter, 1934; Nelson & Winter, 1982; Kogut & Zander, 1992; Fleming & Sorenson, 2004; Fagerberg, 2005; Nerkar, 2003). For example, the polymerase chain reaction combines knowledge from computer science with techniques from chemical engineering, whereas the laser combines fundamentals from physic and optics.

The recombination of knowledge is not a random nor an automatic practice. Indeed, it requires extensive search over existing knowledge and technologies that will be recombined for solving existing problems, satisfying or discovering new economic opportunities. Hence, understanding how economic actors orchestrate technological search is crucial in order to explain how technological development unfolds.

1.2 The Search Debate

The concept of search underlying the inventive process has attracted the attention of several scholars in the attempt to characterize its main aspects. While conventional wisdom conceived search and discovery as a sequential and linear process, recent approaches recognize that the search process is characterized by an intrinsic complexity that increases with the bits of knowledge that is searched and recombined. To solve the complexity, inventors adopt a recursive approach using feedback loops and a continuous refinement of their mental schemes (Magitti et al., 2013; Arthur, 2007). This process, generally triggered by problem-solving and opportunity seeking, stops when a satisfactory result has been achieved (Greve & Taylor, 2000).

Theoretical contributions have conceptualized the search process using a spatial metaphor distinguishing between local versus distant - or ‘boundary-spanning’ - search (Cyert & March, 1963; Nelson & Winter, 1982). Local search relates to the search in the neighborhood of the existing organizational knowledge base (Stuart & Podolny, 1996) whereas boundary-spanning refers to search into distant, unfamiliar knowledge domains and away from existing organizational routines (Katila & Ahuja, 2002). In their empirical work, Katila and Ahuja (2002) distinguish between search depth (the extent to which firms reuse their existing knowledge) and scope (the extent to which the firm explores new knowledge). The greater the depth of search, the greater tend to be firm's knowledge and competences in that field.

Studies based on the behavioral and evolutionary theory of the firm have concluded that firms show a strong tendency to limit their search to familiar domains guided by past routines, experience and practice (March, 1963; Nelson & Winter, 1982). Helfat (1994) uncovered this pattern in the petroleum industry where firms tend to persist in their R&D activities Along this line, Pavitt (1988) highlighted that "*firms seek to improve and to diversify their technology by searching in zones that enable them to use and to build upon their existing technological base*" (Pavitt, 1988, p.130). The repeated search among local domains of knowledge hinder shift in technological paradigms and the combination of ideas from disparate domains. In this regard, Dosi (1982) posited that technological progress often advances along an established trajectory guided by existing paradigms.

The strong tendency towards local search can be explained by two main reasons. First, individuals have limited cognitive abilities, they are unable to process every possible solutions to a problem. Hence, they can only aim for a satisfactory rather than an optimal outcome. This generates bounded rational behavior pushing firms or inventors to search in the neighborhood of their existing expertise where it is easier to deduce clearer conclusions (Cyert & March, 1992; Leonard-Barton, 1992; Simon, 1982). Second, search in familiar areas facilitates a deeper and faster learning of the cause-effects of a phenomenon or problem (Cohen & Levinthal., 1990). Hence, local search is efficient because the costs of selecting and processing familiar information are lower (Rosenkopf & Almeida, 2003).

Searching only in local domains can have important negative repercussions. It generates inertia, myopic behavior, fewer opportunities for knowledge recombination and difficulties in dealing with new problems (Levinthal & March, 1993; Gavetti & Levinthal, 2000; Rosenkopf & Nerkar, 2001; Ahuja & Lampert, 2001). A deep focus on local search leads to cognitive biases and search traps. Firms that search locally tend to overlook possible solutions that are in distant knowledge domains. Another limitation related to a high reliance on local search is the inability to exploit potential markets. For instance, in 1974 Du Pont developed the aramid fiber called Klevar used today in a variety of clothing and accessories (e.g. body armor) that exploit its robustness. However, since Du Pont's strategy was to leverage its competences in the tires market, it was only in 1987, after many failures, that Du Pont decided to enter other markets that were more responsive to this new product (Christensen, 1998).

In order to mitigate the disadvantages of local search, March (1991) has advocated the need to find a balance between the two search strategies. Recent contributions have started to question the prominence of local search strategies by investigating the role of boundary-spanning as a way to introduce variety into firms' routines. (Tripsas & Gavetti, 2000; Rosenkopf & Almeida, 2003; Fleming & Sorenson, 2004; He & Wong, 2004). These studies stress that external collaborations, diversified teams, in-licensing, alliances or staff mobility may solve the problems linked to local search. This stream of literature recognizes the importance of external, diverse and complementary knowledge in facilitating the recombination of knowledge and technologies.

1.3 Overview of the Dissertation

1.3.1 Setting the stage - the dissertation at a glance

This dissertation has two main objectives. The first is to extend the understanding of how the external environment shapes the search process. The trade-off between local and distant search is not only determined by organizational factors. Environmental conditions may affect the type of search performed by firms. The second, is to provide insights about the trade-off between local and distant search. While existing literature has widely discussed the fundamentals of search, our knowledge about the role of external contingencies on the direction and intensity of the search process remain limited. For instance, March (1991) posits that in tight competitive situations it is exploration that, although entailing a higher risk, leads to significant improvements. Katila and Chen (2009) focus on the role of competition in the search process of robotics firms and show that firms that search ahead of competitors introduce more innovative products. Leten et al., (2016) analyze firms' choices to enter into new technology domains - which can be conceived as firms' efforts towards distant search. They argue that in this choice firms are driven not only by firm-level factors but also environmental characteristics, in particular the potential for new technological opportunities. They also stress that in order to exploit technological opportunities in the new domain, firms require related technological expertise.

Other external pressures may shape the search process, for example a decrease in profits, slack resources or contraction in economic growth. Hence, it is important to understand the influence of external environment on the direction and intensity of search process. Another important aspect is the difference in performances and value linked to diverse search processes.

1.3.2 Across the chapters

This dissertation consists of three studies. Based on the foundation of search, the study presented in **Chapter 2** explores the search and knowledge recombination process underlying inventions. The search for new combinatorial possibilities usually occurs in the proximity of existing competences through local search. This process is characterized by lower levels of risks and uncertainty as it builds on extant competences, past failures and previous successful solutions (Cyert & March, 1963; Simon, 1978). However, connecting pieces of knowledge and ideas that are already highly related hinder the possibilities of exploring new trajectories and producing impactful inventions (Perkins, 1995). Although inventions resulting from local search are essential for increasing technological performance (Baumol, 2002), distant search aiming for novel or breakthrough innovations prevent core-rigidities with positive impacts on performance and economic growth (March, 1991; Leonard-Barton, 1992; Dosi, 1982). Distant search entails the exploration of new and unfamiliar technological domains, with larger possibilities to extend the range of combinatorial alternatives (Katila & Ahuja, 2002). The ultimate result of this process is that inventions are more likely to include new or original coupling relationships characterized by higher level of novelty (Levinthal & March, 1993; Simonton, 1999; Schilling, 2005, Katila & Chen, 2009). On the other hand, compared to local, distant search is a costly activity, associated with higher levels of uncertainty and failures, as it requires more effort in the selection and integration of relevant knowledge (Fleming, 2001).

The chapter proposes a measure of the extent to which knowledge is combined within inventions in an unconventional or atypical way. It focuses on the proximity among the knowledge components recombined in inventions. Rather than looking at backward citations, as other measures have done, we examine patent class membership and the joint occurrences of subclasses combination in the entire technological space.

The analysis uncovers that a large fraction of patents is based on conventional knowledge recombination resulting from local search. Inventions that build on more novel combinations are rare but more cited. The analysis is further enriched by a comparison with existing measures of novelty in knowledge recombination. Results show that the measure presented in this study is only weakly correlated with existing measures suggesting that they capture different dimensions of knowledge recombination. This chapter contributes to the stream of literature on recombinant invention by emphasizing the role of distance in the recombination process. Compare to measure based on the first instance of a combination, the unconventionality measure allows to consider also those inventions that are in the continuum between extremely unconventional and conventional inventions.

The study presented in **Chapter 3** investigates the impact of the business cycle on firms' search strategies using the measure built in Chapter 2. The scholarly debate on the relationships between economic crises, business cycles and innovation has mainly dealt with the impact of recessions on the input side of innovation (R&D) suggesting a pro-cyclical response to recessions (Filippetti & Archibugi, 2011). More recently, the discussion has been partially extended to the analysis of the output side (Hud & Hussinger 2015; Cincera et al., 2010; Ouyang, 2011; Berchicci et al., 2013; Fabrizio & Tsolomon 2014).

Theoretical contributions have advanced two opposing arguments, one suggesting pro-cyclicality (Barlevy, 2007; Ouyang, 2011) and the other predicting counter-cyclicality trends in innovation activities (Aghion & Saint-Paul, 1998, Aghion et al., 2012). The first line of argument, focusing on the relevance of financial constraints, states that economic downturns are associated with reduced profitability on existing products, forcing firms to cut back on expenses, including R&D, and to postpone the introduction of innovations (Campello et al., 2010). The second line of argument, claims that firms will react to the reduced profitability on existing products by investing in new projects due to lower opportunity costs (Berchicci et al., 2013). The extant empirical evidence indicates that both R&D investments and innovative outputs are pro-cyclical.

Tighter economic conditions not only affect the propensity of firms to invest in R&D, but are also expected to shape the type of inventions that are generated. Chapter 2 contributes by exploring the relationship between the nature of the inventive process and the business cycle. Results suggest that contractive phases of the cycle are associated with more conventional recombination signaling local search strategies, i.e. knowledge recombination processes that, by combining familiar components, generate inventions characterized by lower level of novelty. Firms respond asymmetrically to expansions and contractive phases showing overall a pro-cyclical trend both at the intensive (a decrease in the degree of unconventionality of patents) and at the extensive margins (an overall decline in number of patents). This process is not uniform across the entire technological portfolio of firms, but it is concentrated in firms' core technologies. Moreover, only financially constrained firms retrench from explorative activities, indicating that the mechanism behind the result acts through a decrease in financial resources. These findings contribute to the innovation literature, enriching it with a discussion on how search and the resulting innovation output vary along the business cycle.

The study in **Chapter 4** examines when and to what extent pharmaceutical firms learn from prior failures in their subsequent drug development efforts. Innovation has been conceptualized as a cumulative process (Scotchmer, 2004) where organizations build on their previous knowledge and experience. The experimental nature inherent to innovation implies high risk and uncertain outcomes. The pharmaceutical industry represents a typical example of an innovation setting where organizations face high failure rates and extensive development costs. Chapter 4 examines the extent to which current drug development projects benefit from experience with previous - successful or failed – related drug development efforts: not only firms' own experience, but also rival firms' experience as a relevant environmental influence. Related prior drug development efforts are prior projects of which the underlying patent is cited by the patent that is exploited in the current drug development project. Benefiting from comprehensive and detailed information on pharmaceutical firms' global drug activities, we find that projects that build on firms' previous successful projects have a higher likelihood to generate marketable drugs, while building on prior failures reduces this likelihood. A similar pattern, though weaker in magnitude, is observed for drug development projects building on prior projects of other firms through vicarious learning. This study also show that local search, measured as drug development in existing or related ATC classes, can increase the likelihood of drug development success The study contributes to the debate on organizational learning by providing a more nuanced view on the role of failure and success for future performance in the drug development process.

Chapter 2

(Un)conventional Combinations: at the Origins of Breakthrough Inventions*

¿Qué, quieren una originalidad absoluta? No existe.
Ni en el arte ni en nada. Todo se construye sobre lo anterior...

Ernesto Sabato (1963), El escritor y sus fantasma p.26

2.1 Introduction

Technical change has been unanimously recognized to be the main engine of long-term economic growth (Schumpeter, 1939). Some inventions like the laser or the turbojet engine are unshakably mentioned amongst the most fundamental achievements of human kind and responsible for shifts in technological paradigms (Arthur, 2007; Dosi, 1982). These inventions are customarily addressed as breakthrough or radical as they overcome existing bottlenecks in technological development and pave the way for new technological advancements. Studies on the origins of radical innovations have long debated on whether radical innovations originate from completely new knowledge or from the combinations of already existing knowledge (Rosemberg, 1982, Schumpeter, 1939; Weitzman, 1998). Much of the academic literature builds on seminal works by Schumpeter (1939) who emphasizes the role of combining existing components in a new way or

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developing new combinations. Hargadon (2004) stresses that many key technologies like the light bulb result from bridging disconnected but pre-existing components. A common assumption made in the literature is that the impact of inventions is a function of the newness of knowledge combination generated during the inventive process. By looking at the inventive process as one of search and recombination of existing ideas (Fleming, 2001; Kaplan & Vakili, 2015; Magitti, 2013), newness is determined by those inventive acts that embed unfamiliar, unconventional or atypical combinations (Simonton, 1999). As the search process is usually local, the extent to which combinations are unconventional or atypical is in turn a function of the distance in the technological space.

In this study we draw on the literature on recombinant search and conceptualize the origins of novelty in the inventive process as a function of the proximity of the elements constituting the invention (Stuart & Podolny, 1996). Drawing on the literature on product market diversification, we adapt the measure of relatedness in product space to account for the distance between each element combined in the invention. The measure proposed in this chapter - "Unconventionality"- is population based and, similarly to the concept of technological regime, reflects the current understanding of the relational structure of the components in the knowledge space (Nelson & Winter, 1982).

To assess the novelty of inventions, the Unconventionality measure presented in this chapter focuses on the proximity among the knowledge components recombined in inventions. Rather than looking at backward citations as other measures have done (Trajtenberg et al., 1997; Keijl et al., 2016), we examine patent class membership and the joint occurrences of subclasses combination in the entire technological space. In so doing, the unconventionality indicator also differentiate itself from other measures based on first instances of combinations (Verhoeven et al., 2016; Fleming, 2001). The focus of this study is on the underlying dimension of the recombinant process responsible for the extraordinary impact of some inventions, i.e. unconventional combinations. Moreover, the unconventionality measure offers an overview over the search and recombinant process exploring all combinatorial possibilities in the technological landscape. The framework upon which this measure builds, shares strong similarities with the exploration

- exploitation concept (March, 1991). This notion defines exploration (or exploitation) relative to the organizational or the inventor existing domain of knowledge Unconventionality measure instead takes a broader perspective by considering the entire technological landscape. We enrich our analysis by comparing the Unconventionality measure to existing measures based on backward citations, in particular the originality measure pioneered by Trajtenberg et al., (1997), and related measures building on technological classes by Verhoeven et al., (2016), Fleming and Sorenson (2001).

Results reported in Section 2.4, show that most combinations are indeed conventional as they occur between elements that are related and that have been similarly combined in the past. Only a handful of combinations bring together components that are substantially far apart. This result is in line with a view of unconventionality as a result of wide search, which spans technical domains to incorporate principles and solutions from other realms. These unconventional recombinant efforts come about in very few inventive acts but show a significant and positive association with technological impact captured by the number of forward citations received by the invention.

In our analysis we also consider the role of team on the search process. Experienced teams are mostly responsible for unconventional combinations in the inventive process, whereas lonely inventors are at disadvantage. Large teams are instead negatively associated with Unconventionality while large organizations produce more unconventional combinations.

From a theoretical standpoint, the results are in line with the body of work on the theory of invention and creativity in general, which posit that agents mostly work in the neighborhood of their competences.

This work belongs to a recent stream of research that inquires the origins of breakthrough inventions and scientific discoveries by means of large scale databases (i.e. Ahuja & Lampert, 2001; Arts & Veugelers, 2013; Dahlin & Beherens, 2005; Fleming et al., 2007; Kelley et al., 2013; Schilling & Greene, 2011; Schoenmakers & Duysters, 2010; Uzzi et al., 2013; Verhoeven et al., 2016). However, most of the studies listed above trace the origins of radical innovation on the base of citations to existing technologies. Measures based on backward citations (Dahlin & Berhens, 2005; Uzzi et al., 2013) however, may be sensitive to strategic decisions (Uzzi et al., 2013) and to changes in the composition of the patent universe.

From a methodological point of view, we are among the first to propose a measure that take into account the proximity aspect in the recombinant process by considering the technological classes recombined in inventions. With the exceptions of Fleming (2001), Dahlin and Behrens (2005), and Verhoeven et al., (2016), most of the empirical studies on the origins of high-impact inventions have assumed that the ultimate source of technological impact had to be found in the generation of unconventional combinations (Ahuja & Lampert, 2001; Fleming & Singh, 2011; Schoenmakers & Duysters, 2010; Kelly et al., 2013). Yet, these studies made no effort to operazionalize this concept. Other attempts have focused on the very first instance of a combinatorial occurrence and have mostly considered backward citations (i.e. Fleming et al., 2007; Operti & Carnabuci, 2013; Verhoeven et al., 2016). Such approaches operationalize novelty in absolute terms, neglecting the cumulative nature of the inventive process. We claim that novelty is often distributed across early attempts but not necessarily constrained to the very first one. In addition, these studies do not take into account that combinations that have not been occurring for a longer time, my emerge again after a long period of non-occurrence (Verhoeven et al., 2016). The approach based on first instances is plagued by a problem of incompleteness, which Unconventionality measure tries to overcome. To identify absolute novelty, a complete knowledge of all human inventions and the exact time at which they came into existence is needed. Unconventionality is instead a population based measure and reflects the state of relationships among the elements of the knowledge space at a given point in time in relation to the wider technological landscape.

Section 2.2 discusses the literature on the origins of radical inventions and the characteristics of the search process (Section 2.2.1) useful for identifying the antecedents of unconventionality (Section 2.2.2). To construct the Unconventionality measure, we take advantage of the patent dataset at the USPTO (Lai et al., 2014) using patent data and their technological classes over more than two decades – i.e. between 1975 and 2000 (Section 2.3). Results are discussed in Section 2.4 while section 2.5 closes the chapter with the concluding remarks.

2.2 Measuring unconventionality: Theoretical consideration

2.2.1 Locus of Search in the Recombination Process

Scholars have identified several different forms characterizing the process through which new knowledge is created: combination of new components, new recombinations of existing components, or reconfiguration of existing combinations[1] (Schumpeter 1939, Nelson & Winter 1982, Weitzman 1998, Henderson & Clark 1990, Fleming & Sorenson, 2001). Therefore, knowledge is generated by integrating new components within an established framework or by modifying the existing framework to accommodate new configurations (Schilling & Phelps, 2007).

Knowledge generation initiates with the search of knowledge components (Cohen & Levinthal, 1990; Rosenkopf & Neckar, 2001). The set of combinable components comprises all bits of knowledge which are potentially available: existing components, previously untried components, or new components.[2] Inventors are expected to operate with an extraordinary large number of possible components and possibly an infinite number of combinations: the search process exponentially increases the number of possible combinations with which individuals should deal. To ease the search process, subjects are used either to take into account familiar components which are locally available for new combinations, or to implement earlier utilized combinations. The choice of the components is therefore usually based on their availability, proximity, and saliency according to the inventor's aims and mental schemas (Fleming 2001; Mugatti et al., 2013). Inventors usually search in the vicinity of their competences (Dosi, 1988; Stuart & Podolny, 1996). They rely on existing and certain solutions, whose past use has been proved successful to their purpose (Cyert & March, 1992). The type of

[1] The reconfiguration of existing components refer to architectural innovation like for example in the case of the aircraft industry as discussed by Henderson & Clark, 1990).

[2] Jung and Lee (2013) report different definitions of the components involved in the recombinant process employed in the literature. Components are considered as "conceptual or physical materials", such as routines or technologies (Nelson & Winter, 1982); "old knowledge," such as existing cultivated plant varieties (Weitzman, 1998); pre-existing "elements," such as materials in periodic tables, and "conditions," such as temperature and pressure (Romer, 1994); and "constituents of invention," such as Schumpeterian "factors" (Schumpeter, 1939; Fleming, 2001).

recombinant effort that results from local searches is characterized by high search depth (Katila & Ahuja, 2002), as it is geared towards increasing the understanding of a limited set of relationships among the components. The exploration of local and familiar domains of knowledge is likely to deliver incremental solutions as the combinatorial possibilities can quickly exhaust (Fleming, 2001). Inventors therefore reproduce or incrementally alter existing combinations, preserving the actual framework of relations among components. As relationships are scrutinized and challenged, the framework in which they are established is reinforced. Agents thus develop expectations on the nature of the relationships among the components forming the knowledge space and tend to constrain themselves to search within the existing boundaries of extant problems (Finke, 1995 as in Schilling & Greene, 2011). The patterns of association of the components therefore reflect conventions and common understanding of the possible interdependencies.

The continuous exploitation of local reservoirs of knowledge can lead to inventive traps, where inventors find themselves trapped in inefficient local optima. Extending the breadth of the knowledge base from which components are sourced is expected to bring outcomes with higher degree of novelty and originality (Levinthal & March, 1993; Fleming, 2001). The number of possible combinations used in an invention increases with the set of elements that are available to the inventor in the generative phase. Furthermore, the broader the search scope, the more likely are inventors to combine components which stand far apart from each other in the technological space.[3] From a cognitive standpoint, being exposed to a variety of sources may lead agents to analyze and re-conceptualize the same problem from different angles, facilitating the integration of new knowledge into an existing interpretative framework (see Schilling and Greene, 2011, for an overview). The inclusion of novel elements in established interpretative frameworks challenges the existing cognitive structures and lead to the generation of novel and overlooked combinations

[3] The psychological literature has also stressed that newer, and thus more creative, combinations are those which are apparently not related among each other. Simonton (1999) pointed out that many of the most famous scientific breakthroughs occurred through a free associative process (what Freudians might call "primary process thinking"). Agents generate many unusual combinations between different bodies of knowledge that set to a screening process of selective retention, keeping only the best variations (much like Darwinian evolution).

(Fleming, 2001; Simonton, 1999). Combinations that relate components that are rarely, if at all used together, are therefore unconventional.

Our measure of unconventionality has strong conceptual similarities with the tension described by Levinthal and March (1993) between distant search, leading toward exploration, and local search, pointing to exploitation. However, the main distinction relies in the perspective that is adopted. While most of the studies on technological recombination discuss the tension between exploration and exploitation in relation to the organizations and inventors' existing knowledge domains, we adopt a broader perspective by considering the recombination process over the entire technological landscape.

The Unconventionality measure presented in this study is population-based[4], in the sense that it reflects the actual state of relationships between elements of the knowledge space at a given point in time. This measure builds around the "principle of survival" as the actual configuration of interdependences among components is the result of successful attempts. Consequently weak or nonexistent links represent overlooked connections or failed trials. This feature enables to delineate the actual boundaries of the conceptual space and consequently any act of modifying sensibly the latter at any time.

2.2.2 Sources of Unconventionality

A growing empirical literature has analyzed high impact, breakthrough or radical inventions, detailing several determinants for their impact (i.e. Fleming, 2001; Kelley et al., 2013; Schilling & Greene, 2011; Schoenmakers & Duysters, 2010 among others). These studies speculate on the role of novelty in the determination of highly impactful inventions advancing arguments that mostly pertain to the sources of novelty (or unconventionality as we define it).

One of the most discussed aspect is whether unconventionality is the outcome of the recombination of existing knowledge or whether relies on completely new solutions. A stream of literature has argued that novelty in the knowledge base used for the generation of inventions relies on completely new

[4] In the derivation of the measure we consider the entire universe of patents. Patents with only one USPC are included in the derivation of the measure but are excluded in the analysis as we are interested in the process of recombination of components within the invention.

technical knowledge, hence not yet embedded in existing inventions (van de Poel, 2003). A second stream of research points to the role of existing components, and their recombination (Schumpeter, 1939; Arthur, 2007; Fleming, 2001). Under the first view, novelty is carried forward by little if not existent references to previous inventive efforts (Ahuja & Lampert, 2001). However, Unconventional combinations might find their rationale in a broad scientific realm (Dahlin & Behrens, 2005). The second perspective instead posits that the knowledge base from which unconventional recombinations are sourced is broadly distributed. Despite being a repository of knowledge with potential technological implications (not yet exploited), Science works as a map of the technological space, allowing inventors to move within the latter with greater foresight (Fleming & Sorenson, 2004). By elaborating and testing theories of general validity, Science helps predict the outcome of scarcely tested combinations, guiding inventors in their search beyond the existing cognitive boundaries.

Despite the different realms comprising the knowledge space, proximity has been defined by variety of terms. The temporal dimension has recently gained noteworthy attention (Neckar, 2003). The debate revolves around the contribution of novel and emerging bodies of knowledge to the generation of original solutions as opposed to the contribution of more mature ones. Emerging technologies usually bring about novel solutions, embed a higher degree of novelty in the proposed solutions and hence expand the current space for recombinations – for instance by bringing to the market new components themselves (Ahuja & Lampert, 2001). Mature technologies, on the opposite, tend to be "*… well understood and offer greater reliability relative to more recently developed and less tested" technologies"* (Ahuja & Lampert, 2001, p. 527). Hence, familiarity with the nature and properties of older technologies will be substantially higher.

Unconventional recombinations are also expected to be the result of combinations of older and emerging knowledge bases. As they result from the association of distant bodies of knowledge, recombinant efforts will most often link bodies of knowledge with high internal coherence – i.e. areas of the knowledge space whose existing interdependences are mostly understood – but loosely recombined among themselves. A useful analogy in this respect is the realm of Science, where new contributions bear a tension between conformity to the “*currently predominant beliefs about the nature of things*” (Polanyi, 1962, p.58) and dissent from it.

The organizational literature has extended the discussion on the sources of impactful inventions to include the role of inventors and teams. The debate focuses on the role of teams in the process of idea generation and retention. The question at the core of the debate is whether teams facilitate the recombination of dispersed competences, distributed across team members (Singh and Fleming, 2010) or whether they generate frictions in the phase of retention of creative ideas (Paulus & Nijstad, 2003). Advocates of the latter view, embrace the “myth of the lone inventor” as source of unconventional solutions because teams are plagued by collaborative frictions in the process of idea generation (Mullen et al., 1991). Proponents of the former view, claim that collaboration enables greater combinational opportunities and that teams are better endowed in the “*sorting and identification of most promising ideas*” (i.e. Singh & Fleming, 2010, p.42). In this respect, inventors’ experience plays a crucial role in that it determines the extent of combinatorial possibilities and the ability to select promising inventive venues (Fleming et al., 2007; Hargadon & Sutton, 1997; Schilling & Greene, 2011).

The debate on the origins of novel or unconventional inventions is also one of the cornerstones of the industrial organization discussion. Scholars have been debating as to whether the type of organization in which inventions occur - large firms vs. small firms – has an influence on the extent of unconventionality in recombination. On the one hand, large firms are considered to be at disadvantage with the generation of unconventional solutions as they are trapped in established routines and product lines, around which new solutions are incrementally developed (Hill & Rothaermel, 2003). On the other hand, firms can be thought as repositories of knowledge and competences (Grant, 1996) whose potential for recombination depends directly on firm size. This assumption is consistent with theories of industry evolutions via corporate spin-offs, where unconventional ideas are rejected by incumbent firms because of mismatch with the firms’ main strategy (Klepper & Thomson, 2010). Hence large firms are a seedbed for unconventional combinations, whose exploitation will depend on strategic decisions.

2.3 Measuring Unconventionality: existing measures.

Indicators established in literature, rely on information from backward citations. The **Originality** measure by Trajtenberg et al. (1997) is defined as the Herfindahl Index on technological classes of cited patents and points to the spread of citations over classes. Rosenkpopf and Nerkar (2001) also use patent citations to identify the number of patent classes that do not belong to the focal patent. Along this line, Dahlin and Behrens (2005) define an invention as radical on three main basis: its novelty (few common citations to patent in previous years), uniqueness (citations to other patents in the same year) and its impact (technological impact). These studies determine novelty as the overlap in backward citations among patents to determine similarity among patents. This methodology is problematic as the universe of patents is ever expanding and similar inventions might share few backward citations as they occur in two different time periods or because the solution they address is grounded in a multitude of former patents, which might end up not being cited in all the future inventions.

Closer to our approach, are the measures based on the recombination of components within inventions (Fleming & Sorenson, 2001; Verhoeven et al., 2016). Fleming and Sorenson (2001) identify new pairwise combinations of patent subclasses as novel inventions. They also account for the number of times that the same combination has been used (**Cumulative Usage**) and for the **Interdependence** of the components recombined in the focal invention.

Verhoeven et al. (2016) adopt a combination of constructs that consider both the newness of the combination of technological classes (**Novelty in Recombination, "NR"**) but also, via citations, the extent to which inventions built on previously unconnected scientific fields (**Novelty in Knowledge Origins, "NSO"**) and different technological classes (**Novelty in Technological Knowledge Origins, "NTO"**). This novelty measure identify ex ante characteristics of novel inventions by adopting pairwise combinations of technological classes and by considering the extent to which focal inventions rely on new technological origins and knowledge.

However, existing measures do not account for the distance among the technological components as expressed by their synergic usage. Moreover, although novelty is often distributed across early attempts, it may not be necessarily captured by the very first combination. A low usage of that combination after the first novel attempt can still have a value for attempts occurred at later time.

Others studies have recognized the importance of considering distance by looking at the number domains (Nemet & Johnson, 2012; Schoeenmaker & Duysters, 2010). Keijl et al, (2016) investigate the recombination process by considering both the number of domains and the distance between them. However, in line with existing studies, they also conceive distance based on the spread of technological components over technological domains through the use of backward citations. They analyze the recombination process in the biotechnology industry distinguishing between focal patents citing others patent in biotechnological classes versus those that cite patents in adjacent classes (chemicals or drugs) or in unrelated classes.

Schilling and Greene (2011) use the Dewey decimal system, a bibliographic categorization for the organization of libraries, to determine which combinations of topics is the least likely to occur within the articles cited as references. Their work however is not informative on the actual procedure to determine unconventional connections.

The study by Uzzi et al. (2013) on the universe of scientific articles in the Web of Science is the closest to the approach used for the Unconventionality measure. They explicitly model novelty in the creative process as the pairwise combination of references in the bibliography of each paper. Similarly to this study, they also take a probabilistic approach as to whether combinations are deterministic or instead the outcome of a random process. They find that highest impact is grounded in exceptionally conventional combinations, yet with the inclusions of unusual combinations. Table 2.1 reports a summary of the related indicators.

2.4 Data and methodology

2.4.1 Data

We use U.S. patent data from 1975 to 2000 (Lai et al., 2014), to measure the degree of Unconventionality of the inventive outputs. In line with most researches on patent data (Hall et al., 2001), only the utility patents are used. [5] The unit of analysis in the derivation of the measure and used in the regression models is the individual patent. The information contained in patents enables to model the extent to which the components used in the generation of inventions are combined in an unconventional fashion. In particular, we used detailed information about patents' technological class and subclass references (there are over 400 classes, and over 100,000 subclasses). Classes reflect broad technological areas, whereas subclasses reflect specific technological components within a given technological area. Central to this study is the listing of the technological components used in the generation of the invention and their joint occurrence across the whole universe of patents at the USPTO level.

Aside from containing a great deal of technical information (e.g. patent number, date of application and grant, number of claims, technological classes), a single patent also provides a rich amount of individual and organizational-level data. Patents documents also list inventors' names (also referred to as the authors) and hometowns, the assignee (i.e., the owner of the patent that typically identifies the organization for which the inventor works, such as a firm, a university or government, or the inventor himself).

2.4.2 Unconventionality measure

The degree of unconventionality in recombination reflects the distance between elements in the space of components as a function of the commonalities they shared.

From the literature on firms' business diversification, we borrow the measure of relatedness and its conceptualization, used in previous studies to describe the diversification of firms in the product market Teece et al. (1994). More recent studies have adapted the relatedness measure to describe the

[5] A patent is a legal instrument that protects a new and useful product, process, machine, or new combinations of materials. Patents are especially useful for analyzing inventions because they are granted only to products and processes that a knowledgeable, objective third party (e.g. United States Patent and Trademark Office USPTO) decides that the work exceeds a minimum threshold of creativity and innovation.

diversification patterns of firms at the technological portfolio level (Dosi et al., 2016; Breschi et al., 2003; Nesta & Saviotti, 2005).

Two elements constituting a diversified set - two products or two technologies in the portfolio of a firm - are said to be related if their joint occurrence is not driven by a random process. This is usually the outcome of existing commonalities or synergies between the two elements.

The concept of coherence extends the rationale behind relatedness to the whole set of elements to capture the systematic relatedness of the elements comprising it.[6] We follow the same line of reasoning and measure the extent to which each pair of components, constituting a single recombinant act, are related to each other or close in the knowledge space.

In line with the empirical literature on the origins of novelty(Fleming, 2001; Dahlin & Beherens, 2005; Schoemakers & Duyster, 2010), we use patent documents and the occurrence of patent classes therein as base for the construction of the measure. A patent has membership in one or more patent subclasses which are the objects to be combined. The extent to which each possible pairwise combination of patent subclasses actually occurs within each patent determines the starting point for the calculation of the measure. Let $C_{iz} = 1$ if patent *z* has membership in class *i*, and 0 otherwise. The number of patents having simultaneously membership in classes *i* and *j* is

$$J_{ij} = \sum_z C_{iz} C_{jz}$$

Raw count of the number of patents having membership in each pairwise subclass combination, however, cannot be taken directly as a measure of relatedness. Although J_{ij} increases with the relatedness of *i* and *j*, it also

[6] By extension, we can think of the degree of relatedness between two components of the knowledge space as the strength of the link between them. Like in the parallel of knowledge or technological landscapes (Fleming, 2001), coherent areas of the knowledge networks are made of highly interrelated components, where the use of one component is usually associated to the use of other ones. Alternatively, there will be combinations of components which link otherwise disconnected areas; these links will be weaker, or less related, than the tighter ones characterizing the coherent sections of the knowledge space. Consequently, the knowledge space can be thought as a network, made of areas of highly interrelated components, eventually connected by unconventional or unconventional combinations (Shilling & Greene, 2011).

increases with n_i and n_j, the number of patents having membership in each class of the couple. Thus, large values of J_{ij} might simply reflect intense inventive activities in *i* and *j*. Therefore, J_{ij} must be adjusted for the number of patents that would have simultaneous membership both in *i* and *j* under the null hypothesis that classes were randomly assigned to inventions. Teece et al. (1994) show that the joint occurrence of two objects *i* and *j* follows an hypergeometric distribution against which the null hypothesis can be tested. Hence, relatedness, τ_{ij}, is measured as the difference between the observed pattern of co-occurrences of *i* and *j* and the expected one:

$$\tau_{ij} = \frac{J_{ij} - \mu_{ij}}{\sigma_{ij}}$$

where μ_{ij} is equal to the expected number of patents with simultaneous membership in *i* and *j* under the observed occurrences of *i* and *j* and σ_{ij} the standard deviation of the observed occurrence.[7] This measure thus reports the extent to which a combination of patent subclasses appears as unconventional or conventional. When this measure is large, components *i* and *j* are systematically recombined. Thus they are highly related in the technological space. When it takes values close to 0 or even negative, the measure indicates that unexpectedly few inventions embed the two components given their separate use; consequently *i* and *j* are unrelated and their joint use will be rather novel or unconventional.[8]

Most combinations are highly conventional; only a handful of them have values of τ_{ij} which are close to zero, and are hence original or unconventional. For instance, among the most unconventional combinations we can find the attempts to explore biotechnology-related applications in the late 1990s. The patent subclass *435/320.1* [Molecular Biology (435); Vector, per se (e.g.,

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[7] Details on the derivation of the measure and formulae to calculate μ_{ij} and σ_{ij} are reported in the appendix.

[8] The index of relatedness τij can also be interpreted as the centripetal strength that ties together the nodes (patent subclasses) of the cognitive space in which inventions occur. High values indicate that two elements are very close in space or interdependent as in Fleming (2001). Intuitively, components which are largely used – large ni – are indeed hardly interdependent with other components.

plasmid, hybrid plasmid, cosmid, viral vector, bacteriophage vector, etc.) (320.1)] [9] appears to be combined in an unconventional fashion with *425/401* [Drug (425); Cosmetics, antiperspirants, dentifrices (401)], and 707/3 [Data Processing: Database and File Management, Data Structures, or Document Processing (707); Query processing (i.e. searching) (3)]. [10] The two examples document the attempts to explore new applications for the nascent biotechnology sector: the first is the application of genetic engineering to the domain of cosmetics, whereas the second relates to the bio-informatics.

Following the construction of the measure, we derive patent-based measures of unconventionality, on the basis of the distributional properties of τ for each pairwise combination of patent subclasses within each patent. To this purpose, we provide two indicators of the degree of unconventionality in an invention: the median and the minimum value of τ among the possible pair-wise combinations contained in an invention.

The median captures the degree of unconventionality around the main bulk of combinations within the invention, whereas the minimum value indicates the most unconventional recombinant act within an invention. Most patents embed a high degree of conventionality in the combination of their constituent parts. More than half of the patents (50,46%) in the sample have a median τ larger than 33, whereas only 28 patents have a median τ below 0. These highly unconventional patents are mostly in drugs and communication domains as for instance the patent number "US 5863736" recombining the subclass 435/6.16, 435/91.2 [Molecular Biology (435); Vector, per se (e.g., plasmid, hybrid plasmid, etc.) and the subclass 715/234 [Data processing, structured documents (e.g. htm, sgml, etc.)]. When we look at the minimum value of τ within each patent, more than half of the patents combine components whose τ is above 17; the occurrence of negative values is a rare event as well. All in all, the preliminary evidence provided so far indicates that the inventive process

[9] Subject matter directed to self-replicating nucleic acid molecules which may be employed to introduce a nucleic acid sequence or gene into a cell; such nucleic acid molecules are designated as vectors and may be in the form of a plasmid, hybrid plasmid, cosmid, viral vector, bacteriophage vector, etc.

[10] Subject matter directed to methods of searching for (i.e., querying) data stored as a database in a computer or digital data processing system, including sequential searching, primary and secondary index searching, and bit-map searching of inverted lists or topological maps.

relies mostly on conventional recombinations and only rarely embed more unconventional efforts.

Table 2.2 and 2.3 report the distribution of the median τ respectively across years of application and technological domain of the focal invention. On average, inventions are less conventional over time; yet, there is a tendency to both exploit established trajectories and to move beyond the existing boundaries as we also observe that the dispersion of conventionality increases over time. Table 2.3 provides further evidence on the goodness of our measure, suggesting that inventions in domains like “Apparel and Textile” and “Furniture, House Fixtures” are more conventional than ICT related inventions like “Semiconductors” or “Computers”, which for instance find applications in a multitude of other domains.

Table 2.1: Description of existing measures.

Article	Measure	Construction	Meaning	Difference
Trajtenberg, Henderson & Jaffe 1997	Originality	Herfindahl Index of distribution of patent classes in backward citations	Novelty is associated to a broader and more balanced knowledge base	Static measure, it doesn't take into account the current practices and the consequent dynamics
Fleming Mingo & Chen 2007	Creativity	New Combination of patent subclasses	Creativity is the result of novel combinations	It does not take into account the extent to which combinations are close in space
Verhoeven, Bakker & Veugelers 2016	Novelty	Pair-wise combination	Inventions are novel when they include combinations connected for the first time	It does not offer suggestions on the technological distance between components
Uzzi Mukherjee Stringer & Jones 2013	Novelty	Frequency of co-citation pairs across all papers published that year in the WOS benchmarked by those expected by chance (randomized citation networks)	Atypical connections across knowledge domains are at the core of novelty	Conventionality is built on yearly base, and the benchmark does not reflect the path-dependency in idea generation
Dahlin and Behrens 2005	Radicalness	Similarity measure with previous and current patents on the basis of the overlap of backward citations	Differences in citation structures across patents indicate differences in the knowledge that inventions rely upon	Prior art differs over time and inventions might not necessarily be substantially different over time – especially when they are incremental changes
Keijl, Gilsing, knoben & Duysters 2016	Novelty	Average distance between the patent classes of the cited patents and the patent classes of the focal patent.	Novelty is associated to a higher distance between the patent classes cited and focal.	It does not take into account the distance among the components recombined in the invention.

Table 2.2: Distribution of Conventionality of Inventions across years.

Year	Conventionality	St.Dev.	N	Year	Conventionality	St.Dev.	N
1980	52.322	43.133	57,185	1991	45.384	41.392	90,331
1981	51.400	42.715	55,584	1992	44.170	40.281	93,781
1982	51.431	42.668	56,723	1993	44.163	41.120	97664
1983	50.915	43.079	54,310	1994	44.066	41.128	111,428
1984	51.028	42.623	59,401	1995	44.039	41.367	130,686
1985	50.133	42.718	63,264	1996	43.079	43.015	129,961
1986	49.411	41.447	66,885	1997	43.314	43.585	152,371
1987	48.884	41.994	72,710	1998	42.327	44.758	151,632
1988	48.056	41.971	80,404	1999	42.086	44.174	161,870
1989	47.301	41.449	85,728	2000	43.550	47.141	176,747
1990	46.470	41.801	89,066	Tot.	45.638	43.012	2,037,731

Table 2.1 displays the distribution of inventions' conventionality over application year. Conventionality decreases over time, namely patents are characterized by combination that are on average more atypical. We find similar trends across technologies which are showed in the Appendix A. In non reported tables, we checked the consistency of this pattern by looking at all pair of combinations supporting the tendency over time to combine components in an unconventional manner. Fixed effects estimates taking as unit of analysis the coupling of subclasses, indicate that a move toward lower levels of conventionality is occurring in the central part of the distribution. On the opposite, conventionality increases for extreme values of initial conventionality: highly unconventional combinations become more conventional, at a faster rate than more conventional ones become unconventional, and conventionality strengthens over time for highly conventional combinations with the current understanding of structural relationship among constituting components.

Table 2.3: Distribution of Conventionality of Inventions across Technology fields.

Technological Category	Mean	Std. Dev.	N
Agriculture, Food, Textiles	47.309	39.323	20,999
Agriculture, Husbandry, Food	57.829	55.266	50,366
Amusement Devices	69.975	56.446	23,936
Apparel & Textile	74.472	66.065	35,871
Biotechnology	77.455	76.561	9,664
Coating	33.406	29.955	56,012
Communications	**34.621**	**30.684**	**194,391**
Computer Hardware & Software	**34.318**	**30.950**	**168,644**
Computer Peripherals	**30.584**	**28.268**	**65,859**
Drugs	32.109	27.785	21,6705
Earth Working & Wells	58.499	49.609	36,765
Electrical Devices	44.266	40.553	88,954
Electrical Lighting	41.609	32.203	48,456
Furniture, House Fixtures	65.429	51.958	57,918
Gas	49.738	37.306	14,111
Heating	51.227	45.500	36,204
Information Storage	**31.759**	**29.479**	**111,469**
Materials Processing & Handlin	50.522	41.838	144,494
Measuring & Testing	41.925	36.087	83,094
Metal Working	47.604	41.869	87,355
Miscellaneous-Drug & Med	54.592	49.141	16,985
Miscellaneous-Electrical	40.620	33.473	112,175
Miscellaneous-Mechanical	59.109	50.274	129,295
Miscellaneous-Others	41.583	40.948	319,628
Miscellaneous-Chemical	38.090	32.894	308,242
Motors, Engines & Parts	54.308	46.397	93,533
Nuclear & X-rays	37.891	32.399	49,659
Optics	41.510	37.187	32,690
Organic Compounds	47.373	42.406	64,715
Pipes & Joints	42.499	32.624	25,122
Power Systems	41.244	35.379	116,500
Receptacles	46.994	33.976	55,378
Resins	27.727	22.517	101,862
Semiconductor Devices	**30.861**	**23.413**	**96,714**
Surgery & Medical Instruments	40.812	34.788	83,323
Transportation	64.758	55.523	83,211
Total	42.561	39.526	3,240,299

Note: Each invention is associated to more than one technology, hence we linked each UPC classes to Technological Categories considering all classes reported in a patent.

2.4.3 Unconventionality and its sources

As the unconventionality measure is positively skewed, we use as dependent variable the natural logarithm of it, ***Log Unconventionality***.[11]

Based on the literature on the origins of novel inventions, the first type of origin we consider is the extent to which the focal invention builds on existing knowledge. In our setup, we will use the (natural logarithm plus one of) number of citations to prior art as measure of the knowledge base on which the focal invention relies on (***Log Citations***). We also differentiate between citations to previous technical and scientific literature (non-patent literature), include the latter as the share of total citations (**Science**).

Furthermore, we include a control for those inventions that do not cite any prior art to account for the possibility that unconventional connections might not find support in any existing knowledge base (***No Prior Art***). We use the average patent number of the patent documents cited as prior art as a measure of the average age of the patent literature which forms the basis of the focal invention (***Age***). Furthermore, we control for the standard deviation of the patent numbers of the patent documents cited as prior art (***Spread Age***). We also control for patents citing no patents in the prior art, because for this group we cannot calculate the variable Age (***No Patent***) and a control for inventions citing a single patent document as prior art because Spread Age cannot be calculated for this group (***Single Citation***). Based on Verhoeven et al., (2016), we also include the log of the number of connection between classes and scientific articles referenced in the focal patents that have never occurred before the focal application year (***NSO-Novelty in Scientific Origins***). Along the same line, we also include the log of the number of references to other technological classes referenced in the focal patent that have not occurred in the years prior the focal patent application year (***NTO-Novelty in Technological Origins***).

[11] As our measure of conventionality takes negative values, we added the absolute of the lowest value taken by *Conventionality*. We then took the natural logarithm of the newly transformed covariate plus one. As the number of co-occurrences among patent subclasses can be highly volatile over time, we use 5 year moving averages. For the sake of exposition, we display the natural logarithm of τ_{ij}

The extent of conventionality embedded in an invention is a positive function of the elements constituting it, that is its components. Hence, we include the number of patent subclasses the patent has membership in (***Component***).

We further control for the main organizational factors affecting the search process. We include the number of inventors comprising the inventive team (**Team**) as well as a measure for single inventor patents (***Single Inventor***). To control for the experience of the inventive team, we include the largest progressive number of patents by the inventors in the team (***Experience***).

We also account for the determinants of organizational inventive behavior, by considering the inventive size of the organizations (e.g. assignee on the patent document) as the (log plus one) of the number of patents at USPTO in the year of the focal invention (***Assignee***) as well as a dummy indicating whether the patent was not assigned to any third party and remained to the inventors (***Self***). We finally add ***Year*** and ***Technology*** dummies to account for macro trends in the degree of conventionality among patents, such as the introduction of novel patent classes in a given year at USPTO which would artificially alter the measure of recombinant conventionality.

Table 2.4: Summary Statistics split by degree of median Unconventionality (10th of the most unconventional inventions).

	Full Sample			90% least Unconventional			10% Most Unconventional		
Variables	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std.Dev.
Unconv.	2,037,731	-3.658	0.675	1,833,956	-3.780	0.593	203,775	-2.561	0.223
Min Unconv.	2,037,731	-3.237	0.758	1,833,956	-3.337	0.728	203,775	-2.345	0.296
Interdependence	2,037,731	1.456	1.068	1,833,956	1.458	1.092	203,775	1.440	0.820
Originality	1,690,973	0.530	0.348	1,512,793	0.523	0.351	178,180	0.583	0.323
Cumulative Usage	2,037,731	20.969	8.2715	1,833,956	21.001	85.766	203,775	20.681	47.062
NR	2,037,731	0.026	0.1787	1,833,956	0.026	0.178	203,775	0.024	0.179
NTO	2,037,731	0.35	0.702	1,833,956	0.356	0.705	203,775	0.289	0.669
NSO	2,037,731	0.017	0.157	1,833,956	0.0167	0.154	203,775	0.022	0.181
Bwd Citations	2,037,731	2.199	0.827	1,833,956	2.185	0.816	203,775	2.326	0.910
Fwd Citations	2,037,731	13.105	21.90	1,833,956	13.014	21.831	203,775	13.923	22.585
Science	2,037,731	0.138	0.256	1,833,956	0.133	0.252	203,775	0.188	0.287
Components	2,037,731	4.659	3.267	1,833,956	4.607	3.213	203,775	5.121	3.691
Age	2,037,731	63.568	4782.242	1,833,956	59.571	4620.925	203,775	99.541	6043.214
Spread Age	2,037,731	102.383	77454.44	1,833,956	99.485	81510.22	203,775	128.464	14026.08
No Patent	2,037,731	0.027	0.163	1,833,956	0.026	0.161	203,775	0.035	0 .185
No Prior Art	2,037,731	0.012	0.110	1,833,956	0.012	0.109	203,775	0.012	0.112
Team	2,037,731	2.216	1.573	1,833,956	2.186	1.556	203,775	2.484	1.695
Max Experience	2,037,731	11.680	27.564	1,833,956	11.330	26.748	203,775	14.837	33.873
Single Inventor	2,037,731	0.423	0.494	1,833,956	0.433	0.495	203,775	0.336	0.472
Assignee	2,037,731	3.839	2.758	1,833,956	3.729	2.740	203,775	4.826	2.722
Self	2,037,731	0.153	0.360	1,833,956	0.162	0.368	203,775	0.073	0.261

2.5 Results

In this section, we analyze the degree of unconventionality in inventions through a multivariate setting (Table 2.4) report the summary statistics of the variables used).

In a first analysis we examine the relationship between Unconventionality and the main indicators of technological novelty discussed in Section 2.3. In particular, we analyze the relationship between Unconventionality the measure of Interdependence and cumulative usage by Fleming and Sorenson (2001), Originality by Trajtenber et al., (1997) and with the measure of Novelty in New Combination (NR) by Verhoeven et al., (2016). Table 2.5 shows the correlation between Unconventionality and other indicators. Correlations among the indicators are weak suggesting that these measures capture different dimensions of knowledge recombination. Table 2.6 reports the OLS estimations of the relation among the indicators.

In a second analysis we analyze the role of the main antecedents and sources of novelty discussed in Section 2.2.2. In this analysis we are mainly interested in the understanding of the extent to which unconventionality is the result of a search process that span different knowledge domains (via the number of technological classes recombined and citations to existing domains of knowledge). In addition, we examine whether unconventionality is affected by the organizational structure, team/organization, in which search occurs. Table 2.6 presents bivariate correlations among the variables that we have identifies as determinant of unconventionality. Table 2.7 shows the correlation table. Table 2.8 reports instead the OLS estimations of this set of analysis

In a third set of regressions reported in Table 2.9 and 2.10 we focus on the extent to which unconventional combinations contribute to overcoming inventive traps and are related to higher technological impact. Also in this analysis we relate the Unconventionality measure with existing Indicators of novelty.

2.5.1 Relation with existing Indicators

In Table 2.6 we report the OLS estimations that include existing measures of novelty, in particular originality by Trajtenberg et al., (1997) and NR by Verhoeven et al., (2016). In Model 1 to 4 we introduce the indicators sequentially while Model 5 reports the full model. Unconventionality is negatively associated with interdependence. Components that are highly interdependent are synergistically recombined. As a consequence they are strongly related and hence associated to well-established combinations. Along this line, a higher cumulative usage (number of times a particular combination has been used since 1975), is associated to a decrease in unconventionality, although with a smaller magnitude relative to the interdependence of components.

As expected, originality and NR are statistically significant and positively associated with unconventionality. Higher scores of Originality as measured by the spread of backward citations over technological classes, indicate that inventions integrate divergent ideas. Inventions with high score of originality may not necessarily be novel per se. This measure suggests the importance of a broad knowledge base. Inventions that source on wide knowledge base are associated with less conventional combinations.

The NR construct points instead to the existence of pair of classes in inventions that were previously unconnected. Higher number of previously unconnected classes within inventions are hence positively associated with unconventionality, although with a smaller magnitude compared to the originality construct.

Model 5 includes all constructs and contrary to model 1 the Interdependence change sign and shows a positive association with unconventionality. To uncover potential underlying patterns among the variables we run a factor analysis that revealed a potential underlying structure between Interdependence and Cumulative usage that drives the change of the sign of Interdependence coefficient. This may suggest the need to have a balance between wide and local search and of having focused search strategy within narrow and synergic components before making connections to unrelated field.

Table 2.5: Correlation tables with existing measures.

Unconventionality	1.0000				
Interdependence	-0.0609*	1.0000			
Originality	0.1020*	-0.1521*	1.0000		
NR	0.0060*	-0.0457*	0.0730*	1.0000	
Cumulative Usage	-0.0363*	0.2057*	-0.0017*	-0.0169*	1.0000

Note: Correlation between Unconventionality and related measure is very low suggesting that the measures pick up different dimensions.

Table 2.6: OLS estimations for the relation with other measures.

	Model 1	Model 2	Model 3	Model 4	Model 5
Interdependence	-0.017***				0.009***
	(0.000)				(0.001)
Originality		0.200***			0.201***
		(0.001)			(0.001)
NR			0.054***		0.024***
			(0.002)		(0.003)
Cumulative Usage				-0.001***	-0.001***
				(0.000)	(0.000)
Constant	-3.930***	-4.032***	-3.948***	-3.945***	-4.041***
	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)
N	2,037,731	1,690,973	2,037,731	2,037,731	1,690973
R^2	0.116	0.115	0.116	0.125	0.124

***, **, and *** indicate respectively 10%, 5% and 1% statistical significance.** Regressions include 21 year dummies and 37 technology dummies; all dummies are jointly statistically significant. Regressions include also controls (dummies) for missing information on the age of the backward citations and.

2.5.2 Sources of Unconventionality

Table 2.8 reports the results of OLS and logit models on the determinants of unconventionality. Model 1 introduces the variables at the level of the invention; Model 2 accounts for the inventive team whereas Model 3 adds the determinants at the level of the assignee. The initial set of variables provide the bulk of explanatory power, most of which is attributable to year and technology effects: regressing Unconventionality only on the 21 year dummies and 37 technological dummies yields an R-squared of 0.1147. Adding the remaining invention controls improves the explicative power of the model to 0.147. Yet, this improvement is by far the largest when compared to the inclusion of team and assignee level controls.

Unconventionality in inventions is positively associated with the amount of backward citations in patents. A 10% increase in the amount of documents cited as prior art is related to an increase of 0.13% in the median level of conventionality of the focal invention. However, references between technological classes and scientific field that occur for the first time (NSO) are associated with a decrease in unconventionality. Originality instead, spread of citations over technological classes, is positively associated with unconventionality. As expected references to non-patent literature contributes to unconventionality. An increase in one standard deviation of Science (Non patent literature) is associated with 2.9% increase in the degree of unconventionality of the focal invention. Ceteris paribus, the more inventions source from other domains than the technical one – especially from Science – the higher the extent of unconventionality in their recombinations.

Inventions carrying forward unconventional recombinations rely to a larger extent on less recent prior art. The results indicate that inventions are more unconventional when they embed a higher number of components. Conventionality is rooted in familiar and mature solutions which happen to be combined with more recent ones. The degree of unconventionality instead increases as the number of components used in the focal invention also increases: one standard deviation increase in the number of patent subclasses in which the focal invention has memberships in is related to an increase of 0.10% in the median value of conventionality of the invention, ceteris paribus.

Teams produce inventions with a higher degree of unconventionality (model 2) as opposed to single inventors. This finding suggest that large teams benefit from knowledge from multiple inventors that are likely to search and built on larger and diversified range of components. Inventions being the result of collaborations are less conventional; yet, larger teams seem to recombine components in a more conventional fashion. The median value of unconventionality in an invention produced by a single inventor is indeed 3.8% lower. More experienced inventors are able to combine components in an unconventional fashion.

The final set of controls suggest that larger firms are more likely to be responsible for the generation of unconventional inventions[12]. Inventions occurring in larger organizations carry forward unconventional solutions, as opposed to “garage” inventions. At the average, doubling the size of the assignee in terms of successful patents applied in a given year increases the degree of unconventionality by 2.1%, all else equal. "Garage” inventors, inventors which do not belong to any existing organization and most likely are self-employed, produce less unconventional combinations. Large firms may leverage economies of scope and scale in R&D. Large firms can spread costs and risks on broader output (Cohen & Klepper, 1996a, 1996b; Henderson & Cockburn, 1996). Moreover, they can exploit a more diversified portfolio and technological base which may facilitate the recombination of knowledge. Adding the final set of variables for the size of the patent assignee, causes some covariates related to the characteristics of the team to change sign: team size become negative and significant. We suspect that this has to do with the ability of large firms to coordinate larger teams. The OLS estimations reported in Table 2.8 has been replicated by using logit models on the 10th centile of the inventions with the highest values of median unconventionality. The most unconventional inventions have a higher probability to combine components in an unconventional way (lower likelihood to be conventional). Consistently with OLS results, a higher likelihood to score in unconventionality, is driven

[12] Note that information on the Assignees are not consolidated. To check the robustness of this finding we uses alternative data sources from Orbis. Results are robust to this alternative specification of the firm patent portfolio. In general we expect that consolidated data would reinforce this finding. The finding that large firms produce more unconventional inventions also holds in non reported analysis that control for the concentration of firm activities computed through the Herfindahl Index.

by the amount of citations and the number of components that are recombined while the odds for large team and experienced inventors suggest a focus on established combinations.

Table 2.7: Correlation table on the determinants of Unconventionality

Table 2.7: Correlation tables on determinants of Unconventionality.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	Unconv.	1.0000																	
2	Min Unconv.	0.8433*	1.0000																
3	NTO	-0.0163*	0.0194*	1.0000															
4	NSO	0.0227*	0.0352*	0.1519*	1.0000														
5	claims	0.0739*	0.1015*	0.0400*	0.0639*	1.0000													
6	orig	0.1020*	0.1288*	0.2313*	0.0471*	0.0212*	1.0000												
7	Citations	0.0839*	0.1322*	0.1875*	0.1627*	0.2269*	0.1000*	1.0000											
8	Science	0.1035*	0.1401*	-0.0358*	0.1869*	0.0798*	0.0417*	0.3515*	1.0000										
9	Components	0.1968*	0.4817*	0.0807*	0.0497*	0.0895*	0.0928*	0.1117*	0.1210*	1.0000									
10	Age	0.0027*	0.0039*	0.0018*	-0.0001	0.0019*	-0.0005	0.0065*	0.0004	0.0011	1.0000								
11	Spred Age	0.0008	0.0014*	0.0028*	-0.0001	0.0003	0.0002	0.0041*	0.0001	0.0000	0.9189*	1.0000							
12	No Patent	0.0110*	0.0225*	-0.0547*	0.0112*	-0.0222*	-0.0005	-0.2126*	0.2721*	0.0296*	-0.0022*	-0.0002	1.0000						
13	No Prior Art	-0.0114*	-0.0142*	-0.0268*	-0.0096*	-0.0157*	-0.0005	-0.2967*	-0.0603*	-0.0008	-0.0015*	-0.0001	0.6630*	1.0000					
14	Team	0.0997*	0.1205*	0.0087*	0.0395*	0.0941*	0.0138*	0.0743*	0.1457*	0.1038*	0.0014*	0.0001	0.0527*	0.0155*	1.0000				
15	Experience	0.0589*	0.0732*	-0.0224*	0.0020*	0.0638*	-0.0240*	0.0419*	0.0293*	0.0639*	0.0010	0.0004	0.0155*	0.0093*	0.1935*	1.0000			
16	Single inventor	-0.1064*	-0.1231*	-0.0037*	-0.0364*	-0.0817*	-0.0158*	-0.0712*	-0.1438*	-0.0882*	-0.0019*	-0.0008	-0.0431*	-0.0084*	-0.6629*	-0.1417*	1.0000		
17	Assignee Size	0.2012*	0.1972*	-0.0894*	0.0035*	0.0468*	-0.0597*	0.0057*	0.1103*	0.0678*	0.0019*	-0.0003	-0.0097*	-0.0312*	0.2818*	0.1942*	-0.2907*	1.0000	
18	Self	-0.1421*	-0.1425*	0.0268*	-0.0221*	-0.0704*	0.0148*	-0.0504*	-0.1278*	-0.0650*	-0.0014*	-0.0004	0.0110*	0.0518*	-0.2347*	-0.0932*	0.3002*	-0.5925*	1.0000

Table 2.8: Determinants of Unconventionality

	OLS			LOGIT		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
NTO	-0.015***	-0.015***	-0.014***	-0.046***	-0.047***	-0.039***
	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)
NSO	-0.002	-0.003	-0.002	0.022	0.021	0.022
	(0.003)	(0.003)	(0.003)	(0.015)	(0.015)	(0.015)
Originality	0.181***	0.182***	0.186***	0.584***	0.586***	0.606***
	(0.001)	(0.001)	(0.001)	(0.008)	(0.008)	(0.008)
Citations	0.009***	0.008***	0.013***	0.009**	0.005	0.021***
	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)
Science	0.029***	0.025***	0.008***	0.173***	0.163***	0.119***
	(0.003)	(0.003)	(0.003)	(0.013)	(0.013)	(0.013)
Component	0.031***	0.030***	0.030***	0.017***	0.016***	0.015***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Age	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Spread Age	-0.000	-0.000	-0.000	-0.000*	-0.000*	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
No Patent	0.148	0.142	0.126	0.251	0.222	0.167
	(0.401)	(0.404)	(0.407)	-1.204	-1.211	-1.211
No Prior Art	-0.148	-0.144	-0.006	-0.333	-0.313	0.265
	(0.401)	(0.404)	(0.407)	-1.205	-1.211	-1.211
Team		0.002***	-0.002***		-0.001	-0.013***
		(0.000)	(0.000)		(0.002)	(0.002)
Experience		0.000***	0.000		0.000***	-0.000*
		(0.000)	(0.000)		(0.000)	(0.000)
Single Inventor		-0.038***	-0.018***		-0.134***	-0.071***
		(0.001)	(0.001)		(0.007)	(0.007)
Assignee			0.021***			0.062***
			(0.000)			(0.001)
Self			-0.024***			-0.214***
			(0.002)			(0.012)
Constant	-4.241***	-4.232***	-4.316***	-5.105***	-5.048***	-5.291***
	(0.007)	(0.008)	(0.008)	(0.084)	(0.085)	(0.085)
N	1,690,973	1,690,973	1,690,973	1,690,973	1,690,973	1,690,973
R^2	0.135	0.136	0.142	0.1020	0.1026	0.1068
Log Lik				-5.11e+05	-5.11e+05	-5.09e+05
Chi squared				83.905.815	84.783.230	89.459.625

***, **, and *** indicate respectively 10%, 5% and 1% statistical significance.** The first three columns reports the results of Ordinary Least Square on the median value of conventionality in patents. The last set of columns report the results of a logit regressions on the likelihood of a patent of belonging to the most unconventional 10%. Regressions include 21 year dummies and 37 technology dummies; all dummies are jointly statistically significant. Regressions include also controls (dummies) for missing information concerning the age of the backward citations and whether the backward citations is made of one single patent. Standard Errors are robust to outliers in the case of the OLS results in the first three columns.

2.5.3 Technological Impact

This section discusses the results of a set of generalized negative binomial models for the technological impact of inventions (forward citations).

Table 2.9 reports the estimations for the technological impact of inventions by considering only the Unconventionality measure and the other indicators of novelty. Unconventionality is positively associated with forward citations. Original inventions and those based on new combination (NR) also received more forward citations. In line with expectations, interdependence and cumulative usage are negatively associated with technological impact. The dispersion of unconventionality is lower compared to the other indicators.

Table 2.10 reports the estimations for the technological impact using all variables. Both median Unconventionality and minimum Unconventionality are positively associated with future citations. This finding indicate that unconventionality, both at median value and at its most unconventional effort, is associated with higher impact on future technological developments. However, when they are introduced together in the analysis, median Unconventionality turns negative and significant, whereas minimum Unconventionality remains positive. Inventions combining components in an unconventional fashion are on average more cited. The effect is more pronounced for those inventions that are unconventional in their most unconventional combination (minimum unconventionality) as compared to inventions that are unconventional at the core of their combinations (median unconventionality). In line with Uzzi et al., (2013), this may suggest that inventions combining unconventional combinations within an established framework may benefit from the highest impact. This result is also in line with Schilling and Greene (2011), who argue that it suffices a very small amount of unconventional combinations to connect large bodies of knowledge, that otherwise would remain distant.

Higher interdependence and cumulative usage of components are associated with lower impact. In line with expectations, higher score of originality and new pairwise combinations on average receive significantly more forward citations. Compared to the other indicators of novelty, the results show that Unconventionality has a lower dispersion. This may suggest that measures based on the first combination are riskier and originate from a process of experimentations characterized by potentially many failures. Unconventionality measure instead captures not only the inventions at are at the extreme of the continuum of novelty (most and least unconventional) but it also includes those inventions that are in between.

Impact is positively associated with the number of claims in a patent used in the literature as a further indication of the originality of an invention. For what concern reference to prior art, the number of backward citations as well as the number of patent classes therein and references to previously unconnected scientific fields have a positive influence on future impact. This finding is in line with the view that inventions spanning across a wide spectra of the knowledge space receive a higher number of citations. The ratio of citations coming from non-patent literature is negatively associated with impact. This result has to be understood in combination with the coefficient associated with the number of backward citations, indicating that patents drawing mostly from outside the patent literature have a limited impact on future inventions[13].

Finally, inventions from larger teams receive a larger number of future citations, whereas inventions by lone inventors and large applicants receive less citations, ceteris paribus.

All in all, these results provide evidence that unconventionality is associated with higher impact, especially when it is related to the most creative act, as long as it remains embedded in established frameworks.

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[13] Regressions include 21 year dummies and 37 technology dummies; all dummies are jointly statistically significant. Regressions include also controls (dummies) for missing information concerning the age of the backward citations and whether the backward citations is made of one single patent. In this regression we also control for the number of claims reported in the focal inventions. The over-dispersion parameter, unreported, is significantly different from zero. High level of conventionality as well as the variable Min Conv and increase the dispersion. However L_Conv and Min Conv decrease the dispersion in the full model. Interdependence decrease the dispersion, Originality and NR increase it. Note that the dispersion parameter is shown only for the main variables of interest.

Table 2.9: Generalized negative binomial regressions estimating the impact of inventions: comparison with exiting indicators.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Unconven.	**0.132***** **(0.002)**					**0.108***** **(0.002)**
Interdependence		-0.065*** (0.001)				-0.061*** (0.001)
Originality			0.122*** (0.003)			0.059*** (0.003)
NR				0.285*** (0.007)		0.260*** (0.007)
Cumu_Usage					-0.000*** (0.000)	0.000*** (0.000)
Constant	2.335*** (0.017)	1.869*** (0.016)	1.891*** (0.019)	1.800*** (0.016)	1.815*** (0.016)	2.386*** (0.020)
lnalpha						
Unconven.	**-0.023***** **(0.002)**					**-0.019***** **(0.002)**
Interdependence		-0.022*** (0.001)				-0.020*** (0.002)
Originality			0.110*** (0.004)			0.092*** (0.004)
NR				**0.097***** **(0.008)**		**0.079***** **(0.008)**
Cumu_Usage					0.000*** (0.000)	0.000*** (0.000)
Constant	0.115*** (0.022)	0.210*** (0.021)	0.056** (0.025)	0.190*** (0.021)	0.197*** (0.021)	-0.004 (0.027)
Observations	2,037,731	2,037,731	1,690,973	2,037,731	2,037,731	1,690,973
Pseudo R^2	0.0190	0.0189	0.0192	0.0187	0.0184	0.0202
Log Lik.	-7.14e+06	-7.14e+06	-6.04e+06	-7.15e+06	-7.15e+06	-6.04e+06
Chi squared	1.75e+05	1.73e+05	1.49e+05	1.71e+05	1.68e+05	1.61e+05

***, **, and *** indicate respectively 10%, 5% and 1% statistical significance.** Regressions include 21 year dummies and 37 technology dummies; all dummies are jointly statistically significant. Regressions include also controls (dummies) for missing information concerning the age of the backward citations and whether the backward citations is made of one single patent. In this regression we also control for the number of claims reported in the focal inventions. The over-dispersion parameter, is significantly different from zero.

Table 2.10: Generalized negative binomial regressions estimating the impact of inventions.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Med. Unconven.	0.074***		-0.041***	-0.152***	-0.174***	-0.168***	-0.173***	-0.042***
	(0.002)		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Min Unconven.		0.100***	0.137***	0.303***	0.307***	0.321***	0.327***	0.124***
		(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Interdependence				-0.026***				-0.014***
				(0.001)				(0.001)
Originality					0.065***			-0.007**
					(0.003)			(0.003)
NR						0.252***		0.198***
						(0.006)		(0.006)
Avg_Cumu_Usage							-0.000***	0.000
							(0.000)	(0.000)
NTO	-0.024***	-0.025***	-0.025***					-0.044***
	(0.001)	(0.001)	(0.001)					(0.002)
NSO	0.142***	0.143***	0.143***					0.115***
	(0.010)	(0.009)	(0.009)					(0.007)
Citations	0.225***	0.223***	0.223***					0.228***
	(0.002)	(0.002)	(0.002)					(0.002)
Science	-0.025***	-0.025***	-0.025***					0.017***
	(0.005)	(0.005)	(0.005)					(0.006)
Component	0.039***	0.030***	0.027***					0.025***
	(0.000)	(0.000)	(0.000)					(0.001)
Age	-0.000**	-0.000**	-0.000**					-0.000
	(0.000)	(0.000)	(0.000)					(0.000)
Spread Age	0.000*	0.000**	0.000**					-0.000
	(0.000)	(0.000)	(0.000)					(0.000)
No Patent	-0.125***	-0.131***	-0.132***					-1.342*
	(0.014)	(0.014)	(0.014)					(0.747)
Team	0.033***	0.033***	0.033***					0.036***

	(0.001)	(0.001)	(0.001)					(0.001)
Experience	-0.000	-0.000	-0.000					0.000**
	(0.000)	(0.000)	(0.000)					(0.000)
Single Inventor	-0.039***	-0.038***	-0.039***					-0.036***
	(0.003)	(0.003)	(0.003)					(0.003)
Assignee	-0.006***	-0.007***	-0.007***					-0.009***
	(0.000)	(0.000)	(0.000)					(0.001)
Self	-0.048***	-0.048***	-0.049***					-0.057***
	(0.003)	(0.003)	(0.003)					(0.003)
claims	0.013***	0.013***	0.013***					0.012***
	(0.000)	(0.000)	(0.000)					(0.000)
Constant	1.251***	1.363***	1.341***	2.260***	2.266***	2.223***	2.238***	1.396***
	(0.018)	(0.018)	(0.018)	(0.017)	(0.020)	(0.017)	(0.017)	(0.021)
lnalpha								
Med Unconvent	-0.039***		-0.025***	-0.010**	-0.015***	-0.023***	-0.020***	0.002
	(0.002)		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Min Unconvent		-0.038***	-0.016***	-0.030***	-0.016***	-0.013***	-0.012***	-0.036***
		(0.002)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)
Interdependence				-0.025***				-0.031***
				(0.001)				(0.002)
Originality					0.110***			0.064***
					(0.004)			(0.004)
NR						0.103***		0.033***
						(0.008)		(0.008)
Avg_Cumu_Usage							0.000***	0.000***
							(0.000)	(0.000)
	(0.012)	(0.012)	(0.012)					(0.008)
Constant	0.033	0.039	0.021	0.046**	-0.083***	0.020	0.046**	0.064**
	(0.025)	(0.025)	(0.025)	(0.022)	(0.027)	(0.023)	(0.023)	(0.030)
N	2037026	2037026	2037026	2037731	1690973	2037731	2037731	1690504

***, **, and *** indicate respectively 10%, 5% and 1% statistical significance.**

2.6 Discussion and Conclusion

In this study we investigate the origins of unconventional combinations of knowledge components. Unconventional or novel combinations are largely believed to be at the foundation of breakthrough inventions as they establish new connections between distant and overlooked domains of knowledge. In so doing, they remove obstacles and bottlenecks to the combinatorial power of research and development efforts, thus favoring an upsurge of follow on inventions.

By considering the inventive process as a process of recombinant search, in our analysis, we first discuss the concept of distance in the search process and then how it influences the extent of unconventionality in the inventive process.

As inventors typically search locally, they will mostly recombine technological components in a conventional manner, i.e. according to the structure with which relationships have proved to work in the past. By extension, most inventions will be the outcome of conventional combinations. We thus propose a measure to determine the distance among the elements of the technological space - Unconventionality measure. We borrow the concept and operationalization of relatedness from the literature on product market diversification (Teece et al., 1994) and adapt it to our purpose in the same fashion as in Breschi et al. (2001) and Nesta and Saviotti (2005). We use patent documents at USPTO between 1975 and 2000 to measure unconventionality in combinations, in inventions at the core of their combinatorial effort (median) and at the most unconventional instance (minimum). Our approach rests on a fairly stable feature of the patent system, the patent classification, which is only marginally subject to variations, and therefore more reliable in the determination of the measure. We claim that this indicator captures the extent of unconventionality in the recombinant process over the technological landscape.

Our results confirm that most of the recombinant and inventive activities are grounded in conventional efforts, with some rare instances of unconventional connections. Furthermore, we show that average conventionality decrease over time providing indirect evidence that unconventional combinations may contribute to shifts of the technological paradigms.

We identified the main drivers of distance in the search process, which we expected to be responsible for unconventional combinations. We find that patents that take a broader view by citing a widespread spectrum of previous results, both in science and technology, have a higher chance to identify unconventional connections. Moreover, patents having no backward citations of any kind are more conventional. Unconventionality is more likely to occur with experience, and in large organizations.

We provide suggestive evidence on the relationship between unconventional combinations and future impact. We observe a premium on future impact from unconventionality: inventions embodying conventional combination in their core but carrying forward unconventional combinations in their most unconventional acts are cited more by future patent applications than conventional inventions.

The contributions of this study are manifold. From a theoretical standpoint, the results are in line with the body of work on the theory of recombinant invention and creativity in general. This stream posit that agents mostly work in the neighborhood of their competences. Combinations mostly occur with components whose associations have proved to be effective by past use. Inventors eventually experiment with a limited set of components at a time (Fleming, 2001). Much like in Schilling and Greene (2011), this outcome confirms that novel and unconventional combinations are at the origin of high impact solutions as they bridge deep pools of coherent and established knowledge. Unconventional combinations bring together distant concepts and ideas, reshaping the associative framework within which concepts are related and rendering associations that had been overlooked suddenly feasible.

Chapter 3

Sailing in all Winds: Technological Search over the Business Cycle⁕

3.1 Introduction

The Global Financial Crisis of 2007-2009[14] has showed how deep recessions may affect the ability of firms to persistently invest in innovation, with important consequences for long-term competitiveness and economic growth (OECD, 2012). Despite the heterogeneous response across countries and sectors, a large fraction of firms in the European Union have curtailed their R&D expenses, calling for a deeper understanding of the effects of crises on the innovative strategies of firms (Filippetti & Archibugi, 2011). The scholarly debate on the effects of economic crises, business cycle in general, and innovation, has identified a pro-cyclical relationship and the centrality of financial constraints in the R&D investment decisions of firms (Aghion & Saint-Paul,1998; Aghion et al., 2012; Campello et al., 2010).

⁕ This chapter is based on working paper, joint with Antonio della Malva (KU Leuven) and Massimo Riccaboni (IMT Lucca / KU Leuven). We thank Gino Cattani, Reinhilde Veugelers for their valuable comments and suggestions as well as participants at the internal seminars at MSI-KU Leuven, the 3rd KTO workshop at SKEMA Business School, the XXXI EGOS Conference, the 5th SEEK Conference in ZEW, the T2S Annual Conference in Dublin , the Large-scale Crises: 1929 vs. 2008 Conference in Ancona and the 50th Anniversary SPRU Conference at the University of Sussex. We also thank Andrea Morescalchi for assistance on the first version.

[14] The 2007-2009 Financial Crisis motivated this study however due to data constraint our analysis only include the period 1980-2000. The measure of conventionality that we use in this study to assess the recombination process only include inventions up to 2000 before the introduction of new technological classes that can influence our results. We leave to future research the expansion of our dataset and hence the inclusion of the 2007-2009 Financial Crisis.

In this study we extend this line of research by exploring the relationship between the inventive process and business cycle. We argue that tighter economic conditions not only affect the propensity of firms to invest in R&D, but also shape the type of inventions that are pursued and generated. In response to a decline in output and profits, firms can be expected to focus on less challenging roads through local search in the attempt to innovate incrementally. Innovations departing from conventional technological paradigms have a fundamental impact on society (Dosi, 1982) motivating this study to investigate the recombination process along the business cycle.

Inventions are the final result of a process of search and recombination of knowledge into new domains of applications or reconfiguration of existing knowledge into novel combinations (Fleming, 2001). The search for novel combinatorial possibilities usually occurs in the proximity of firms' competences through local search, characterized by lower levels of risks and uncertainty as it builds on past failures, extant competences and previous successful solutions (Cyert & March, 1963; Simon, 1978). However, connections of pieces of knowledge that are already highly related, or complementary, are likely to hinder the possibility of producing impactful inventions (Perkins, 1995). Unlike local search, distant search explores new and unfamiliar technological domains, with greater possibilities of extending the range of combinatorial alternatives (Katila & Ahuja, 2002). The ultimate result of this process is that inventions are more likely to include new, atypical or original coupling relationships characterized by higher level of (un)conventionality (Levinthal & March, 1993; Simonton, 1999; Schilling, 2005; Katila & Chen, 2009). Compared to local, distant search is a costly activity, characterized by higher levels of uncertainty and failures as it requires more efforts in the selection and integration of relevant knowledge (Fleming, 2001). Although inventions resulting from local search have a positive impact on productivity growth (Baumol, 2002), novel or breakthrough innovations, resulting from distant search, prevent from core rigidities traps with positive impacts on performances and long term competitiveness (March, 1991; Leonard-Barton, 1992).

To study how firms adapt their search strategies to the business cycle, we analyze the variation of the degree of unconventionality in patented inventions at the USPTO over the business cycle between 1980 and 2000. For this purpose, we have assembled an original database which links patent data from the USPTO (Li et al., 2014) to financial information of firms listed in Compustat and macro-economic data related to the business cycle from the NBER-CES Manufacturing Industry database. To capture the degree of technological unconventionality, we employ a measure of relatedness of knowledge components recombined in inventions (see Chapter 1 and Appendix A for the derivation of the measure). In line with the extant literature acknowledging the link between economic growth and impactful innovations, we also consider the technological impact of inventions by analyzing the relationship between business cycle and unconventionality on forward patent citations. Unlike previous studies which used measures of innovation input and output, aggregated at the level of countries, sectors and firms, our approach relates individual inventions, and their characteristics, to the phases of the business cycle, allowing for a finer analysis of the relationship.

Our results indicate that, during contractive phases, firms retrench from novel inventive activities. Inventions generated during the recessive phase of the cycle embed more established combinations, resulting from a process of search which is more localized in the technological space. Therefore, not only are downturns associated with a reduction in the amount of innovative inputs and outputs, as the financial constraint arguments predict, but also the resulting output is characterized by lower levels of novelty. We further investigate some mechanisms that affect the relationship between inventiveness and the business cycle by analyzing the extent to which the decision to cancel or postpone novel inventive projects depends on the reliance on external financing and the technological competences of firms. We find that the retrenchment from unconventional inventive activities is pronounced among financially constrained firms, whereas unconstrained firms do not change their inventive behavior along the business cycle. Looking at the technological portfolio of firms, we notice that firms become more conservative in their inventive efforts in the core of their technological competences. Finally, impact-wise, the results suggest that the consequences of retrenching from novel inventive activities can be most harmful for financially constrained firms. We claim that this is due to the fact that they are forced to cancel or postpone projects in the core of their technological competences.

This study extends the scholarly debate that has mainly dealt on the impact of recessions on the input side of innovation, i.e. R&D expenditures (Barlevy, 2004, 2007; Ouyang, 2011; Aghion et al., 2012; Amore, 2015; Pauvnov, 2012; Filippetti and Archibugi, 2011). Our findings also contribute to a more recent stream of literature that has focused on innovation outputs and on the effectiveness of technology policies (Hud & Hussinger 2015; Berchicci et al., 2013; Cincera et al., 2010; Ouyang, 2011; Fabrizio & Tsolmon 2014). Finding that managers are less willing to embark in novel inventive activities during downturns, characterized by higher uncertainty, indicates that the reduced profitability and the lower availability of resources experienced by firms affect investment decisions not only at the *extensive* margins (the amount of resources dedicated to innovation expressed by a change in the size of the portfolio), but also at the *intensive* margins (the riskiness of the inventive projects being pursued, expressed by the degree of unconventionality in the surviving portfolio). These results extend the literature on the behavioral theory of the firm in general and the role of slack resources in particular (Cyert & March, 1963; Troilo et al., 2014). An increase in uncertainty following challenging economic conditions shortens the time horizon with which managers make their investment decisions (Kahneman & Lovallo, 1993), especially with regards to innovation, as they prefer to invest in projects whose returns are more predictable.

From a policy perspective, the evidence that firms engage in less novel inventive projects during contractive phases, in particular financially constrained firms, call for an active role of policy makers not only to sustain the level of R&D investments but also to intervene in the decisions and incentives of which type of innovation to pursue (Mazzuccato, 2015). Indeed, a recent contribution by Hud and Hussinger (2015) has documented a crowding-out effect from subsidy recipients in Germany during the last financial crisis, especially among SMEs. Our result add to their finding suggesting that firms may use R&D subsidies to finance less novel projects.

The remainder of the paper is organized as follows. The next section presents a review of the literature on the relationship between innovation and business cycles. Section 3.3 describes the data and the empirical model whose results are discussed in section 3.4. The chapter concludes with section 3.5

with a summary of the main findings and a discussion of the policy implications.

3.2 Innovation and the Business Cycle

Dating back to Schumpeter (1939), scholars have questioned the relationship between business cycles and innovation. Two competing arguments have emerged. A first approach states a counter-cyclical relationship between downturns and innovations, i.e. innovation increases during downturns. This argument is based on a lower opportunity costs that firms can exploit for investing in innovation (Saint-Paul, 1997; Aghion & Saint-Paul, 1998). Firms have higher incentives to allocate internal resources to the development of innovations via new products (Berchicci et al., 2013). As returns from existing product lines and activities decline, firms are more prone to search for new market niches less affected by the downturn, reducing the risks through diversification. Geroski and Walters (1995) advocate that firms have higher incentives to innovate when the loss associated with a decline in current activities is larger than the relative returns to be gained from implementing new product or process. The introduction of new products during downturns enables firms to establish a leading position in the eyes of consumers when the demand recovers (Steenkamp & Fang, 2011). Firms also have higher incentives to introduce cost-saving process innovations in order to reduce the costs of production and therefore match the lower demand. Moreover, the advantages stemming from more efficient production processes can provide firms with an advantage when the economy recovers (Saint-Paul, 1997).

A second perspective theorizes a pro-cyclical relationship, stating that innovative activities decrease during downturns due to a reduction in resources allocated to R&D. Following this argument, profit-maximizing firms will time their innovation activities to periods of high-demand to capture higher profits (Schleifer, 1986). As the demand for goods and services decreases during downturns, firms usually experience a reduction in profits. The reduced profitability translates in fewer resources, especially liquidity, which limits firms' ability to invest in innovation (Barlevy, 2007; Fabrizio & Tsolmon, 2014). Moreover, the availability of external resources to finance innovation, such as bank loans, decline as financial institutions may deleverage from existing investments and be more reluctant to finance risky projects (Aghion et al., 2012). The limited amount of liquidity and a higher perceived risk, bias firms' decisions in the pursuing more conservative approaches, whose returns are certain and closer in time (Bovha Padilla et al., 2009).

The empirical evidence has mostly documented a pro-cyclical relationship between general economic, industry-specific fluctuations and input/output measures of innovation (Barlevy 2007; Geroski & Walters, 1995; Ouyang, 2011; Fabrizio & Tsolmon, 2014). Using data for manufacturing sectors over four decades, Ouyang (2011) finds that the cyclical pattern of R&D investments is due to the existence of financial constraints that limit the ability of firms to sustain high levels of R&D during downturns. However, the author finds that sectors react negatively to positive shocks in the economy, advancing that the opportunity cost argument, despite not being predominant, is also in place. Using a sample of French firms, Aghion et al. (2012) complement these findings by showing that the effect of financial constraints is not uniform across firms and sectors. The relationship between R&D and business cycle is pro-cyclical for firms with higher dependence on external capital and fewer collaterals and in sectors more exposed. Moreover, the authors find that the ratio of R&D to total investments is counter-cyclical, supporting the view that firms limit the negative effects of cash-flow fluctuation on R&D by relying on internal reserves of cash (Himmelberg & Petersen, 1994). Using patents as measure of output, Geroski and Walters (1995) find that in the UK patent output clusters around periods of boom over a period of 40 years. The results suggest that economic fluctuations drive inventive activities, in line with the view that firms time their innovative activities with periods of high customer demand. Along these lines, Fabrizio and Tsolmon (2014) show that the relationship between business cycles and patenting differs across sectors. The authors use firm data from Compustat from 1975 to 2002 to show that the relationship is positively moderated by the likelihood of imitation and the rate of product obsolescence of sectors. Berchicci et al., (2013) have analyzed the relationship between industry fluctuation and types of innovation, namely product and process innovation. The results of this study suggest that the opportunity cost and the financial constraint arguments co-exist when product and process innovations are considered separately. The authors show that, for a panel of Italian firms, product innovation is most likely to occur during downturns, therefore supporting the counter-cyclical argument. During industry downturn, firms engage in product innovation while holding back on process innovation (Berchicci et al., 2013). The authors suggest that engaging in process innovation is less likely since it may be not profitable to improve the efficiency of producing existing lines of products whose value is dropping. Process innovation is thus more likely to coincide with upturns, as the financial constraint argument indicates (Devinney, 1990).

Based on the first line of argument, we would expect firms to engage in distant search during the contractive phases of the industry cycle. Firms incentives to orchestrate more unconventional innovations would be higher during this phase due to a decrease in profitability on existing products. Firms may also experience an excess of slack resources that may be reallocated to more explorative search at lower marginal costs.

Based on the second line of argument, we would expect firms to be less prone to engage in distant search due to higher constraints in financial resources. Moreover, due to a lower demand, firms may perceived the exploration of new domains as a riskier activity relative to periods of more favorable market conditions.

3.3 Data and Methodology

Our research strategy tracks the degree of Unconventionality of patent production over time with respect to the technological portfolio and financial characteristics of firms, as well as economic conditions in the manufacturing industry business cycles. The unit of analysis is represented by the single patent[15]. We use data on utility patents granted by the United States Patent and Trademark Office (USPTO) between 1980 and 2000[16] (Li et al., 2014). The

[15] The focus of this study is the recombination process which is manifested in the final invention. As a consequence our analysis are patent based as allow us to examine the recombination process at a more disaggregated level. Firm level analysis are provided in the appendix for robustness checks.

[16] We consider only granted patents between 1980 and 2000 in order to guarantee consistency in the conventionality measure used in this Chapter. In 2001 new technological classes were introduced and for consistency we only computed conventionality measure up to 2000. Details on the derivation of the measure are available in the Appendix to this Chapter and in Chapter I.

database includes procedural information about patents (i.e. publication and application number, grant and application date, claims), inventor and assignee data and complete references to the technological classes and subclasses according to the US Patent Classification (USPC) system. The USPC system is articulated in more than 400 classes, representing broad technological fields, and about 100,000 subclasses, that point to specific technological divisions within each class. Patent subclasses identify, in our framework, the knowledge components available for the search and recombination process (Fleming, 2001). We complement the dataset with the relational table of patents and firms from Orbis Bureau Van Dijk. Orbis provides information on about 70.000 listed companies. We matched the patent dataset with firms' financial accounts database and we used the companies' sector of operation to retrieve sector-level information.[17]We matched firm-level data with the NBER-CES Manufacturing Industry Database, which contains annual industry-level data (i.e. number of workers, total payroll, value added) for the U.S. manufacturing sector from 1958 to 2009 (Becker et al., 2013).[18] Our final dataset comprises 166,168 patent observations belonging to 1,077 US firms with at least one listed activity operating in the manufacturing sector between 1980 and 2000. Table 3.1 reports the summary statistics.

3.3.1 Dependent Variables

We measure the degree of unconventionality (***Unconventionality***) in the technological space by the extent to which an invention is the result of a search and recombinant process that departs from established and conventional practices. Leveraging on the concept of relatedness, previously used to assess the diversification of business activities (Teece et al., 1994) and technological portfolios of firms (Breschi et al., 2003; Nesta & Saviotti 2005), we define as novel those combinations of knowledge components embedded in inventions that are distant in the knowledge space, or rarely coupled together. We conceptualize distance as the strength of the relationship among the

[17] The exclusion from Compustat of non-listed firms may generate possible sample selection bias as typically smaller firms are not included. However, the potential bias is diminished by the fact that normally US firms have a high recourse to stock markets and R&D is concentrated in publicly listed firms which enable Compustat to have a reliable coverage on long historical data and extensive financial and operating accounts for a large time window, 1950-2013.
[18] The manufacturing sector includes a large concentration of R&D investments which ranges between 70-80% (Barlevy, 2007).

components underlying inventions. Hence, two components will be close in the technology space, if their joint occurrence is highly frequent. This is likely to be the outcome of a systemic search towards related or familiar paradigms. Conversely, two components are more distant if their joint occurrence in previous inventions is rarer with respect to what a random process would predict. The combination of strongly related components indicates that inventions build on an established technological base, as opposed to the combination of distant and rarely combined elements in the knowledge space which are associated with more novel inventions. Based on the USPTO patents population and its classification system, we derive a patent-based measure of unconventionality by computing the yearly frequency of the joint occurrence[19] of each possible combination of subclasses within the same patent. We then compare the observed occurrence to the outcome of a purely random process.[20]

3.3.2 Independent Variables

Drawing on prior studies about innovation and business cycles (Barlevy, 2007; Fabrizio & Tsolmon, 2014), we compute nominal gross output by summing annual value added and material costs for each of the three-digit SIC industries in the NBER Manufacturing and Productivity database (Bartelsman & Gray, 1996). Then we calculate the annual real gross output (RO) for each industry by dividing the nominal gross output by each industry's shipments deflator as provided by the NBER database. We use the variation of the natural log of real gross output (lagged by 1 year) to identify ***Contraction***[21] (e.g. negative growth rate of RO). As we are mostly interested in the relationship between search strategies and the downturn phases of the business cycle, we multiply

[19] Note that we identify the joint occurrence of the components at year *t* and observe the recombinations of these two components with other technologies in the knowledge space in the previous 5 years. See Chapter 1 and Appendix B for details on the derivation of the measure.

[20] As an example, the patent "US6180351", assigned to Agilent Technologies Inc., has a high degree of unconventionality in the knowledge recombination process. In 1999 (application year) this patent recombined two components, i.e. database maintenance principles [class 707/200] and nucleic acid base hybridization processes [class 435/6 for molecular biology and microbiology], that were previously used mostly independently.

[21] In line with previous studies (de Rassenfosse & Guellec 2009; Hall et al.,1986; Kondo, 1999) we use a one year lag of this variable. These studies have showed that R&D investments create patent applications within a time lag of about a year and half. Results with two years lag are provided in Appendix B.

Contraction by (-1), higher value are associated with a deeper contraction in Real Output.

Positive growth is output is captured by the variable ***Expansion***. However, firms may have different responses to a variation in the growth rate of RO depending on the total level of output at which the variation occurs. Hence, we also include in our empirical setting the natural log of real gross output lagged by 1 year (***RO***).

3.3.3 The role of Financial constraints

Due to the inherent riskiness and uncertainty, innovations, in particular novel inventions, are more difficult to finance through external sources of capital than other types of investments (Amore et al., 2013; Hall & Lerner, 2010; Peia, 2016). These problems are exacerbated during downturns, when profitability and availability of internal finance decrease and the financial sector lends a lower share of their total asset (Himmelberg & Petersen, 1994). Moreover, financially constrained firms will be more exposed to credit shortage during downturns (Aghion et al., 2012). It follows that during recessions retrenchment from original inventions is expected to be more pronounced in firms which mostly depend on external capital. To understand how the degree of unconventionality varies according to the dependence on external finance, we use the ***Kaplan and Zingales Index*** (1997) that measure firms' dependence on external financial capital. The Index is a linear combinations of cash flow, market value, debt, dividends, cash holding and assets.[22] Firms with fewer availability of liquid assets, lower ratio of cash flow and dividends to assets, higher ratio of debt to assets and Tobin's Q are

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[22]The Kaplan and Zingales Index is defined as:

$$KZ_{it} = -1.002\frac{CF_{it}}{PPE_{it-1}} - 39.368\frac{Div_{it}}{PPE_{it-1}} - 1.315\frac{CHE_{it}}{PPE_{it-1}} + 3.139LEV_{it} + 0.283Q_{it}$$

where cash flow (CF) is the sum of Income before extraordinary items and depreciation and amortization (Compustat IB+ DP items), dividends (Div) common and preferred (Compustat DVC+DVP items), CHE refers to cash and short term investment. These variables are normalized by lagged PPE. Leverage (LEV), is the ratio of long term debt (DLTT item) and debt in current liabilities (DLC item) to stockholders equity (SEQ item). Tobin's Q (Q) is the ratio of total asset (AT), Market Value of Equity (CSHO*PRCC_F) minus the book value of equity (CEQ) and deferred taxes (TXDB) to total assets. According to Kaplan and Zingales (1997), firms are financially constrained as the wedge between internal and external funds increases with increasing cost in rising external sources of capital.

expected to be more financially constrained and hence have more difficulties in financing their ongoing operations when economic conditions tighten. High values of the Index flag firms that rely heavily on external sources of funds and are characterized by high debt, low cash-flow and low dividends whereas lower value are associated with more resilient firms. We use the median value of the index to split the sample according to firms' reliance on external finance (Table 3.2).

3.3.4 The Competences of the firm

The perceived risks and uncertainty related to distant search are not uniform across the technological portfolio of firms (Brusoni et al., 2001). Firms indeed mostly operate in the core of their technological competences, being those technologies in which they dedicate a large amount of resources and have secured a strong advantage. Conversely, non-core technologies are associated with activities aimed at expanding the technological base of the firm (Granstrand et al., 1997). Core technologies can support the ramification in new technological domains by allowing a more efficient search for solutions (Granstrand et al., 1997; Katila & Chen, 2009). Technologies in this set of activities are frequently recombined and are usually linked to the upgrade of existing products or to ongoing R&D projects. On the other hand, technologies that are at the periphery of the firm's activities entail a deeper experimentation process functional to the exploration of new technologies, knowledge and ideas that lead over time to the development of new products or processes (Gatignon et al., 2002). As the exploration phase requires time, these activities are usually associated with more time to market.

To measure whether inventions belong to the core versus the peripheral competences of the firm, we use the Revealed Technology Advantage (***RTA***) index (Patel & Pavitt, 1997), calculated on the 36 technology categories proposed by Hall et al. (2001). Patents are assigned to technological categories using their primary patent class[23] (Li et al., 2014). The RTA index has been computed at the company level. It is given by the firm's share of patents in a particular technology divided by the share of patents in that technology at the

[23] USPTO assigns patents to "Original Class" or primary classes on the base of the broadest claim reported in the patent. This class best describe the inventive step of the patent and is generally reported in bold font in the first position on the front page of a patent (USPTO, 2003).

USPTO level. We labeled as ***Core*** all those technology fields whose RTA is above one and ***Non-core*** those with values less or equal to one. It turns out that the distribution of patents is highly skewed with 88% of inventions in the core technologies of firms (Table 3.3).

3.3.5 Control variables

We introduce a battery of controls concerning the invention (patents) and the firms. On the invention side, we account for the extent to which the focal patent builds on prior knowledge using backward citations (***Citations***). We calculate the natural logarithm (plus 1) of the number of backward citations to prior art. However, original recombination of components might be the result of completely new combinations which are not based on pre-existing knowledge (Ahuja & Lampert, 2001). Hence, we also account for the possibility that inventions do not cite prior art (***No Prior Citations***). The degree of novelty characterizing each invention is a positive function of the number of knowledge components that are recombined. In our framework, the ***Number of Technological Components*** are represented by (the natural log of) the number of technological subclasses on which the patent is based. Drawing on the organizational literature, we also include a set of controls for the inventive process at the level of inventive teams. Since knowledge is distributed among individuals, teams may facilitate the recombination of competences and hence draw solutions from a more diversified pool (Singh & Fleming, 2010). We capture the composition of teams by accounting for the number of inventors in every patent, ***Team***. We also control for the experience of inventors by considering (the natural logarithm of) the total number of patents of the most prolific inventor in the team, i.e. ***Experience***. We also include company characteristics that may influence the propensity to engage in novel search strategies. Large firms have been found to be path dependent, usually confined within their established routines and practices showing resistance towards new or more radical solutions (Hill and Rothaermel, 2003). Yet, they also build on a larger knowledge base from which they can easily diversify their technological portfolio (Leten et al., 2007). Hence, we control for the firm inventive size ***Assignee Size***, computed as the (log plus one) of the total number of patents at the USPTO in the year of the focal invention**.** The concentration of firms' R&D portfolios may affect the knowledge recombination process. Hence, we control for the technological ***Concentration*** of firms over technological classes through the use of the Herfindahl index of concentration. This measure will take the value of one for firms having a very concentrated patent portfolio, whereas it will approach zero for technologically diversified firms. We also identify patent whose assignee show a tendency to cut in R&D during the contraction phases of the cycle. These firms may be more sensitive to fluctuations in the industry and prone to engage in local search (***Cut in R&D***). We finally add dummies for ***Year, Technologies*** and ***Sectors*** to account for possible trends over time and differences among technologies and sectors. Summary statistics of the variables are showed in Table 3.1. Table 3.2 presents summary statistics for low versus high financially constrained. Table 3.3 presents the correlation among the variables.

3.4 Results

In our empirical strategy we focus on the effect of business cycle on the type f knowledge recombination undertaken by firms. The unit of analysis is represent by the patent (Appendix B reports the firm level analyses that provide a better understanding on the intensive and extensive margins). Specifically, we distinguish between the growing and contractive phases of the business cycle, controlling for invention, inventors and organizational characteristics as well as years, technologies dummies and firm fixed effects Table 3.4-(model 1). Demand driven factors play a significant role in the timing and characteristics of innovations (Fabrizio & Tsolmon, 2014). During downturns, demand decline. The main consequence is that firms could perceive distant search as highly risky and uncertain relative to the expansion phases of the cycle. Hence, firms become more sensitive to risks associated with novel inventions which are likely to be postponed to the upturns of the cycle (Yang et al., 2004; Steenkamp & Fang, 2011). As we cannot directly test any effect due to changes in the behavior of consumers, in Table 3.5 we shed light on the relationship between unconventionality and downturns by focusing on the financial health of firms (model 2). In model 3 we show the estimations for patent in the portfolio of firms having a tendency to cut during the contractive phases of the cycle versus those that do not have this tendency. The retrenchment from novel projects does not impact the entirety of technological competences of firms. Firms develop specialized competences in core activities where the exposure to risks is lower due to a robust and cumulated knowledge base (Nickerson & Zenger, 2004). Along this line, we distinguish between core and non-core inventions to highlight potential differences between this set of firms' activities during the contractive and growing phases of the cycle (model 4). In a second set of regressions we use the same models to investigate how the technological impact of inventions is influenced by the reorientation of firms’ search strategies along the business cycle (Table 3.6)

Table 3.1: Summary statistics

Description	Variables	Obs.	Mean	Std. Dev.	Min	Max
Higher values are associated to more atypical combinations	Unconventionality	166,168	-3.543	0.619	-6.679	-1.316
RO_{t-1}	Real Output	166,168	10.422	1.545	5.255	13.61
$(R.O_t - R.O_{t-1}/ R.t_{t-1}) > 0$	Expansion	166,168	0.012	0.015	0	0.112
$(R. O_t - R. O_{t-1}/ R.O_{t-1}) < 0$	Contraction	166,168	0.001	0.004	0	0.107
Ln(number of bwc.cits+1)	Citations	166,168	2.418	0.896	0	7.064
No prior citations	No Prior Citations	166,168	0.008	0.093	0	1
Ln of the number of technological subclasses recombined	Components.	166,168	1.441	0.561	0.693	5.099
Number of inventors in the team	Team	166,168	2.371	1.565	1	34
Ln (tot. number of patents of most prolific inventor in a team)	Experience	166,168	15.965	29.05	1	485
1- Hirschman-Herfindah index	Diversification	166,168	0.120	0.114	0.0138	1
Ln(tot. number of patents) by the firms	Patent Portfolio Size	166,168	4.882	1.717	0	7.470

Table 3.2: Summary statistics for High and Low Financially constrained firms.

	Low reliance on external financing					High reliance on external financing				
	Obs.	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Unconventionality	103,943	-3.57	0.610	-6.602	-1.551	43,399	-3.48	0.621	-6.679	-1.795
Real Output	103,943	10.107	1.314	5.255	13.610	43,399	11.070	1.719	5.568	13.610
Expansion	103,943	0.009	0.0133	0	0,112	43,399	0.017	0.017	0	0.112
Contraction	103,943	0.001	0.004	0	0.107	43,399	0.001	0.004	0	0.067
Citations	103,943	2.414	0.903	0	7.064	43,399	2.397	0.856	0	6.311
No Prior Citations	103,943	0.088	0.093	0	1	43,399	0.008	0.0926	0	1
Components	103,943	1.441	0.571	0.693	4.962	43,399	1.449	0.540	0.693	4.127
Team	103,943	2.413	1.629	1	34	43,399	2.262	1.388	1	26
Experience	103,943	13.14	18.276	1	298	43,399	23.61	46.58	1	485
Concentration	103,943	0.112	0.115	0.013	1	43,399	0.135	0.115	0.014	1
Assignee	103,943	5.723	1.608	0	9.469	43,399	6.035	2.037	0	9.504

Note: We used the median value of the Kaplan and Zingales Index to split the sample between financially constrained and unconstrained firms with a slightly higher percentage in the group of financially constrained firms (57,39%).

3.4.1 Technological Search Over the Business Cycle

Table 3.5 shows the results of our main analysis of the effect of business cycles on the type of inventions. In model 1 the coefficient of Real Output suggest that a higher level of Output is associated with more unconventional inventions in line with the pro-cyclical view (Fabrizio & Tsolomon, 2014). The coefficient of Expansion suggests that a 1% increase in total Output generates an increase in the level of unconventionality equal to 0.082%. The coefficient of Contraction indicate that a 1% decrease in Output produces a decline in the level of Unconventionality of 0.077%. A Chow test confirms that these coefficients are statistically different from each other. These results indicate that during contractive phases of the cycle, towards the trough, firms retrench from more novel inventions, recombining components in a more conventional way through the use of established combinations. Downturns therefore are not only associated with a reduction in R&D expenditures, as extensively discussed in literature, but also to a decrease in the degree of unconventionality characterizing the search and recombination of knowledge which result in less innovative outputs.[24] It is relevant to note that Unconventionality varies proportionally less in recessions. Hence, firms response to a variation in the level of Output is not symmetric, a variation in the output of the same magnitude generate different responses in downturns and in upturns. The decline in unconventionality is proportionally lower during contractions phases compare to the increase in unconventionality in expansions.

The controls are in line with our expectations. Inventions based on a larger number of components recombine elements in the technological space which are more distant providing possibilities for more novel solutions. Finally, inventions originating from larger teams are based on less novel technological combinations. This result, surprisingly at first, can be explained by the fact that larger teams have the advantage of recombining components from a broad set of competences, but also require a common "language" before integrating very distant domains.

[24] In a separate regression, available in Appendix B (Table B.1), we investigated the evolution of the number of patents.

In line with the pro-cyclical relationship between business cycle and innovation, managers are more cautious with regards to risky investments, such as original innovative projects, during the contractive periods of the cycle. Firms may focus on problems which leverage on established knowledge domains and require the exploitation of existing solutions; they are therefore reluctant to pursue innovative projects based on the exploration of new technological domains through distant search (Cyert & March, 1963; Troilo et al., 2014). Two main factors play a role in the pro-cyclical relationship between novel inventions and the business cycle. On the supply side, firms experience a reduction of resources to allocate to innovation during downturns. On the other side, firms facing lower availability of resources are more concerned about efficiency than efficacy, favoring more conservative projects (Himmelberg & Petersen, 1994).

3.4.2 Technological Search over the Business Cycle: the role of financial constraints and firms' competences

Model (2) in Table 3.5 reports the results for the two subsamples. The coefficient for Contraction is significant only for firms with high dependence on external finance. A 1% decrease in Output produce a decline of 0.08% for firms that are financially constrained. The reaction of low financially constrained firms to variations in the level of Output (expansion and contraction) remain similar in magnitude. A Chow test confirm that the response of low and financially constrained firms is statistically different.

This finding supports the view that the decrease in demand and profitability occurring during downturns mostly affects the innovation strategies of financially constrained firms, which are hindered from undertaking novel inventive projects, characterized by higher risks and uncertainty. Financially resilient firms instead do not change significantly their strategies during downturns and are able to sustain similar levels of unconventionality in their inventions. These results suggest that the availability of slack resources is critical for the pursuit of novel projects based on the exploration of new technological domains. Firms with higher slack resources are more likely to engage in innovative activities characterized by distant search as organizations are less concerned about immediate returns (Danneels, 2008; Levinthal &

March, 1981). Nohria and Gulati (1996) argue that slack resources allows firms to pursuit innovative projects associated with higher levels of uncertainty but also a potentially high pay-off. Financially constrained firms might also have a harder time in retaining top scientists with a consequent decrease in the innovativeness of firms patenting strategies (Hombert & Matray, 2016).

Model 3 differentiate between patents belonging to assignee that tend to cut in R&D during the contractive phases of the cycle versus those firms that do not show this tendency. The coefficient of Contraction is significant only for firms that cut in R&D (a 1% decrease in Output produces a reduction in unconventionality of 0.06%).

Model (4) in Table 3.5 shows that, during the contractive phases of the cycle, firms cut back on novel inventions in the core of their technological competences (-0.08%), whereas the retrenchment in non-core activities is not significant. Also for this set of regression the Chow test confirm that the coefficient for Core and Non-core are statistically different from each other. During downturns firms select carefully their R&D projects to limit potential risks, thus reducing their exposure. It follows that during downturns, when the availability of resources decreases and firms become more sensitive to expected returns, firms will selectively cut back on more uncertain projects and reorient scarcer resources on projects characterized by more predictable outcomes. As most of the patents belong to the core competences of the firms, it is likely that firms will hold back innovative product in this set of activities.

Table 3.2 Correlation Table

		1	2	3	4	5	6	7	8	9	10	11
1	Unconvention	1.0000										
2	Real Output	0.1827*	1.0000									
3	Expansion	0.1313*	0.4862*	1.0000								
4	Contraction	-0.0853*	-0.2372*	-0.2632*	1.0000							
5	Citations	0.0410*	-0.0197*	0.0078*	-0.0237*	1.0000						
6	no Bwd cits	0.0042	0.0052*	-0.0142*	-0.0091*	-0.2547*	1.0000					
7	Components	0.2155*	0.0323*	0.0092*	-0.0370*	0.1204*	0.0052*	1.0000				
8	Team	0.0323*	-0.0204*	-0.0424*	-0.0375*	0.1544*	0.0067*	0.0926*	1.0000			
9	Experience	0.0802*	0.2151*	0.1082*	-0.0590*	0.1046*	0.0120*	0.1110*	0.1526*	1.0000		
10	Concentration	0.0263*	-0.0778*	0.0406*	-0.0583*	0.1842*	0.0073*	0.0356*	0.0692*	0.1276*	1.0000	
11	Assigne	0.1024*	0.4312*	0.1747*	-0.1054*	-0.0658*	-0.1139*	0.0314*	0.0326*	0.1856*	-0.4452*	1.0000

Table 3.4: Estimations for technological search over the business cycle. OLS models for the degree of Unconventionality.

	All	Low KZ	High KZ	Cut R&D	Non Cut R&D	Core	Non Core
	Model 1	Model 2		Model 3		Model 4	
Real Output	0.0899***	0.0895***	0.0829***	0.0752***	0.0795***	0.0938***	0.0490***
	(0.0032)	(0.0043)	(0.0076)	(0.0056)	(0.0044)	(0.0034)	(0.0098)
Expansion	-0.7923***	-0.9712***	-0.5963*	-1.0775***	-0.8543***	-0.8678***	-0.2935
	(0.1522)	(0.2211)	(0.3267)	(0.2678)	(0.1957)	(0.1607)	(0.4741)
Contraction	1.2091***	1.1576**	1.1004	1.3258***	-0.6826	1.1630***	1.1204
	(0.3869)	(0.5154)	(0.9574)	(0.4443)	(0.8881)	(0.4098)	(1.1709)
Citations	-0.0103***	-0.0093***	-0.0110***	0.0031	-0.0196***	-0.0121***	-0.0005
	(0.0018)	(0.0023)	(0.0037)	(0.0028)	(0.0024)	(0.0019)	(0.0057)
No Bwd Cits	-0.0179	-0.0100	0.0215	-0.0072	-0.0314	-0.0236	0.0095
	(0.0164)	(0.0203)	(0.0353)	(0.0257)	(0.0212)	(0.0173)	(0.0504)
Components	0.2182***	0.2170***	0.2343***	0.2072***	0.2258***	0.2121***	0.2482***
	(0.0027)	(0.0034)	(0.0056)	(0.0041)	(0.0037)	(0.0029)	(0.0081)
Team	-0.0030***	-0.0032***	0.0002	0.0036**	-0.0084***	-0.0042***	0.0056*
	(0.0010)	(0.0012)	(0.0020)	(0.0015)	(0.0013)	(0.0010)	(0.0031)
Experience	-0.0000	-0.0004***	0.0001*	-0.0001	0.0001*	0.0000	0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Concentration	-0.1711***	-0.2080***	0.1176	-0.0434	-0.2507***	-0.1647***	-0.2267
	(0.0358)	(0.0497)	(0.0779)	(0.0569)	(0.0474)	(0.0362)	(0.2348)
Assignee	0.0002	0.0057*	0.0051	0.0053	-0.0049	-0.0005	0.0033
	(0.0023)	(0.0030)	(0.0047)	(0.0035)	(0.0031)	(0.0024)	(0.0067)
Constant	-4.9184***	-4.8989***	-5.2361***	-4.0849***	-4.7838***	-4.9274***	-5.7305***
	(0.0896)	(0.0959)	(0.5705)	(0.5642)	(0.1037)	(0.0901)	(0.6127)
N	166168	103943	43399	77432	88736	146559	19609
R^2	0.1730	0.1575	0.2251	0.1700	0.1586	0.1790	0.1659

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
The models report the results of the Ordinary Least Square on the median value of the degree of novelty in patents. Models include 20 year, 36 technology and sector dummies. Models also include controls (dummies) for missing information about backward citations. All models include firm fixed effects.

3.4.3 Technological Search over the Business Cycle: Technological Impact

The analysis so far has highlighted a reduction in the level of technological novelty during downturns, especially for financially constrained firms and in core research activities. The implications for firm performance however remain unclear and may depend on the ability of firms to choose effectively the projects to pursue during downturns. Due to reduced availability of resources, firms may be more efficient in the selection of innovative projects, reducing their involvement in riskier projects and focusing on inventions with more certain outcome (Almeida et al., 2013). However, novelty, and the uncertainty underlying it, is usually associated to inventions with both higher failure rates and higher impact. Therefore one should expect firms, especially those with limited access to financial resources, to be more selective in the pursuit of novel projects and therefore generate novel inventions with higher impact during downturn, due to the discontinuation of more uncertain projects.

In this section we analyze the relationship between the business cycle and the technological impact of the inventions as measured by forward citations[25] (Trajtenberg, 1990). If firms are more efficient in the selection of projects, we should expect novel inventions generated during negative variations of output to receive more forward citations, as unproductive projects are discontinued or postponed. Moreover, this premium should be higher for novel inventions from financially constrained firms.

The models in Table 3.6 show that the coefficient for the degree of unconventionality is not significant in model (1). This result is possibly due to the lower level of unconventionality, and consequent impact, of inventions during downturns. Model 1 shows that expansion phases, namely positive variation of the output, are associated with higher number of forward citations.

In model (2) we split the sample according to the dependence on external financial capital. The results indicate that the decision to discontinue novel projects is not associated with the availability of financial resources in contractive phases while an increase in the number of forward citations is

[25] In this section we rely on the same regression models to investigate the effect of search strategies on the (natural logarithm plus one of the) number of the forward citations received by patents.

observed for low and high financially constrained firms inventing in innovation during pro-cyclical phases.

The coefficient of the degree of unconventionality in inventions is negative in non-core activities while it is positively associated with forward citations in non-core technologies (model 4). This finding is consistent with the view that unconventionality in non-core areas is potentially associated with more explorative inventive approaches, providing the basis for the development of future inventions. Indeed, these inventions receive a higher number of forward citations, indicative of a higher technological importance and economic significance. Model 4 also shows that positive variation of the output are associated with higher forward citations in the core and non-core activities whereas negative variations in output are associated with lower forward citations in non-core activities only.

Overall the results suggest that inventions characterized by higher level of unconventionality developed in non-core areas have a higher impact. Firms are however risk averse showing sensitivity in the contractive phases by cutting on unconventional inventions characterized by higher risk and an unpredictable outcome.

Table 3.5: Technological Impact. OLS models for the number of forward citations.

	Model 1	Model 2	Model 3	Model 6	Model 7
Unconventionality	-0.0028	0.0039	-0.0220**	-0.0097**	0.0374***
	(0.0042)	(0.0053)	(0.0086)	(0.0045)	(0.0124)
Real Output	-0.0621***	-0.0583***	-0.1048***	-0.0580***	-0.0991***
	(0.0055)	(0.0074)	(0.0135)	(0.0059)	(0.0169)
Expansion	1.8317***	1.8886***	1.2563**	1.8927***	1.6090**
	(0.2626)	(0.3796)	(0.5783)	(0.2774)	(0.8167)
Contraction	-0.6313	-1.2235	0.6388	-0.2339	-3.6037*
	(0.6672)	(0.8851)	(1.6945)	(0.7075)	(2.0169)
Citations	0.1327***	0.1417***	0.1277***	0.1288***	0.1577***
	(0.0032)	(0.0039)	(0.0065)	(0.0034)	(0.0098)
No_bwd cits	0.0991***	0.1486***	0.0516	0.0877***	0.2301***
	(0.0282)	(0.0348)	(0.0624)	(0.0298)	(0.0868)
Components	0.2045***	0.1980***	0.2185***	0.2000***	0.2383***
	(0.0048)	(0.0059)	(0.0100)	(0.0051)	(0.0143)
Team	0.0509***	0.0523***	0.0481***	0.0515***	0.0415***
	(0.0017)	(0.0020)	(0.0036)	(0.0017)	(0.0053)
Experience	-0.0000	-0.0002	0.0001	-0.0001	-0.0000
	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0003)
Concentration	0.2095***	0.2140**	0.3746***	0.1998***	0.3651
	(0.0618)	(0.0853)	(0.1379)	(0.0625)	(0.4045)
Size	-0.0549***	-0.0425***	-0.0528***	-0.0583***	-0.0179
	(0.0039)	(0.0052)	(0.0084)	(0.0042)	(0.0116)
Constant	1.4528***	1.4529***	3.0383***	1.4070***	1.5953
	(0.1558)	(0.1667)	(1.0108)	(0.1572)	(1.0576)
N	166168	103943	43399	146559	19609
R^2	0.2526	0.2758	0.2180	0.2633	0.1888

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ The models report the results of the OLS on the median value of the degree of novelty in patents. Models include 20 year, 36 technology and sector dummies. Models also include controls for missing information about Bwd cits.

3.5 Discussion and Concluding Remarks

Innovation dynamics tend to be pro-cyclical, with a sizeable contraction of R&D investments during downturns. This pattern has serious implications for long term R&D efforts and growth. This study contributes to the debate on pro-cyclical versus counter-cyclical innovation by showing a re-composition of patent portfolios during downturns toward less novel inventions, especially as far as financially constrained firms are concerned. Reduced profitability form ongoing projects, lower availability of external funding and higher level of uncertainty affect firms' decisions with regards to R&D investments and innovation search strategies at large. Our results are consistent with empirical evidence showing that in the contractive phases of the cycle, firms tend to be more risk averse. They have higher preferences towards inventions that build on more established knowledge bases that are expected to provide close in time returns.

From a theoretical standpoint, our results provide interesting insight in the debate on the relationship between innovation and business cycle. We found that the negative phases of the business cycle are associated with lower degree of unconventionality. This implies that during economic downturns, the recombination process is characterized by local search as knowledge components are recombined among familiar and less riskier technological domains. This especially occurs in financially constrained firms and core technologies. This finding is linked to the vast economic literature describing the effects of financial constraints on the ability of firms to undertake more novel inventive processes when environmental conditions are most challenging.

From the managerial point of view, the results of this study advocate the design of proper strategies that sustain adequate level of innovation during contractive phases. Deep pocket firms should be aware of the risk of canceling or postponing projects with higher uncertainty during recession phases as competition from competing technologies may decrease.

From a policy perspective, our results inform that the contractive phases of the cycle not only limit the amount of R&D investments in innovation but, more importantly, change investments decisions, with a higher preferences towards more conservative and less impactful innovation projects. This finding may inspire future research on the design of policies that are not limited to the economic support to R&D through tax incentives and credit packages but are also able to drive firms' incentives towards more explorative innovation that have higher social returns. Research in this direction should also focus on a better understanding the extent to which firms reshape their patent portfolio in a more efficient way by cutting less valuable project and carry on most promising and eventually novel ones. This would be in turn a very interesting aspect to consider in the design of innovation policies.

This study is not without limitations. As recognized in the literature, patents data have the major drawback of capturing only successful inventions. Besides, they don't have a uniform value and not all sectors are equally patents intensive (Cohen et al., 2000). Yet, patents data reveal major and important innovations patterns. Moreover, patent classification system is rather stable over time and regularly updated making it a reliable source for the computation of the level of unconventionality in the recombination of knowledge. In this analysis we consider only the primary patent class which make difficult to clearly differentiate between core and non -core activities of the firms. In our analysis we try to identify the heterogeneity of firms reactions to variation in the level of output by considering the role of financial constraints. However, other sources of heterogeneity can play a role in shaping the relationship between type of innovation and business cycle. Future research will further extend the richness of the dataset by including and differentiating between single and multi-business firms using Compustat segment-level data. The rational is that multi-business firms are likely to be less exposed to negative shocks. The scope of future research is to provide further insights on how recombination process are reshaped along the business cycle. Hence, it is interesting to consider potential premium associated with better performances (i.e. sales) in the aftermath of downturn for firms that are able to sustain adequate levels of technological innovation.

In this analysis we tackle the role of market concentration on the level of patent unconventionality. Future research may emphasize further this aspect driven by the rational that during expansion competition may increase innovation because firms have incentives to increase their technological lead over rivals (Aghion et al., 1998). However, a decrease in competition during the contractive phases may translate in a decline of patent race pushing more resilient firms to invest in unconventional innovations.

The impact of economic recessions on innovation is not homogeneous among industries. In complex industries as in the information technologies, economic crises may serve as an opportunity to reallocate resources to new projects and to build a forthcoming market demand for more radical products. Thus future research may explore the relation between search process and business cycle in different industries.

Although its limitations, this study contributes to a stream of research aiming at advancing the understanding of the search process along the business cycle, a topic that have important implications for economic recovery and growth.

Chapter 4

Sowing Failures, Reaping Success? Evidence from Pharmaceutical R&D Projects

4.1 Introduction

In November 2016 Eli Lilly announced that its potential blockbuster drug against Alzheimer's disease, Solanuzemab (Sola), expected to generate about $1.6bn in sales by 2020, failed once again the Phase III clinical trial. After two previous failed attempts in 2012, Eli Lilly decided to retest the drug targeting 2100 patients with mild Alzheimer. Although the drug performed slightly better than individuals taking a placebo, the improvement was too small to be considered as statistically significant[26] (Chen et al., 2016). The announcement of the failure caused a sudden drop by 10.5% in Eli Lilly's stock price and a fall by 5% in the stock price of Biogen, which is developing a rival drug, Aducanumab[27]. Eli Lilly has been working on a drug for Alzheimer's disease for 15 years, spending about $3bn in the past three decades on experimentation and drug development.

Sola is only one of the many examples of drugs that have repeatedly failed in late clinical trials reflecting the intrinsic experimental nature inherent to drug development processes characterized by soaring costs and uncertain

[26] https://investor.lilly.com/releasedetail.cfm?ReleaseID=1000871
[27] https://www.ft.com/content/ec01d882-b618-11e6-ba85-95d1533d9a62

outcomes[28]. The estimated average pre-tax industry cost per new drug approval (inclusive of failures and capital costs) amount to over USD 2.5 billion per marketed drug (Di Masi et al., 2016). Therefore, the pharmaceutical industry represents one of the key examples of an innovation context marked by uncertainty, high failure rates, repeated trials, and long development trajectories. Drug development is an innovation process where organizations built on cumulative knowledge and experience (Scotchmer, 2004). These conditions induce pharmaceutical firms to specialize in certain domains to exploit specialized knowledge cumulated over time and the existing competences developed from previous trials conducted in-house and by others firms (Cyert & March, 1963; Simon, 1978, Herriot et al., 1985).

As widely described in the literature, organizations can use their previous experience to identify potential inefficiencies and effective practices, and adjust them in follow up R&D projects (Haunschild & Sullivan, 2002). The organizational learning literature has stressed the important role of learning from positive and negative experience as one of the mechanisms that can improve firms' subsequent innovation process, and at the same time generate knowledge spillovers to other firms operating in related technological areas (Teerlak & Gong, 2008; Francis & Zheng, 2010; Levinthal & March, 1993). It has been advocated that firms can learn from failures in a process of trial and error (Tucker & Edmondson, 2003; Chesbrough, 2010) and be guided by the motto "*Fail often in order to succeed sooner*"[29]. Prior studies have emphasized the experimental nature of learning by analyzing the role of catastrophic failures such as in the case of the design and organization of the value chain of the Airbus A380 (Dörfler & Baumann, 2014) and the orbital launch of Columbia in 2003 (Madsen & Desai, 2010).

Studies in this stream of research have focused on the role of experience from failure on performances enhancements (Ingram & Baum, 1997; Haunschild & Miner, 1997; Baum & Dahlin, 2007) disregarding, with only few exceptions, mechanisms of learning from successful experience (Hoetker & Agarwal, 2007; Magazzini et al., 2012). Since organizations have a

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[28] For a more comprehensive example see the report from the FDA "*22 case studies where phase 2 and phase 3 trials had divergent results*", retrieved from "file:///C:/Users/Daniela/Downloads/1%204%2016%20final%20final%20(1).pdf

[29] This statement is from Tom Kelley, general manager of IDEO.

tendency to de-emphasize negative outcomes and to highlight positive results (Levinthal & March, 1993; Denrell, 2003), there are arguments to suggest that learning from success may be more salient than learning from failures. Existing studies have however not systematically compared the extent to which firms learn from prior failures and successes.

This paper contributes to the literature by investigating to what extent pharmaceutical firms learn from prior failures and successes in their subsequent drug development efforts through either in-house experiential learning or through vicarious learning (learning from the experience of other firms). Relevant experience in related prior drug development efforts is identified by considering prior drug development projects of which the underlying patent is cited by the patent that is exploited in the current focal drug development project. This study examines whether (i) learning from successes is more decisive than learning from failures; ii) experiential learning is more important than vicarious learning. Unlike previous studies adopting aggregated measures of experience at the organizational level (Kim et al., 2007; Ingram & Baum, 1997; Darr et al., 1995), we leverage a comprehensive and detailed micro-level dataset on drug development projects to examine the relationship between the probability that a drug development is successful and prior relevant experience in drug development efforts.

Results show that projects that build on firms' previous successful efforts have a higher likelihood to generate marketable drugs, while building on prior failures reduces this likelihood. A similar pattern, though much weaker in magnitude, is observed for drug development projects building on prior related projects of other firms. The findings of this study show that contrary to common wisdom, previous failures increase the incidence of failures. This pattern may be related to the higher potential market value of risky projects. Projects targeted to certain disease like Alzheimer face less competition due to the lack of existing drugs in the markets for the cure of this disease. At the same time, they represent fruitful opportunities of investments given the higher associated rewards. As a consequence, firms may be willing to accept higher failure rates linked to the experimentations in this high risk markets. In turn the experimentation in this type of markets also requires a deeper search efforts in order to understand the cause-effects linkages related to the cure of the disease. The results also point out a certain degree of organizational inertia as firms continue familiar research trajectories. In addition to informing the literature on organizational learning and innovation, our study facilitates a more nuanced view on the learning mechanisms playing a role in the pharmaceutical sector.

The remainder of this paper is organized as follows. The next section presents the relevant literature on organizational learning theory and develops our two main research questions. In Section 3 we describe the data and report descriptive statistics. Section 4 presents the empirical results. The final section discusses the results and the potential implications.

4.2 Theory and Research Questions

4.2.1 Organizational Learning

Organizations learn through a dynamic process where information and knowledge are acquired, generated, interpreted, stored and retrieved (Huber, 1991; Senge, 1990). A key insight of organizational learning theory is that organizations adapt their knowledge base in response to lessons drawn from past experience and cumulated knowledge (Cyert & March, 1963; Huber, 1991; Levitt & March, 1988). Depending on the extent of adaptation, the learning process may generate minor adjustments and refinements of existing routines through exploitation of previous knowledge or rather significant changes of existing practices through exploration of alternatives approaches (March, 1991). Changes in organizational knowledge is typically observable by improvement in future performances (Argote, 1999; Baum & Ingram., 1998). Hence, organizations' ability to learn and adapt has been recognized as an important source of competitive advantage (Senge, 1990; Redding & Catalenello, 1994) in particular when knowledge generated through learning is difficult to imitate quickly (Baumard & Starbuck, 2005).

The learning process is usually triggered by feedback received from the environment and performance below aspirations that calls for adaptation of strategies, and search for improved solutions (Cyert & March, 1992; Nelson & Winter, 1982; Levitt & March, 1988; Simon, 1978; Stalk et al., 1992). Through performance feedback, organizations set benchmarks or reference points to reinforce actions and decisions that generated a positive outcome while questioning those that lead to negative results (Levitt & March, 1988; Cyert & March, 1992).

Theorists from the behavioral theory of the firm define aspirations as the lowest level of performance acceptable by organizational decision makers (Greve, 2003). The decision process is thus driven by aspirations which are used to appraise organizational performance into successful or negative outcomes (Cyert & March, 1963). Organizational learning literature has typically considered learning from prior aggregated organizational experiences (Argote & Epple, 1990; Darr et al., 1995) whereas other studies looking at more disaggregated dimensions have mostly analyzed responses to failed experiences (Desai, 2015; Haunschild & Sullivan, 2002). However, as suggested by the behavioral theory of the firm, organizations may respond differently to failed and successful experiences calling for a comparison between learning from success and failures.

4.2.2 Learning from Failures and Success

Although the important role of experience has been acknowledged in organizational theory (Cyert & March, 1963; Levinthal & March, 1993), the bulk of studies have typically focused on the role of failed experience on subsequent performances by looking at knowledge generated by accidents (Madsen & Desai, 2010; Desai, 2015; Haunschild & Sullivan, 2002; Desai 2016; Dörfler & Bauman, 2014), errors (Ramanujam & Goodman, 2003), product recalls (Haunschild & Rhee, 2004; Rhee & Haunschild, 2001), strategy failures (Chuang & Baum, 2003). This stream of literature has acknowledged the importance of investigating failures to understand the root causes, identify potential inefficiencies and design proper procedures in subsequent trials. Researchers in this stream of research advocate that negative catastrophic experiences stimulate "problemistic searches" for new solutions leading to a significant change of the status quo, away from the comfort zone of what the firm has already tried (Maslach, 2016; Cyert & March, 1963; Lant, 1992; March & Shapira, 1992).

Cyert and March (1963) suggest that organizations have stronger incentives to change their actions in reaction to failures through behavioral innovation.

Organizational learning in response to failure is characterized by a sense of urgency, especially for large failures, that is likely to trigger the search and adoption of new knowledge (Cameron, 1984; March, 1981). By questioning the practices and strategies that lead to negative outcomes, failures are expected to stimulate a search towards routes that wouldn't have been taken otherwise. Baum and Dahlin (2007) suggest that organizations performing far from their aspiration levels engage in more distant search following failure experience relative to those that meet the desired aspirations. Greve 2003 demonstrates empirically that performance below aspiration not only makes decision makers search for solutions, it also makes them more likely to try inherently risky solutions.

Following this logic, organizations should tolerate some degree of failure in order to gain valuable new knowledge and discover new learning opportunities for their innovation strategies (Leonard-Barton, 1995; Edmondson, 2011). A number of studies have provided initial indirect evidence of the learning effects from failures. Magazzini et al., (2012) examined the value of patents resulting from pharmaceutical R&D projects and found that patents from both successful and failed R&D projects generate a higher number of forward patent citations than those from projects not entering clinical trials. Khanna et al. (2016) is an exception in examining how ‘small’ failures, proxied by voluntary patent expiration, affect the amount and quality of firms R&D output. They find that small failures are associated with a decrease in patent applications but with an increase in their quality measured by forward citations.

The above arguments contrast with the theoretical argumentation that learning from failures is not an automatic process, as organizations are usually reluctant to openly share and divulge their own mistakes (Husted & Michailova 2002; Cannon & Edmonson, 2001). Thus, organizational learning is considered as myopic since firms often tend to overlook failures and overemphasize knowledge generated by previous successes (Levinthal & March, 1993). This is largely due to cognitive limitations and to a different approach to learning from failures and success. Miller and Ross, (1975) asserted, for instance, that individuals are much more likely to ascribe success to personal capability and failure to luck, than they are to attribute success to luck and failures to a deficit in ability. Similarly, Edmonson (2011, 2005) suggested that individuals deal with mistakes by looking for explanations that support their existing beliefs, detaching themselves from the real causes of failures.

Among studies stressing the importance of learning from failures, a number have argued that organizations may fail to learn from failed experience by generating incorrect lessons (Baumard & Starbuck, 2005; Staw et al., 1981). For instance, Eli Lilly was ready to discard is chemotherapy drug Alimta after failure in clinical trials. Only after a deeper investigation it was found out that the failure was due to a deficiency in folic acid in patients used in the trials. By simply associating folic acid with Alimta the problem was solved (Edmonson, 2005). In this regard, Edmonson (2005) emphasizes the importance of identify, analyze and experiment failures. Other studies have instead identified organizational and psychological barriers that hinder learning from failures (Cannon & Edmonson, 2001; 2005). On the flip side of learning from failures, Levinthal and March (1993) highlight that although firms can benefit from failures through explorative search, they have to be careful not to end up in a continuous cycle where failures result in more failures. Firms that respond to failure by constantly searching for new technology, develop limited knowledge on a domain which can lead to an increase in the risk of future failures. This cycle of failures can also be generated by the fact that compared to previous success, failures are the evidence of what is not properly working out of many possibilities without necessarily narrowing down avenues for future development on right trajectories.

Relatively few studies have examined whether firms benefit from knowledge generated by previous successes (Madsen & Desai., 2010; Magazzini et al., 2012; Hoetker & Agarwal., 2007). Successful outcomes represent the proof that previous decisions and practices worked well (D'Este et al., 2014) and that search for alternative solutions or development of further knowledge is unnecessary to reach the desired aspiration level (Lant, 1992; March & Shapira, 1992). Building on previous success trigger decision makers to search locally in the proximity of their existing knowledge leading to a refinement of previous assumptions and actions (Maslach, 2016). This strategy allow firms to economize on scarce resources and search cost while at the same time reducing uncertainty on the decision making process as the cause-effects linkages are well known and became established in organizational practices (Cyert & March, 1963; Shaver et al., 1997; Gimeno et al. 2005). However, learning from repeated success can also have a flip side as it increases self confidence that the expected aspiration levels will be reached. Based on cognitive limitations, organizations tend to attribute success to the quality of their decisions, actions and managerial capabilities, ignoring other circumstances and external factors that may have influenced the outcome (Miller & Ross, 1975). This may lead to the underestimation of risks and limited opportunities to adapt to technological changes and to respond to unexpected results (Levinthal & March, 1993). Hence, drawing solutions only from past success may trap firms into organizational rigidity and inertia. This may actually increase the likelihood of future failures, since the opportunities to adapt and look for alternative approaches are limited by the institutionalization of existing routines (Baumard & Starbuck, 2005; Madsen & Desai, 2010).

Although organizational theory has drawn attention to the opportunities and caveats of learning from failures and success, the actual ability of organizations to capitalize on knowledge from positive and negative outcomes remains empirically underexplored (Magazzini et al., 2012; Baumard & Starbuck, 2005; Staw et al., 1981). Moreover, extant literature has rarely focused on a direct comparison of organizational learning from success and failure, with a few exceptions.

Haunshild and Sullivan (2002) focused on accident rates of U.S. airlines proxy organizational experience in the field by the time the firms was operating in the sector. They find that established firms were less likely to experience accidents than younger firms but without a clear distinction on the effects of previous success and failures. Haunschild and Rhee (2004) analyzed automobile recalls on the likelihood of future recalls. They found that experience on prior automobile production decreases the rate of future recalls suggesting learning.

Madsen and Desai (2010) instead provided a direct comparison of learning from failures and success by analyzing the orbit launch accident in 2003. They found that launch vehicle companies learn more effectively from failure experience than from success in line with the argument that failures intensify search activities in urgency circumstances (Wildavsky, 1998).

This study augments understanding on the role of learning from success and failure in previous drug development projects in the pharmaceutical industry, for which both failures and success are intrinsic components. In this context successes are rare but have an important impact on firms performances, while failures occur frequently leading to serious losses of capital due to the large investments required for experimentation. This pushes firms to learn from their previous mistakes and from the knowledge that is generated from previous successful experimentation.

A first focal question for research hence is *whether pharmaceutical firms have a higher propensity to learn from success than from failure in their drug development efforts (RQ1).*

4.2.3 Vicarious Learning

Organizational learning theory advocates that organizations learn and develop knowledge not only through their direct experience - experiential learning - but also through the observation of the experience of other organizations - vicarious learning - by imitating or avoiding specific practices or strategies (Baum & Dahlin, 2007; Cyert & March, 1963; Greve, 1998; Levitt & March, 1988; Ancona & Bresman, 2007; Hatinschild & Miner, 1997; Huber, 1991; Levitt & March, 1988; Madsen & Desai, 2010; Miner et al., 2008; Meyer & Scott, 1983). Inferential learning occur by selectively copy others firms in a mimetic way (Katila & Chen, 2008) or for example by observing R&D activities of competitors, interpreting and copying other's firm search (Katila, 2002). Observing other firms' search can also work as a signal of opportunities (Katila & Chen, 2008).

While direct experience with a certain task generates deep and tacit knowledge that may improve future performances in subsequent trials (Argote et al., 1990; Argote, 1996; Pisano & Bolmer, 2001), this is expected to be less so when firms learn vicariously by imitating successful experience and best practices of other firms (Conell & Cohn, 1995; Haunschild & Miner, 1997) or by analyzing failures of other firms (Baum et al., 2000; Beckman & Haunschild, 2002; Kim, 2000; Miner et al., 1999). In the case of vicarious learning firms do not obtain the same level of detailed information and firsthand experience as with direct experiential learning. Since firms lack direct access to other firms' knowledge repositories, other firms' actions influence firm strategy by changing expectations about current and future outcomes (Strang & Macy, 2001). The literature on vicarious learning through inference has debated the limits of this mechanism, as it can lead firms ns to adapt their practices or to take decisions on the basis of expectations rather than more objective facts (Abrahamson & Fairchild, 1999). On the other hand, vicarious learning may still be beneficial as firms can integrate new valuable knowledge in their practices in high uncertainty environments when experiential knowledge alone is not sufficient to interpret the current state of the world (Beckman & Haunschild, 2002). The integration of new knowledge can be facilitated when the other firms work in a common domain, sharing comparable knowledge bases, organizational forms and routines (Hannan & Carroll, 1992; Miner et al., 1999).

Research focusing on vicarious learning from other firms' failures have empirically shown that failures decrease as the number of prior failures experienced by similar firms increases (Baum & Dahlin, 2007; Chuang & Baum, 2003; Haunschild & Sullivan, 2002; Ingram & Baum, 1997; Kim & Miner, 2007). Failures have a signaling role, indicating promising and less promising trajectories of experimentation under uncertainty (Hoetker & Agarwal, 2007). In this regard, Krieger (2016) examines how biopharmaceutical firms react to news about competitors' failures in clinical trial and showed that firms react to failures from related projects in the same market (disease indications) and technology (inhibitor or antagonist approaches) by doubling their propensity to terminate their projects. Failure in different markets but in the same technology also increase significantly the exit rate, whereas failures in the same market but in different technologies does not affect projects survival rates.

Although failures by other firms can provide salient information about efficacy of the compounds, firsthand experience in the pharmaceutical industry may still play a prominent role as firms can leverage tacit knowledge from their explorative research on the compound and their experimental experience.

A second focal question for research is then to examine whether *pharmaceutical firms learn more from their own drug development experience than from other firms' experience (RQ2).*

4.3 Data

4.3.1 Research Setting: Innovation in the Pharmaceuthical Industry

The drug development process is structured as a chain of well-defined phases in which the firm leading the project need to achieve precise milestones reporting the results of the study to the FDA and to the Center for Drug Evaluation (CDER) in the US (see Figure 1). The development of a new drug relies heavily on basic research usually conducted during the discovery phase. This phase includes the screening of potential compounds that are biological active for the medical treatment of a disease. The next step is the preclinical phase aimed at collecting information on dosing and toxicity level by testing the compounds on living animals. In case the test show lack of toxicity, the firm file an Application for the Investigation of New Drug (IND) to the FDA

	RESEARCH				DEVELOPMENT						
					CLINICAL				FDA REVIEW		POST MARKET MONITORING or PHASE IV
	DISCOVERY	Patent Application	**PRECLINICAL**	IND Application	**PHASE I**	**PHASE II**	**PHASE III**	NDA/BLA Application		FDA Approval	
Objective	Compound Discovery and screening		Toxicology & safety assessment		Safety dosage pharmaco kinetics	Effectiveness, Side effects, dosage	Efficacy adverse reactions		Priority Review:for breakthrough drug Standard		Evaluate safety and generate data about how drug affects
Num. Subjects			Test on animals (in vitro/in vivo)		20 - 100 healthy	<300 with disease	300 - 3000 with disease				
Success Rate					70%	33%	25-30%				
Costs (out of pocket)	$281				$128	$185	$235		$44		
length	3/4 years				18 months	38 months	61 months		6-12 months		indefinite
Example: Solanezumab	Available: Beta-Amyloid Beta-Secretase Tau protein 5HT6 receptor	2002	Target: Beta-Amyloid Therapy: Immunotherapy Indication: Alzheimer Test: on mouse		9/33 disease: mild-moderate no placebo 8	Year: 2006 patients:52 disease: placebo 12 week-1 year	Expedition: 1) 1012 2)1040 3)2100 (3 year) (mild) placebo				

Figure 1: Drug development Process with Example. Data are extracted from several sources: DiMasi et al., 2003; Campbell 2005; AlfForum, Abrantes et al., 2004; Mestre et al., 2012.

and proceed further to the Clinical trials for human tests. Clinical trials are organized into three main phases with different requirements and costs. In Phase I the drug is administered to a restricted number of healthy volunteers to identify potential toxicity issues in humans. If the drug doesn't show any major side effect it is administered to a larger number of volunteers with the specific disease object of the study, Phase II. This phase determines drug effectiveness and stability as well as the appropriate dosage. During Phase III the drug is administered to a larger sample of patients that are monitored over time to determine the drug effectiveness on a larger scale and potential side effects that didn't arise in previous phases. A New Drug Application (NDA) is filed if all phases are successfully completed to provide scientific reports on the drug effectiveness and safety in contrasting the diseases compared to pre-existing drugs. In case of approval, the drug is made available for prescription to patients and goes into pre-registration and registration phases until it is finally marketed. However, even after the drug is launched, the company is still responsible to report any potential side effect raised after the approval in order to withdrawn from the market possible toxic drugs[30].

The pharmaceutical industry is characterized by high technological uncertainty, extensive costs and risks. Typically, only 22% of compounds that are tested in clinical trials conclude with a successful market launch (DiMasi et al., 2003). In absolute number, for every 250 compounds that enter pre-clinical testing, 5 advance to clinical testing and only 1 is eventually approved by the Food and Drug Administration (FDA) (Campbell, 2005). Uncertainty in the drug development is also related to the length of the project that takes on average 12 years from the research lab to the market (EFPIA, 2014) with possible failures occurring also in later stages of development.

Researchers have showed that between 2007 and 2010 on a sample of 83 projects in Phase III, almost 90% of the failures across all therapeutic areas were attributed to safety reasons (21%), or to a lack of efficacy (66%) in demonstrating a statistically significant improvement versus placebo (Arrowsmith, 2011). Similar trends are found in a more recent contribution by Harrison (2016) who document that in the period 2013-2013, there were 218

[30] Some well-knon cases of market withdrawal are the Fen-Pen recalled in 1997 after 24 years in the market; Cerivastatin by Bayer, recalled in 2001 after causing 10000 deaths; Rofecoxib by Merk in 2004 or Valdecoxib by Pfizer in 2005.

failures in Phase I/II. Of these, 52% of drugs fail due to a lack of efficacy while 24% of failures are due to lack of safety. The majority of failures occur for the medical treatment of complex pathology especially cancer and neuro-degeneration (DiMasi, 2003; Julia, 2013). During the drug development process, pharmaceutical firms sustain extensive investments that have rapidly surged over time from 231 million of US $ in 1987 to over US $ 800 million in 2000 (DiMasi et al., 2003; Adams & van Brantner, 2006). The highest share of R&D is concentrated in Phase III with about 32.1% of investments (EFPIA, 2014) making failures at this stage very costly for organizations.

4.3.2 Sample and Data

To explore the role of success and failures in drug development, we leverage on the Pharmaceutical Industry Database (PHID) maintained at IMT Institute for Advanced Studies in Lucca (Italy). This database provides fine-grained data on more than 30,000 pharmaceutical R&D projects including their Anatomical Therapeutic Chemical (ATC) classification, the indication on the treated disease, the development history of the project, the company leading the project as well as other companies that were involved during the trial as licensor or licensee. This database relies on information collected from governmental agencies, industry conferences, press relies, contacts with firms. For a subset of 9,496 projects, the PHID database also reports the associated patent publication number used by the firm to protect the compound under development[31]. We enrich the patent information by extracting the patent family relative to each patent publication number from PATSTAT (version 2013) matching 9,165 projects that are associated with at least one patent family (96.51% of projects reporting a patent). We further cleaned the subsample remaining with 8,243 projects whose development process occurred in countries having comparable standards and procedures (Europe, Japan, USA, North America, Canada) or whose final drug has been marketed worldwide. We use patent data to link, via citations, the focal project to previous research efforts as well as controlling for knowledge spillovers that

[31] The information over patent is available only for a subsample since natural compound are excluded from patent protection. The information on patents is available in the database where a patent search has been conducted for each compound and one or more patents were identified.

can generate an advantage for the successful outcome of the focal project. The theoretical and empirical literature in innovation suggests that patent citations represent a source of knowledge spillover (Trajtenberg, 1990). This literature also posits that highly cited patents are the most innovative as other firms are willing to imitate their ideas (Carpenter & Narin, 1983; Narin, Rose and Olivastro, 1989; Trajtenberg, 1990). In the pharmaceutical industry, patents are a good proxy of innovation, not only because compounds are patented early-on in the development process, but also because the propensity to patent is amongst the highest across industries (Arundel and Kabla, 1998; Campbell, 2005; Jaffe, 1989; Cohen et al., 2000) and represent an important source of technological advantage in this industry (Levin et al., 1987).

The rich amount of information included in the dataset, allows us to control for a series of patent-projects characteristics as well as organizational factors that may affect the final stage of follow-up compounds. After the cleaning procedure our sample includes 8,243 focal projects linked to 8,112 distinct patent families[32]. However, we restrict our analysis only to focal projects whose development process initiated between 1980 and 2005 to allow enough time in clinical trials,[33] remaining with 7,350 projects linked to 7,042 patent families and lead by 1,374 distinct firms (Table 4.1).

Table 4.2 provides some summary statistics about project performances in clinical trials. A large majority of focal projects in our sample has failed (35.58%) whereas only a smaller fraction has reached the final stage in the development(21.47%). A high fraction are still in progress (ongoing) or have never been officially discontinued being listed as ongoing despite no development update for long periods of time (42.95%).This trend is consistent with prior literature, acknowledging the high attrition rates and uncertainty characterizing the drug development process (DiMasi, 2003; Kola & Landis, 2004). The average length of projects ranges on average from 8 years for failed

[32] The relationship between focal project and patent is one-to-many. In our analysis we considered all the patents associated to the projects.
[33] In order to enable learning mechanisms to take place we restricted the analysis to the focal projects that started after the cited.

projects up to 14 years for successful projects, a trend that find consistency with previous studies (Abrantes-Metz et al., 2004). [34]

There are 3,851of focal projects (52.39%) that built on previous research efforts citing 3,720 existing projects. The large majority of firms in our sample have between one and fifty projects for a total of 4,239 distinct projects. There are 20 large pharmaceutical companies with more than 50 projects that alone contribute to a total of 3,111 projects (Table 4.1).

[34] For projects with market drugs we extract also the first date of sales. The average length of projects with marketed drugs then is 11 years, consistent with the trend described in the literature.

Table 4.1: Most representative firms

	Num Proj.	Succ.	Fail	Ong		Num Proj.	Succ.	Fail	Ong.
Takeda	56	9	29	18	Bayer	144	46	46	52
Johnson & Johnson	58	15	17	26	Novartis	149	39	81	29
Mitsubishi Tanabe Pharma	58	13	20	25	AstraZeneca	162	46	78	38
Boehringer Ingelheim	66	23	36	7	Astellas	167	61	63	43
Eisai	83	24	40	19	AbbVie	203	69	55	79
Daiichi Sankyo	89	38	25	26	Bristol-Myers	216	44	86	86
Actavis	91	51	15	25	Merck & Co	243	47	83	113
Roche	94	6	61	27	Sanofi	243	26	176	41
Amgen	106	20	34	52	GlaxoSmithKline	320	81	117	122
Lilly	114	8	42	64	Pfizer	449	45	160	244

4.3.3 Dependent Variable

In our analysis we measure learning as the cumulated experience generated by previous R&D efforts, direct and vicarious, that operate to produce better outcomes in following attempts.

Projects status. Successful projects are those that are lunched in the market or are in the process of registration or pre-registration. Failed projects are those that have been discontinued or suspended during development trials. Our third group is represented by all the projects that are still in the preclinical or clinical trials (ongoing projects). Every project, along the development process, may go through different status at different time, for different indications and in different markets. Therefore, to correctly identify the status we analyzed the development history of every project and we classified as *Success* those projects that have at least one success, as *Failure* those projects that have experienced only failed events while projects that have experience both a success and a failure in their development history are classified as success since at least for one indication or in certain geographical market have been approved by the FDA[35]. The remaining projects that along their development path did not experience any success or failure are classified as *Ongoing* (this group is not considered in the main analysis but will be presented in the Appendix Table A.6). Figure 4.2 and 4.3 show the distribution over time of the projects by starting and outcome date. Table 4.2 reports the final phase reached by focal and cited project before termination. Table 4.4 reports the status of focal projects that build on previous efforts versus those that do not.

[35] The projects that have both a Failure and a Success event in their development history are in total 509. In non reported regression we tried different classification for our dependent variable with results robust to alternative classifications. As an example Dronabinol in its development history has a successful events, namely being marketed for treating anorexia nervosa, nausea and vomiting related problems. During its development history, clinical trials have been started also to cure migraine and dementia but with unsuccessful outcome. However, since at least for one indication the experimentation was successful, Dronabinol is classified as Success.

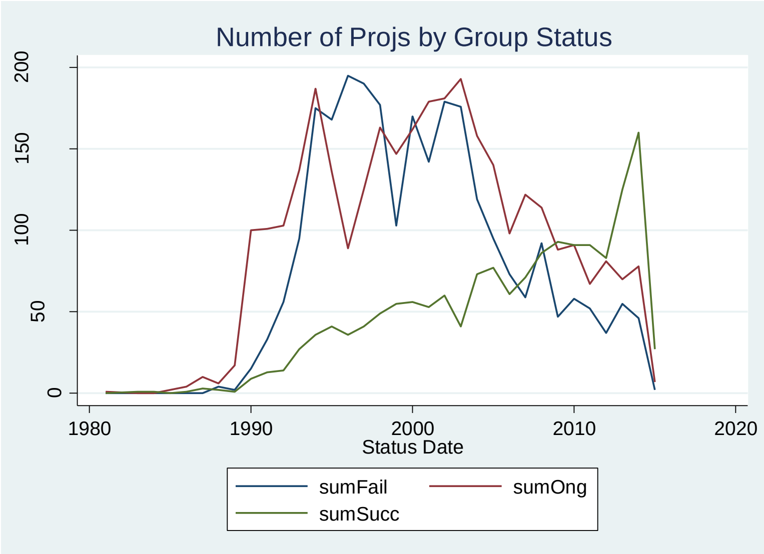

Figure 2: : Number of Successful/Failed and Ongoing projects over time.

Table 4.2: Final Phase reached by the focal and the cited project before termination.

	FINAL PHASE OF FOCAL BEFORE TERMINATION		*FINAL PHASE OF CITED BEFORE TERMINATION*	
	Freq	***%***	***Freq***	***%***
Discovery	6	0.23	3	0.23
Preclinical	829	31.70	387	29.25
Clinical	8	0.31	5	0.38
Phase I	486	18.59	238	17.99
Phase II	936	35.79	478	36.13
Phase III	330	12.62	205	15.50
Terminated	20	0.76	7	0.53
Tot	2615	100	1,323	

We extracted the most advanced phase reached by the project before termination in countries having comparable standards (Europe, Japan, USA, North America, Canada). This enable us to know at which phase in the trial process the failure has occurred.

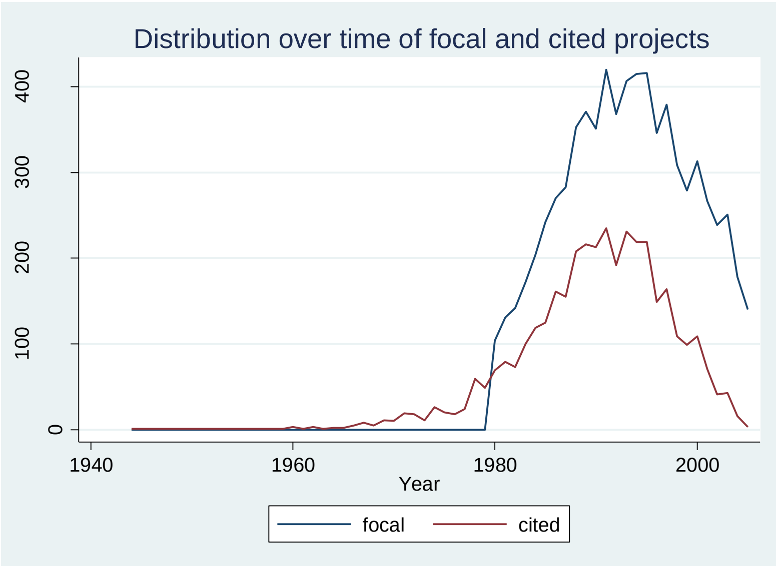

Figure 3: Distribution over time of focal and cited projects

	STATUS OF FOCAL			***STATUS OF CITED***		
	Freq	***%***	***Cum***	***Freq***	***%***	***Cum***
Failure	2,615	35.58	35.58	1,323	35.56	35.56
Ongoing	3,157	42.95	78.53	1,319	35.46	71.02
Success	1,578	21.47	100.00	1,078	28.98	100.00
Tot	7,350	100	100	3,720	100	100

For 2,325 focal projects and for 1,123 cited projects in the Ongoing group we don't have any update on the development process since more than 10 years. We use a cut off value of 10 years of no updates to distinguish between projects that are likely to have failed but didn't reported the termination event and projects that are still in the development process. We choose 10 years which is a longer time compared to what described in the literature in order to ensure that the group of suspicious ongoing actually include only projects that although not formally failed have performed badly. Focal: 2325 Suspicious Ongoing and 832 Real Ongoing. Cited: 1123 Suspicious Ongoing and 196 Real Ongoing.

Table 4.3: Status of Focal and Cited project.

Table 4.4: Status of focal projects that build on previous projects versus those that don't built on previous projects

	Focal projects that built on previous R&D efforts		Focal projects that DONT built on previous R&D efforts	
	Freq.	%	Freq.	%
Failure	1,340	34.80	1,275	36.44
Ongoing	1,637	42.51	1,520	43.44
Success	874	22.70	704	20.12
	3,851	100	3,499	100

The 52.39% of focal projects built on previous R&D efforts via patent citations with a success ratio equal to 22%. Patent citation link may identify incremental development projects, whereas non-linked patents may be based on true innovations and new drug development opportunities. However, the success rate in the two group is quite similar ruling out this possibility.

4.3.4 Independent Variables

Reliance on previous projects: we analyze the reliance of the focal project on previous research efforts via patent citations. We distinguish ***Building on own projects***, when focal project cites patents linked to projects developed by the same Lead Company, from ***Building on others' projects***, when instead the focal build on research efforts by other firms. Self-citations refer to the ability of the firm to build on previous experiences and knowledge with possible benefits on following research projects[36] (Hall et al., 2001). Literature has also considered citations of other organizations as a good proxy of knowledge flows (Jaffe et al., 2000). We further distinguished between citation to previous Successful, Failed and Ongoing efforts both by the Same Lead as well as other firms' projects (*Building on own Failure / Success / Ongoing* versus *Building on others' Failure / Success / Ongoing*)[37]. We distinguish Self-

[36] Nerkar (2003) uses a similar approach and consider patent citations as a proxy for knowledge recombination - patents citing previous patents using knowledge embodied in the cited ones.
[37] In order to avoid multicollinearity we use exclusive dummies only among the two main set of independent variables: Building on own previous own projects and Building on previous projects by other firms. As an example, the variable "Building on own Failure" flags focal projects that only built further on their own previous failures. At the same time the focal can also build on previous failure by other firms or previous success by others.

citations from citations to other organizations since they convey different patterns of knowledge diffusion and learning mechanisms. On one side self-citations measure the extent to which the organization is able to benefit from its previous research efforts in a cumulative way (Hall et al., 2001). On the other side, citations to other firms' efforts capture the extent to which the focal firm built on external knowledge through vicarious learning. Table 4.5 reports the citation patterns whereas Table 4.6 shows the success ratio of focal projects building on previous R&D efforts.

Table 4.5: Citations patterns.

		Building on:			
		Success	**Ongoing**	**Early Fail**	**Late Fail**
Focal:	**Success**	679	272	182	254
	Ongoing	701	968	614	666
	Early Fail	11	509	306	277
	Late Fail	636	291	238	308

There are 3851 focal projects that built on previous research efforts, Repetition in the citation patterns in this table are possible due to multiple citations per focal project. On average focal cites 2 previous projects while the average number of cited patent families is 15.

Table 4.6: Success Ratio

	Freq.	**Succ**	**Succ. Ratio (%)**
Focal building on Success	**1039**	**440**	**42,34%**
Focal building on Failures	**1223**	**112**	**9,15%**
Focal building on Succ. & Fail	**986**	**190**	**19,26%**
Focal building on Ongoing	**603**	**60**	**9,95%**

4.3.5 Control Variables

We introduce a series of control variables related to the project, the associated patents as well as firms' characteristics.

4.3.5.1 Project Controls

The drug development projects may refer to several Medical Indications and Anatomical Therapeutic Chemical Classification (ATC). The Indication refers to the use of the drug for treating a certain disease. For instance, *diabetes* is an indication for *insulin* or stated in another way insulin is indicated for the treatment of diabetes. The ATC points to the active ingredients of drugs according to the organ or system on which they act and their pharmacological and chemical properties. In the ATC classification System drugs are classified into 5 levels: the first indicates the anatomical main group (metabolism "A"; cardiovascular system "C", and so forth), the second level indicates the therapeutic main group, up to the last level indicating the chemical substance. A drug that targets diabetes may for example report indications also for obesity and other metabolic disease and it is usually associated to ATC classes A10X, Drug used in Diabetes, A10L, Alpha-glycosidase Inhibitor, A84, Anti-obesity preparation. This study uses ATC- 3 level to identify the relevant drug market in line with standard procedure commonly used by the European Commission and pharmaceutical companies. A drug in ATC-3 class can only be substitute with another drug in the same ATC-3 class but not by a drug in a ATC-2 level even if pointing at the same Therapeutic Indication. For instance drugs in ATC-3: A10B and A10A are both associated to the treatment of diabetes but use different target action (insulin versus non-insulin), therefore they are not substitute. The inclusion of multiple indication and ATC per project might increase the possibility of success as scientists may leverage on a common knowledge and testing models on the same molecule applied to Indication sharing similar biological characteristics. Therefore we control for the ***Number of Indication and ATC classes*** associated to the project (Table 4.7).

The risk embedded in the development of a drug in the ATC classes can vary over time. We measure a dynamic ***ATC Success Rate*** associated with each ATC included in each project by computing the share between Successful project over the total project with known outcome (Success and Failure) before the starting date of the focal projects.[38]

We also control for the R&D Opportunity in ATC by taking into account the total number of projects by other firms in the same ATC having a time overlap with the focal project (***R&D competition in ATC).*** We also control for the possibility that unobserved characteristics of therapeutic areas may generate different project outcomes by considering the most representative ATC Classes in our sample associated to more than 30 projects (***87 ATC dummies***). Projects that are more recent in time may be less likely to have a final outcome status, either being marketed or terminated. To control for year effects, we include ***Starting Year dummies***.

Table 4.7: Number of Indication and ATC Classes of focal projects

	Number of Indications		***Number of ATCs***	
	Freq.	***%***	***Freq.***	***%***
1	3,931	53.48	5,357	72.88
2	1,609	21.89	1,439	19.58
≥3	1,810	24,60	554	7.55
	7,350	100	7,350	100

4.3.5.2 Patent Controls

Our sample includes development projects of compounds that are protected by patent law. Chandy et al., (2006) et al., suggested that the ability of pharmaceutical firms to translate patents into final drugs is higher for firms that develop an intermediate number of drug-related patents. Thus, we include in our control variables the ***Number of Patent families*** the focal project is associated to, while also identifying, through dummies, projects that share the same patent family (***Same Patent Family***). In this study patent families are also useful to capture additional knowledge from previous patents via citations.

We include the total ***Number of Backward Citations (Bwd cits)*** to other patent families and also a control for the citation to ***Non Patent Literature (Citing NPL Scientific)*** in the form of scientific references as existing studies

[38] In case of multiple ATC per project we computed the mean of (ATC Success Index).

have shown an important link between science and technology (Narin et al., 1997; Griliches, 1986; Koenig, 1983; Van Looy et al., 2003). Patent information also allows us to observe whether the focal project build on previous research efforts, the characteristics of the projects it builds on as well as other related patents. We consider the average quality of cited patent family proxy by the ***Forward citation.*** As failure may be linked to the intrinsic quality of both the focal and the cited patent. More novel or original patents are usually associated with a higher risk. To control for these factors we include the ***Originality*** measure by Trajtenberg et al., (1997) based on the spread of backward citations to technological classes. Novelty is also associated with the number of elements that are combined within patents, thus we control for the ***number of technological components*** that are recombined within the focal and cited patent[39]. We also flag common characteristics between focal and previous projects by identifying projects developing drugs in at least one common therapeutic area reported (***Same ATC focal cited***).

Patents embody valuable knowledge upon which firms rely for the development of drugs. Therefore, we control for knowledge spillovers by identify the projects in which the company leading the R&D project is also the owner of the patent protecting the compound (***Same Company Lead-Patent***)

4.3.5.3 Firm Controls

Large firms have been found to be path dependent, usually confined within their established routines and practices showing resistance towards new explorative solutions (Hill & Rothaermel, 2003). Yet, they also build on a larger knowledge base that allow them to leverage on direct failed ad successful events, benefit from scope economies on related projects, and better assessment of potential risks. The concentration of R&D portfolios of firms in specific therapeutic areas may increase the likelihood of a project to reach the market.

Danzon et al., (2005) show that firms with focus experience rather than broad knowledge are able to leverage economies of scope with higher probability of completing Phase III in clinical trials. Hence, we control for the ***Concentration of firm portfolio*** over ATC classes pointing to the span of firm

[39] These measures are computed at the family level.

research strategies using the Hirschman-Herfindahl index. Note that each projects may include multiple ATC classes thus we capture the breadth of projects portfolio using a fractional count and then collapsing everything at firm level[40]. This measure will take the value one for firms having a very concentrated project portfolio, whereas it will approach zero for more diversified firms.

Nerkar and Roberts (2004), find that experience in proximal technologies has a positive effect on commercial success of new pharmaceutical products. Hence, we control for the firm success ratio by computing the number of failed projects over time prior the starting date of the focal (***Firm Failures Ratio***). Since this variable is not cumulative, it controls for a different propensity of the focal firm to succeed or failed over time, possibly due to experience[41]. Projects that are more recent in time may be less likely to have a final outcome status, either being marketed or terminated. Finally, to capture variation in trends across firms and ATC classes over time, we also use ***Firms, ATC and Starting Year dummies***. Table 4.8 provides an overview of the variables with a short description and summary statistics.

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[40] For the derivation of the Index see: Gruber, M., Harhoff, D., & Hoisl, K. (2013). Knowledge recombination across technological boundaries: scientists vs. engineers. *Management Science*, *59*(4), 837-851.

[41] We also used an alternative and more direct measure of experience by computing the cumulative years of firm activity in the focal ATC in previous projects (***Years of Experience in ATC***).To control for firm-year unobserved effects we use the ratio of failed project prior the starting year of the focal. The main results are robust in both specification.

Table 4.8: Overview of Variables, their description and summary statistics for the group of Failure and Success excluding ongoing (4193 obs)

Variable	Description	Measure	Obs	Mean	Std. Dev.
Project Status	Status of the focal projects (Success/Failure)	Dummy	4193	0.376	0.484
Building on:	Focal projects building on previous own failed, successful or ongoing projects. (Focal Lead=Lead of previous proj.)	Exclusive Dummies			
Self Failure			4193	0.052	0.222
Self Success			4193	0.031	0.175
Self Succ.& Fail.			4193	0.057	0.233
Self Ongoing			4193	0.014	0.117
Building on:	Focal projects building on previous failed, successful or ongoing projects by other firms. (Focal Lead≠Lead of previous proj.)	Exclusive Dummies+			
Others' Failure			4193	0.118	0.322
Others' Success			4193	0.157	0.364
Others' Succ & Fail.			4193	0.137	0.344
Others' Ongoing			4193	0.047	0.213
Focal Projects controls:					
Num. Indication	Number of Indications	Number of Indications	4193	2.35	2.49
Num. ATC Class	Number of ATC classes	Number of ATC classes	4193	1.428	0.765
Num. Families	Number of patent families	Number of families	4193	1.137	0.407
Sharing the same patent	The focal project is associated to a patent family shared by other focal projects. Extent to which same technological efforts are re-used.	Dummy	4193	0.201	0.401
Focal Patent Controls:					
Patent Originality	Originality Index		3793	0.829	0.137
Number of Components			3888	41.02	76.84
Same Company - patent	The lead company and the owner of the patent are the same entity (Jaccard similarity)	Dummy	4193	0.922	0.289

Citations controls:					
Cite NPL - Scientific. Lit.	Extent to which the focal project refers to Scientific NPL.	Dummy	4193	0.802	0.398
Bwd cit.	Extent to which the focal project builds on previous technological efforts	Number of Backward patent references	4193	2.31	0.973
Cited Patent controls:					
Fwd cit.	Average quality of cited patent family	Mean of Fwd citations 5year	4193	8.74	8.035
Patent Originality	Originality Index		3808	0.806	0.103
Number of Components			3835	28.55	36.403
Same Company - patent	The lead company and the owner of the patent in focal projects are the same entity (Jaccard similarity)	Dummy	4193	0.0922	0.289
Same ATC focal-previous proj.	Focal building on previous projects having at least 1 ATC class in common (via patent citations)	Dummy	4193	0.349	0.476
ATC Controls:					
ATC success rate	Number of Successful projects in ATC prior to the starting of the focal project	Number of Success in ATC	4193	0.469	0.237
R&D competition in ATC	Number of projects by other firms in the ATC with time overlap	Number of projects	4193	5.62	1.664
Firm Controls:					
Failure Ratio over time	Number of failed projects over time prior the focal		4193	1.05	1.22
Breadth of firmactivities	Breadth of the focal Lead's research activities	1-Herfindahl Index	4193	0.118	0.179

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
1	StatusS_F	1.0000																										
2	SelfF	-0.1160*	1.0000																									
3	Others F	-0.1164*	0.1500*	1.0000																								
4	SelfS	0.1403*	-0.0425*	-0.0662*	1.0000																							
5	Others S	0.2286*	-0.1014*	-0.1580*	0.1387*	1.0000																						
6	SelfSF	-0.0031	-0.0582*	-0.0907*	-0.0449*	-0.1071*	1.0000																					
7	Others' SF	-0.0063	-0.0936*	-0.1459*	-0.0722*	-0.1722*	0.5777*	1.0000																				
8	SelfO	-0.0510*	-0.0280	-0.0437*	-0.0216	-0.0516*	-0.0296	-0.0476*	1.0000																			
9	Others' O	-0.0476*	-0.0527*	-0.0821*	-0.0406*	-0.0969*	-0.0557*	-0.0895*	0.0964*	1.0000																		
10	NumInd	0.1150*	-0.0302	0.0016	-0.0261	0.0085	0.0250	0.0491*	0.0066	0.0693*	1.0000																	
11	NumClass	0.1695*	-0.0138	-0.0165	-0.0053	0.0270	-0.0335*	-0.0420*	-0.0246	-0.0017	0.2917*	1.0000																
12	NumFam	0.1784*	0.0154	-0.0020	0.0023	0.0503*	0.0489*	0.0831*	0.0093	-0.0073	0.0883*	0.0738*	1.0000															
13	f_Lead=f_Pat	-0.1437*	0.0685*	0.0304*	-0.0089	-0.0444*	0.0723*	0.0315*	0.0195	0.0029	-0.0077	-0.0153	-0.0534*	1.0000														
14	Same Family	-0.0614*	0.1172*	0.0336*	0.0719*	0.0167	0.1222*	0.1091*	0.0207	0.0209	-0.0058	-0.0319*	0.0914*	-0.0395*	1.0000													
15	f_originality	-0.0747*	0.0504*	0.1007*	-0.0037	0.0111	0.1121*	0.1751*	0.0101	0.0683*	0.0529*	-0.0049	-0.0153	0.0396*	0.0481*	1.0000												
16	f_Num Comp	-0.0644*	0.0477*	0.0666*	-0.0141	-0.0314	0.0903*	0.1210*	0.0100	0.0492*	0.0942*	0.0324*	-0.0354*	0.0918*	0.0291	0.2017*	1.0000											
17	c_fwd	0.0205	0.0526*	0.0568*	0.0286	0.0893*	0.1298*	0.1929*	0.0615*	0.0291	0.1055*	0.0010	0.0163	-0.0214	0.1017*	0.2055*	0.1443*	1.0000										
18	c_originality	-0.0974*	0.0639*	0.0460*	-0.0283	-0.0427*	0.0865*	0.1097*	-0.0075	0.0518*	0.0443*	0.0015	-0.0523*	0.0783*	0.0484*	0.3812*	0.1669*	0.2135*	1.0000									
19	c_Num Comp	-0.1195*	0.0764*	0.0856*	-0.0305	-0.0760*	0.0673*	0.0897*	0.0226	0.0828*	0.0711*	-0.0001	-0.0599*	0.1036*	0.0165	0.3506*	0.3525*	0.2371*	0.3244*	1.0000								
20	cite Npl Scien.	0.0552*	0.0007	0.0162	0.0146	0.0233	0.1000*	0.1263*	0.0287	0.0132	0.0765*	0.0163	0.1174*	-0.0427*	0.0700*	0.1195*	0.0713*	0.0391*	-0.0029	-0.0002	1.0000							
21	totBwd	0.1844*	0.0058	0.0734*	0.0840*	0.1821*	0.3049*	0.4173*	-0.0123	0.0390*	0.0688*	0.0396*	0.2388*	0.0160	0.1317*	0.3416*	0.1851*	0.2060*	0.0292	-0.0051	0.2545*	1.0000						
22	maxsameATC	0.1102*	0.1446*	0.1718*	0.1514*	0.3344*	0.2378*	0.3510*	0.0705*	0.0432*	0.0717*	0.0031	0.0887*	0.0285	0.1267*	0.1588*	0.0868*	0.2555*	0.0841*	0.0678*	0.1142*	0.3949*	1.0000					
23	Jf_Lead_Pat	-0.0453*	0.3066*	0.0595*	0.1351*	-0.0245	0.3511*	0.2034*	0.1298*	-0.0407*	0.0077	-0.0085	0.0257	0.3221*	0.1089*	0.0918*	0.0811*	0.1182*	0.0695*	0.0922*	0.0526*	0.1629*	0.2442*	1.0000				
24	Succ ATC	0.3129*	-0.1012*	-0.1252*	0.0583*	0.1698*	-0.0970*	-0.1147*	-0.0539*	-0.0757*	-0.1043*	0.0750*	0.1123*	-0.0888*	-0.0207	-0.0988*	-0.1652*	-0.1640*	-0.1582*	-0.1795*	-0.0774*	-0.0654*	-0.0399*	-0.0827*	1.0000			
25	Competition	-0.0446*	0.0197	0.0283	-0.0638*	-0.0558*	-0.0088	-0.0078	0.0066	0.0340*	0.3041*	0.4486*	0.0100	-0.0402*	0.0137	-0.0067	0.0682*	0.0515*	-0.0118	0.0294	0.0656*	0.0349*	-0.0182	-0.0196	-0.2914*	1.0000		
26	Ratio failures	-0.2457*	0.1324*	0.0497*	0.0093	-0.0672*	0.1252*	0.0863*	0.0520*	0.0399*	-0.0208	-0.1308*	-0.1361*	0.1279*	0.0234	0.0935*	0.1217*	0.1039*	0.1453*	0.1462*	0.0048	0.0298	0.0790*	0.1574*	-0.2824*	-0.0145	1.0000	
27	1-Hi	-0.0449*	0.0697*	0.0292	0.0445*	0.0008	0.0457*	0.0271	0.0341*	-0.0151	-0.0452*	0.0246	-0.0120	0.0242	-0.0045	0.0417*	0.0781*	0.0182	0.0555*	0.0805*	-0.0772*	-0.0009	0.0487*	0.0586*	0.0616*	-0.0791*	0.3705*	1.0000

Table 4.9 11: Correlation table

4.4 Results

In our empirical strategy we focus on the effects that learning from previous R&D efforts has on the outcome of current drug development projects. The unit of analysis is therefore represented by the single project. In our empirical analysis we use logit model and take the likelihood of achieving project success (approval and market introduction of the drug) as the dependent variable. We exclude ongoing projects to focus on projects with a clearly defined outcome (in the appendix we examine ongoing status as an additional outcome, using a multinomial logit specification Table C.5). The estimates on prior success and failure indicate the likelihood of success of focal projects that build on previous projects versus those focal projects that do not build on prior projects of the focal or other firms. In Tables 4.10 and 4.12 we consider all citations linked to previous projects. In Tables 4.11 and 4.13 we instead control for the timing of the citation. In order to do that, we redefine the independent variables to take into account only citation linkages where the focal project ends after the cited projects (projects that ends before the cited are flagged by the dummy ***Projects before cited outcome****)*. Models 1 show the results when only the control variables are considered. Models 2 presents the estimations of the full model.

Our first research question proposes to examine whether pharmaceutical firms have a higher propensity to learn from success rather than from failures. Table 4.10 shows that previous successful attempts (both by the focal firm and by other firms) have a positive and significant effect on the likelihood of achieving a successful outcome in focal drug development projects. We find the opposite result when the focal project builds on previous failures or ongoing projects. In other words, the estimates indicate that failure experience has a tendency to trigger future failures whereas previous success induces further success. The increase in the odds of achieving a successful outcome given previous success is substantially high (189%) for own success and about 42% for others firms' success. Prior failure instead decrease the odds of success, by 50% for the coefficient (own Failure) and 37% for other firms' failure. The strong results for prior success provide a confirmative answer to research question 1, while the negative effect of failure contrast with prior research findings on learning from large failures.

Table 4.10: Estimations for experiential and vicarious learning on project status

	Model 1	Model 2
Self Failure		**-0.7033*** **
		(0.2500)
Others' Failure		**-0.4666** **
		(0.1973)
Self Success		**1.0643*** **
		(0.2576)
Others' Success		**0.3574** **
		(0.1668)
Self Succ. & Failure		0.1532
		(0.2579)
Others' Succ. & Failure		**-0.3599* **
		(0.2139)
Self Ongoing		**-0.8032** **
		(0.3411)
Others' Ongoing		-0.4418*
		(0.2391)
Num Indication	0.2634***	0.2603***
	(0.0263)	(0.0261)
Num ATC classes	0.9800**	1.0038**
	(0.4801)	(0.4857)
Num Patent Family	0.5677***	0.5980***
	(0.1457)	(0.1445)
Shared patent Family	-0.5597***	-0.5637***
	(0.1613)	(0.1624)
Focal Patent originality	-1.8145***	-1.6375***
	(0.4446)	(0.4431)
Focal Patent Num.Comp.	-0.0006	-0.0005
	(0.0006)	(0.0006)
Focal Lead=Focal Pat	-0.6037***	-0.5965***
	(0.1450)	(0.1468)
Citing NPL Scientific	0.1024	0.1056
	(0.1159)	(0.1171)
Bwd Cits	0.4072***	0.4206***
	(0.0612)	(0.0688)

Fwd cited	0.0011	0.0008
	(0.0060)	(0.0058)
Cited Patent Originality	0.2305	0.2138
	(0.4827)	(0.4782)
Num.Comp. cited Patent	0.0004	0.0012
	(0.0015)	(0.0015)
Focal Lead=Cited Patent	0.0614	0.1352
	(0.1855)	(0.2329)
Same ATC focal-cited	0.4009***	0.4288***
	(0.1021)	(0.1211)
Succ in ATC	1.2301***	1.0494***
	(0.2585)	(0.2609)
R&D competition in ATC	-0.0742	-0.0359
	(0.0639)	(0.0654)
Failure Ratio	-1.0150***	-1.0015***
	(0.2287)	(0.2310)
Breadth of firm activities	0.7859**	0.7762**
	(0.3389)	(0.3404)
Constant	-1.5869**	-1.9228**
	(0.7684)	(0.7621)
Observations	3568	3568
Pseudo R^2	0.3270	0.3414
log Lik.	-1593.3710	-1559.2313
Chi squared	1983.3707	2045.8247

Standard errors in parentheses; * p<0.1, ** p<0.05, *** p<0.01. Standard errors clustered by firm.
Models report logit for Success and Failures with inclusion of 25 year, 87 ATC classes dummies.

Table 4.11: Estimations for experiential and vicarious learning on project status. Time Restriction

	Model 1	Model 2
Cites Self Failure		**-0.6089****
		(0.2575)
Cites Others' Failure		-0.2919
		(0.2063)
Cites Self Success		**1.5979*****
		(0.3639)
Cites. Others' Success		**0.5949*****
		(0.1913)
Cites Self Success and Failure		0.3124
		(0.2679)
Cites Others' Succ&Failure		-0.2619
		(0.2265)
Cites Self Ongoing		**-0.7875****
		(0.3436)
Cites Others' Ongoing		-0.3655
		(0.2451)
Project before cited outcome	-0.8634***	-0.8283***
	(0.1561)	(0.1879)
Num Indication	0.2622***	0.2601***
	(0.0264)	(0.0260)
Num ATC classes	0.9506**	0.9527*
	(0.4788)	(0.4869)
Num Patent Family	0.5528***	0.5727***
	(0.1479)	(0.1442)
Shared patent Family	-0.5487***	-0.5801***
	(0.1634)	(0.1718)
Focal Patent originality	-1.8058***	-1.6527***
	(0.4521)	(0.4606)
Focal Patent Number of Comp.	-0.0006	-0.0004
	(0.0006)	(0.0006)
Focal Lead=Focal Pat	-0.6233***	-0.6116***
	(0.1437)	(0.1452)
Citing NPL Scientific	0.0822	0.0816
	(0.1174)	(0.1162)

Bwd cits	0.3820***	0.3662***
	(0.0617)	(0.0676)
fwd cited	0.0007	0.0001
	(0.0061)	(0.0058)
Cited Patent Originality	0.2543	0.2637
	(0.4794)	(0.4798)
Num. Comp. of cited Patent	0.0002	0.0010
	(0.0015)	(0.0015)
Focal Lead=Cited Patent	0.0772	0.0863
	(0.1812)	(0.2259)
Same ATC focal-cited	0.5302***	0.5202***
	(0.1118)	(0.1311)
Succ in ATC	1.2495***	1.1178***
	(0.2698)	(0.2740)
R&D competition in ATC	-0.0903	-0.0562
	(0.0649)	(0.0661)
Failure Ratio	-1.0000***	-0.9749***
	(0.2280)	(0.2288)
Breadth of firm activities	0.7978**	0.7532**
	(0.3395)	(0.3375)
Constant	-1.4437*	-1.7596**
	(0.7812)	(0.7886)
Observations	3568	3568
Pseudo R^2	0.3325	0.3478
log Lik.	-1580.3527	-1544.0172
Chi squared	1945.5579	1977.0382

Standard errors in parentheses; * p<0.1, ** p<0.05, *** p<0.01. Standard errors clustered by firm.

Models report logit for Success and Failures with inclusion of 25 year, 87 ATC classes dummies.
The independent variables only include citations where the focal project ended after the cited. Focal projects that end before are included in the dummy Projects before cited outcome.

In the second research question, we proposed to examine whether there is a stronger influence from previous own success or failure than from other firms' experience. A Wald test confirms that other firms' prior success has a smaller effect on success than firms' own prior success. Similarly, the difference in coefficients of own and other firms' failure is significant as well. Citing ongoing projects has similar effects as citing failures. The difference in the coefficients between prior own and other firms' success provides a confirmative answer to research question 2. Imposing a stricter time ordering between focal and prior projects (Table 4.11) leads to a similar pattern as in the models showed in Table 4.10, but with the effects generally larger in magnitude for citing previous own and others' success.

Control variables reveal results that are overall consistent with our expectations. Focal projects with more medical indications and therapeutic areas have a higher probability to succeed as well as projects with more than one patent family. These variables shows the same trends and magnitude also in Tables 4.12 and 4.13. The reuse of the same patent family among several projects increases the incidence of failure, which is likely to be due to the lower costs of reusing the same patent for several projects allowing more risks to be taken through local search (the effects of reusing the same patent is better examined in the Appendix, Tables C.3 and C.4). The other controls at the patent level suggest that a higher originality of the focal patent on which the project is based, decrease the likelihood of success of the drug. This result suggests that projects that build further on patents that are original (combining knowledge from different sources) may have a higher intrinsic risk and distant search which may explain a higher failure rate. As found in previous studies (Narin et al., 1997) backward citations to patents increase the likelihood of success. A generally higher success ratio for projects in the same ATC significantly drives the success rate as well. Interesting is the positive effect of projects having the same ATC of the cited project suggesting that building further on common ATC classes facilitates learning and leads to a higher probability of success due to specific experience in the therapeutic category. Firms that develop specialized expertise in certain fields can limit the probability of failures since they can build further on cumulated knowledge. This finding is in line with studies pointing to the refinement of performance through repeated experience (Argote, 1996) and to the benefits of developing focused experience enabling firms to rely on economies of scope (Danzon et al., 2005). In line with expectation, a higher success rate in the ATC increase the likelihood of success. At firm level, higher failure rates prior the starting date of the focal projects decrease the likelihood of success. Other control variables have no significant effects.

Given the importance of within-ATC class learning shown in Tables 4.10 and 4.11, we provide in Table 4.12 further insights on the effect of previous success and failure depending on whether prior projects cover the same ATC class or not. Interestingly, the negative effect of previous failures is limited to prior own and other failures in different ATCs by other firms', while it is not significant when prior projects cover the same ATC. The results also indicate that the probability of project success is enhanced in case prior experience relates to firms' own and others firms' projects within the same ATC class.

Table 4.12: Estimations for experiential and vicarious learning on ATC

	Model 1	Model 2
Self Same ATC Failed		-0.1645
		(0.2790)
NO Self Same ATC Failed		0.1585
		(0.1556)
Self Different ATC Failed		-0.3654
		(0.2690)
No Self Different ATC Failed		**-0.5343*** **
		(0.1715)
Self Same ATC success		**0.7179*** **
		(0.2436)
No Self Same ATC Success		**0.7608*** **
		(0.1198)
Self Different ATC Success		0.2101
		(0.2349)
No Self Different ATC Success		-0.0256
		(0.1532)
Self Same ATC Ongoing		-0.3479
		(0.3213)
No Self Same ATC Ongoing		-0.0213
		(0.1720)
Self Different ATC Ongoing		-0.1114
		(0.2764)
No Self Different ATC Ongoing		-0.2729
		(0.1730)
Num Indication	0.2640***	0.2667***
	(0.0261)	(0.0269)
Num ATC classes	0.9704**	1.0192**

	(0.4763)	(0.5152)
Num Patent Family	0.5647***	0.6072***
	(0.1479)	(0.1502)
Shared patent Family	-0.5350***	-0.5070***
	(0.1579)	(0.1663)
Focal Patent originality	-1.8362***	-1.6799***
	(0.4500)	(0.4449)
Focal Patent Number of Comp.	-0.0007	-0.0005
	(0.0006)	(0.0006)
Focal Lead=Focal Pat	-0.6162***	-0.6080***
	(0.1437)	(0.1506)
Citing NPL Scientific	0.1226	0.0984
	(0.1163)	(0.1192)
Bwd cits	0.4640***	0.4670***
	(0.0604)	(0.0725)
fwd cited	0.0046	0.0036
	(0.0059)	(0.0059)
Cited Patent Originality	0.3000	0.1797
	(0.4848)	(0.4881)
Num. Comp. of cited Patent	0.0005	0.0013
	(0.0015)	(0.0015)
Focal Lead=Cited Patent	0.1734	0.2290
	(0.1794)	(0.2134)
Succ in ATC	1.2952***	1.0039***
	(0.2512)	(0.2625)
R&D competition in ATC	-0.0825	-0.0391
	(0.0645)	(0.0668)
Failure Ratio	-1.0141***	-0.9813***
	(0.2306)	(0.2344)
Breadth of firm activities	0.8277**	0.8091**
	(0.3384)	(0.3418)
Constant	-1.7576**	-2.0055***
	(0.7569)	(0.7665)
Observations	3568	3568
Pseudo R^2	0.3239	0.3457
log Lik.	-1600.6820	-1548.9970
Chi squared	1928.4928	2140.3781

Standard errors in parentheses; * p<0.1, ** p<0.05, *** p<0.01. Standard errors clustered by firm.
Results of logit for Success and Failures and include 25 year and 87 ATC classes dummies.

Table 4.13: Estimations for experiential and vicarious learning on ATC. Time restriction

	Model 1	Model 22
Self Same ATC Failed		-0.0403
		(0.2557)
NO Self Same ATC Failed		0.2800
		(0.1870)
Self Different ATC Failed		**-0.4706***
		(0.2627)
No Self Different ATC Failed		**-0.7904*****
		(0.1775)
Self Same ATC success		**1.4817*****
		(0.2984)
No Self Same ATC Success		**0.9820*****
		(0.1539)
Self Different ATC Success		0.2361
		(0.2906)
No Self Different ATC Success		0.1287
		(0.1495)
Self Same ATC Ongoing		-0.4513
		(0.2995)
No Self Same ATC Ongoing		-0.1596
		(0.1886)
Self Different ATC Ongoing		**-0.6671*****
		(0.2575)
No Self Different ATC Ongoing		-0.2868
		(0.1810)
Cited before outcome	-0.6705***	-0.4064***
	(0.1414)	(0.1553)
Num Indication	0.2633***	0.2653***
	(0.0261)	(0.0266)
Num ATC classes	0.9385**	0.9199*
	(0.4730)	(0.5098)
Num Patent Family	0.5520***	0.5771***
	(0.1500)	(0.1534)
Shared patent Family	-0.5200***	-0.4966***
	(0.1593)	(0.1681)
Focal Patent originality	-1.8332***	-1.6822***
	(0.4590)	(0.4578)
Focal Patent Number of Comp.	-0.0007	-0.0004
	(0.0006)	(0.0007)

Focal Lead=Focal Pat	-0.6355***	-0.6323***
	(0.1428)	(0.1509)
Citing NPL Scientific	0.1102	0.0757
	(0.1175)	(0.1206)
Bwd cits	0.4590***	0.4456***
	(0.0610)	(0.0725)
fwd cited	0.0053	0.0042
	(0.0061)	(0.0060)
Cited Patent Originality	0.3290	0.1846
	(0.4829)	(0.4797)
Num. Comp. of cited Patent	0.0004	0.0014
	(0.0015)	(0.0015)
Focal Lead=Cited Patent	0.2186	0.2602
	(0.1737)	(0.2089)
Succ in ATC	1.3260***	1.0747***
	(0.2578)	(0.2670)
R&D competition in ATC	-0.0961	-0.0499
	(0.0653)	(0.0667)
Failure Ratio	-1.0009***	-0.9546***
	(0.2303)	(0.2354)
Breadth of firm activities	0.8483**	0.8139**
	(0.3385)	(0.3454)
Constant	-1.6889**	-1.9843**
	(0.7638)	(0.7831)
Observations	3568	3568
Pseudo R^2	0.3274	0.3562
log Lik.	-1592.2983	-1524.1035
Chi squared	1914.9722	2045.0624

Standard errors in parentheses (clustered by firm); * p<0.1, ** p<0.05, *** p<0.01. 25 year and 87 ATC dummies

4.5 Discussion and Conclusion

The knowledge that both failures and success convey is of paramount importance in the drug development process due to knowledge advancements and spillovers that can benefit the focal as well as competing firms (Hoetker & Agarwal, 2007). Although prior studies have stressed the role of balancing learning from failures and success (Levinthal & March, 1993) empirical research has focused, with few exceptions (Madsen & Desai., 2010; Magazzini et al., 2012) on benefits generated from failures (Desai, 2015; Haunschild and Sullivan, 2002; Eggers, 2014). This study extends our understanding of learning from failures and successes by examining the effect that learning from previous failed or successful drug developments efforts has on the success rate of related subsequent projects. It compares the roles of firms' experiential learning with that of vicarious learning from other firms' prior related drug development efforts. The pharmaceutical industry provides an interesting setting as failures and successes are generally disclosed, while the high propensity to patent and the fact that drug development projects relate to specific patents allow to identify linkages between projects through patent citations.

We find that both prior success in related drug development efforts of the focal firm and prior success of other firms positively affect the probability of success of subsequent drug development efforts. Contrary to common wisdom on learning from failures, our findings suggest that prior failures lead to a greater likelihood that firms fail again in their drug development efforts with a similar pattern observed for other firms' prior failures. For both learning from success and failures, direct experiential learning effects are larger than vicarious learning effects.

We offer a number of potential explanations for these findings. First, the results point to a degree of inertia in firms' drug development strategies when failing in R&D. In the pharmaceutical industry, firms specialize in therapeutic areas, and previous investments and cumulated knowledge may lead to escalating commitments and reluctance to withdraw from a development trajectory, in particular in the context of high expected, although very uncertain, returns (Maslach, 2016; Nerkar & Roberts, 2004). One illustration is Eli Lilly, which embarked on further trials for its Sola drug although having experienced two previous failures in Phase III trials. Given the high investment sustained, one possible explanation of why failures drive further failures is that pharmaceutical firms may tend to replicate previous trajectories since the costs of starting projects, or diversify them in related indications within the same ATC-3 or through the reuse of the same patents, are lower. Thus firms may have incentives to start new projects even though they are likely to fail. This explanation is further supported by the findings that the patterns of prior failures and following failures are only visible for drug development projects sharing the same ATC and the finding that projects sharing the same patent family are more likely to fail, pointing to higher failures when firms are expected to face lower costs. Results show that firms tend to learn from success in the same ATC which point on one side to a resolved uncertainty of experimentation by the existence of previous success and on the other to possible imitations among pharmaceutical firms. On the other hand, firms encounter a higher probability of failure when they build on failures in different ATC since there may still be uncertainty about proper compounds to cure certain diseases.

A second explanation is that pharmaceutical firms may continue with failed lines of research because the expected gains in case of success are very high, compensating the higher risk of failure. A marketable drug for the treatment of a disease for which a drug is still not available, as in the case of Alzheimer, can provide very high profits. Therefore, the higher risk associated with failures may be mitigated by the greater expected returns if the firm can market a drug that has no competitors in the market. In contrast, building on previous success, although increasing the probability of a positive outcome, is likely to implies more incremental rewards since there are already competing drugs in the market. This is in line with previous studies suggesting that being the first to introduce an innovative product on the market is positively associated with sales (Grabowski & Vernon, 1990; Roberts, 1999). In the pharmaceutical industry, managers select experimentation of compounds that are most promising, taking into account commercial considerations and the probability of success (Arora, 2009).

We examined the power of this explanation by analyzing yearly sales for successful projects (10% of the total sample), distinguishing between projects building on previous failure versus and projects building on previous successes. Computations on drug sales launched since 2003 in the US based on IMS data, reveal that average yearly sales value in the US is 7.6% higher for drugs citing failures only (686 versus 638 million US dollars). While this is in line with expectations, the magnitude of this difference is too small to consider this a major explanation for the observed patterns.

A last explanation for firms' behavior in building on previous failures is that there is no treatment of certain diseases on the market, such that as a consequence pharmaceutical firms experimenting on the cure of these disease have no other choice than building further on previous failures. In these circumstances, failures may give insights about the possible causes of what went wrong in previous experimentation but do not narrow down many other alternatives that the firms need to search through before finding the right route. Hence, failure may lead to subsequent failure.

The explanations presented are drawn mainly on technical reasons that lead firms to suspend or discontinue their projects. However, firms strategic decisions related to competition may also play a role and need further investigation.

Although these explanations may be part of the answer for the patterns observed, our results also suggest further research on alternative explanations on the incentives for building on previous failures. We note that the absence of a significant negative effect of learning from failures for projects that share the same ATC suggests that positive learning effects may occur for the most related projects, but may be outweighed by cost considerations.

Our study contributes to the organizational learning theory by demonstrating that pharmaceutical firms have the possibility to improve significantly their performance if they build on prior successes, while our results also emphasize the difficulties in learning from failures. Our study provides a different perspectives on the finding by Magazzini et al., (2012) showing that failed projects receive more patent citations and highlight that the fact that patented compounds are followed up in future related drug development does not mean that the knowledge they convey increases the probability of success.

Our study informs the policy debate on the advantages and disadvantages of enforcing disclosure on the reasons for unsuccessful trials. Recognizing the value of information from clinical trials, the FDA has released in 2007 an Amendment Act to include the results of trials of successful drug in public registers. Along these lines, in September 2016 the FDA has extended this Act (FDAAA801) by requiring the submission of results information for trials of unapproved products. Our findings indicate that these new regulations may be helpful. If firms have a better understanding of the reasons behind other firms' prior failures, they may fail less in their subsequent drug development.

This study also presents limitations. The design of this study enables us to capture only partially the mechanisms through which learning operates. Through the use of citations between focal patents underlying drug development projects, the analysis benefits from the understanding of which kind of prior research the focal firm builds on, but the analysis may not capture broader learning processes. Also, our analysis does not take into account the organizational context in which learning takes place (Argote and Todorova 2007) nor how effectively knowledge disseminates across units involved in the experimentation process.

Notwithstanding the findings of this study, additional research is necessary to improve our understanding of the complex relationship between previous success and failures and the performance of subsequent R&D projects.

Chapter 5

Concluding Remarks and Direction for Future Research

5.1 Summary of main findings

This dissertation draws on, and contributes to, the innovation literature that conceives innovation as a search and recombination process based on cumulative experience and constrained by cognitive limitations, uncertainty and challenges of value appropriation. Although there has been a fruitful discussion on firms' search processes in the existing literature, the question of how the external environment influences firms' search process remains still underexplored (Katila & Chen, 2009, Leten et al., 2016). This dissertation contributes to a better understanding of the crucial role of environmental characteristics in shaping the direction and success of firms' search process through the studies presented in Chapter 2, 3 and 4.

Chapter 2 explores the process of search and knowledge recombination over the entire technological landscape. This chapter presents a new measure of the extent to which knowledge is combined in an unconventional way. Compared to existing measures, built on patent citations, the indicator presented in this chapter focuses on the actual combinations of knowledge components (proxied by USPTO patent classes) within inventions. The analysis uncovers that a large fraction of patents is based on conventional knowledge recombination, pointing towards local search. Inventions that build on more novel combinations are rare but also more cited. In particular, inventions that search in established frameworks but introduce a disruptive combination in their most creative effort. The correlation with existing novelty measures like ‘originality’ by Trajtenberg et al., (1997) and ‘new first combinations' by Verhoeven et al., (2016) is only weakly related, suggesting that they capture different dimensions of knowledge recombination.

Chapter 3 analyzes how unfavorable economic conditions shape the search process that firms pursue. This chapter provides interesting insights relevant for debate on the pro-cyclicality or the counter-cyclicality of innovation. Results suggest that contractive phases of the business cycle are associated with more conventional recombination, signaling local search strategies. Firms respond asymmetrically to expansions and contractive phases of the sector business cycle showing overall a pro-cyclical trend both at the intensive (a decrease in unconventionality) and at the extensive margins (an overall decrease in the rate of patenting). This process is not uniform across the whole technological portfolio of firms but it is concentrated in firms' core technologies. Moreover, not all firms retrench from explorative activities, but only financially constrained firms.

Chapter 4 examines when and to what extent pharmaceutical firms learn from others' firms failures and success in their subsequent drug development efforts. Utilizing comprehensive and detailed information on pharmaceutical firms' global drug development projects we find that projects that build on firms' previous successful projects have a higher likelihood to generate marketable drugs, while building on prior failures reduces this likelihood. A similar pattern, though weaker in magnitude, is observed for drug development projects building on prior projects of other firms in their environment through vicarious learning.

Two general conclusions can be drawn from the studies presented in the dissertation. The studies confirm the tendency of firms to search mostly in local or familiar domains. Chapter 2 shows a general tendency towards local search through the recombination of knowledge according to established schemas. Chapter 3 shows that firms are sensitive to the contraction phases of the business cycle and respond by reducing more explorative search and the intensity of inventive activities in general. In addition, in Chapter 4 it was observed that local search, measured as drug development in existing or related ATC classes, can increase the likelihood of drug development success.

The dissertation also contributes to the debate on the pay-off from local versus distant search (Gavetti, 2012; Winter, 2012). Prior studies have focused on the implications of local or distant search processes on firms' competitive advantage and survival. Two main streams of literature have emerged. The first stream of literature highlights the myopic and cognitive biases driving firm activities. The second stresses the importance of introducing variety into organizational routines in order to mitigate the local-search trap. The studies in this dissertation are consistent with the notion of higher innovation rewards associated with distant search. Chapter 2 highlights that novel inventions that are based on established paradigms but at the same time introduce a disruptive combination are on average more cited. This finding confirms that local search with distant ‘jumps’ provides advantages in terms of technological impact. Chapter 4 shows that local search through the reuse of related ATC classes, while increasing the rate of drug development success, is also associated with relatively smaller marketing rewards. Markets requiring distant search may provide higher economic rewards, as no prior drugs are available, pushing firms to accept higher failure rates.

5.2 Limitations and avenues for future research

This dissertation is subjected to a number of limitations that open up possibilities for future research. First, the studies of this dissertation use patent data as main source of information about innovation. As recognized in the literature, patents data have the major drawback of capturing only successful inventions. Besides, they do not have a uniform value and not all sectors are equally patents intensive (Cohen et al., 2000). Yet, patents data reveal major and important innovations patterns.

The citation approach used in Chapter 4 may be an imperfectly trace learning. The design of the study reported in Chapter 4 captures only partially the mechanisms through which the environment, via vicarious learning, shapes the search process. Nonetheless, citations helped in identifying the kind of prior research the focal firm builds in terms of prior projects, patents and scientific literature.

A first avenue for research is in stream of literature on the origins and measurement of radical innovations (Fleming, 2001; Rosenberg, 1982; Ahuja & Lampert, 2001; Schoenmakers & Duysters, 2010). This stream of literature discusses whether radical innovations originate from totally new knowledge or from new combinations of existing knowledge. The most prominent view is that "*innovation combines components in a new way, or that it consists in carrying out new combinations*" (Schumpeter, 1939, p.88). Empirical studies based on patent data have investigated the combination of technological and knowledge components within inventions, utilizing a number of different measures with the challenge to use patent information to delineate the boundaries of the recombination process. This stream of literature represents an interesting avenue for future work for refining and improving existing measures as well as provide a better understanding of their explanatory power. The measure proposed in Chapter 2 points in this direction. Recent efforts exploit text mining techniques that allow to capture technical and scientific components reported in patents (Magerman et al., 2010). Qualitative work would also provide a better understanding of the recombination process.

A second avenue for future research deals with the investigation of the search process at the inventor level. While the overall strategy of firms is highly important in determining how inventive search is performed, individual inventors are at the core of inventions. Inventors with a diversified knowledge base may see promising routes of research that other don't notice. In addition, understanding the importance of diversity in an inventor team may contribute to the debate about the "fantastic four" or the "superman" role of the inventor in the search and recombination process (Taylor & Greve, 2006). Future research could inspire improved human resource practices conducive to different search strategies.

Another area of research relates to the study of regulations in the pharmaceutical industry and their effects on the success of drug development. In September 2016 the FDA has extended a prior Act (FDAAA801) requiring the submission of results of trials of unapproved products. If this disclosure leads firms to have a better understanding of the reasons behind other firms' prior failures, they may fail less in their subsequent drug development. Legislation that stimulates the development of orphan drugs may also influence the success rate in the pharmaceutical industry. Pammolli et al., (2011) highlight that since 1990 the R&D productivity in the pharmaceutical industry has decreased. Future research focusing on the learning effects of previous R&D efforts could assist in understanding this relative productivity decline in order to inspire remediating policy instruments.

A last avenue for future research is triggered by the unexpected finding in Chapter 2 that large firms are better at producing unconventional combinations compared to small firms. Further research would contribute to the debate on whether radical innovations are generated by large or small firms. Earlier studies have suggested that young firms develop breakthrough innovations (Henderson, 1993; Prusa & Schmitz, 1991). However, large firms are better at diversifying risks and have greater scale and scope advantages. The results in Chapter 2 go against this conventional view and call for further research investigating the role of size and incumbency in the inventive search process. Apart from organizational structure, further research may investigate whether and how large firms leverage a diversified technological base to combine deep competencies in core fields with knowledge from non-core fields. The debate might benefit from moving beyond a mere distinction based on size and incumbency and include a range of environmental factors that might drive search outside extant paradigms.

The study discussed in Chapter 3 provides an interesting ground for future research. Firms postpone or hold back more unconventional innovation during downturns. However, they may also become more efficient in selecting the most promising projects discontinuing those that have a lower value or that are eventually more incremental. This would be an important aspect to consider for the design and implementation of innovation policies. The study in Chapter 3 uses as proxy of impact the forwards citations. However, it would be interesting to provide deeper insights about other measures of firms performances (Tobin's Q ratio for example) in order to understand the premium of firms that either don't cut back in R&D or un novelty. As common practice in the literature, this study uses industry business cycle. Future works may complement the analysis with macro level shocks.

Appendix A

Appendix to Chapter 2

A.1 Analytical derivation of the Unconventionality measure

Teece et al. (1994) developed measures of relatedness and coherence for the diversification activities of firms. In the present study these measures are adapted to describe the diversification patterns in the knowledge space (Breschi et al., 2003; Nesta & Saviotti, 2005; Piscitello, 2005). Following Teece et al. (1994), let $C_{ik} = 1$ if invention *k* has membership in patent class *i*, and 0 otherwise. The number of inventions with membership in class *i* is $n_i = \sum_k C_{ik}$. It follows that the joint occurrence of each possible combination of subclasses within the same patent over the whole universe of USPTO patents granted in the previous five years is:

$$J_{ijt} = \sum_k C_{ik} C_{jk} \qquad \text{(A.1)}$$

where J_{ijt} provides the number of inventions having simultaneously membership in class *i* and class *j*. Raw counts of the number of inventions having membership in each couple of patent classes, however, cannot be taken directly as a measure of relatedness. Classes must be present at a rate greater than what one would expect if combinations were made at random.

We first computed the conditional probability that a patent belongs to class *i* given that it also belongs to class *j*, $P(i|j)=J_{ij}/n_j$ where n_j represents the number of patents citing class *j* only. The main issue is that $P(i|j)$ and $P(j|i)$ are not equal as n_i is different from n_j. The fact that $n_i \neq n_j$ implies that J_{ij} increases with the relatedness of *i* and *j*, but also with n_i and n_j, the number of inventions having membership in each class of the couple determining potential overestimations of the actual co-occurrence of the couple of classes in the same patent.

We then benchmarked the observed number of co-occurrences against their expected number, had the combinatorial process followed a random process. We adjusted J_{ij} for the number of inventions that would appear in the couple *ij* under the null hypothesis that inventors combine patent classes at random. To operationalize the null hypothesis, the distribution of J_{ij} must be derived by assuming that inventions are assigned to classes at random, call this random variable x_{ij}. Teece et al. (1994) identify the distribution of the random variable, but they do not derive it in their paper. For the sake of exposition, we derive the distribution in order to clarify the construction of the measure. This brief exposition is based on Bryce and Winter (2006).

Draw a sample of size n_i from the population of K multi-class inventions. Now draw another sample of size n_j and observe x_{ij}, or the number of inventions that were also in the n_i sample. The number of ways of selecting x inventions to fill x positions in sample n_j is equivalent to the number of ways of selecting x from a total of n_i inventors, or $\binom{n_i}{x}$.

The number of ways of selecting inventions not receiving assignment to class i for the remaining $(n_j - x)$ positions in the n_j sample is equivalent to the number of ways of selecting $(n_j - x)$ from a possible $(K - n_i)$ inventions, or $\binom{K - n_i}{n_j - x}$.

Then the number of possible permutations of the n_j sample is the number of ways of combining a set of x inventions assigned to class i (n_i) multiplied by $(n_j - x)$ inventions not assigned to class i, or:

$$\binom{n_i}{x}\binom{K-n_i}{n_j-x}$$ [42]. (A.2)

The number of different samples of size n_j that can be drawn from K is $\left(\frac{K}{n_j}\right)$. The number of possible permutations of the n_j sample divided by the number of ways of choosing a sample of size n_j is the probability that x inventions from population K are assigned to both class i and class j. Thus, the number x_{ij} of inventions having membership in both class i and class j is a hypergeometric random variable with probability given by:

$$P[X_{ij}=x]=\frac{\binom{n_i}{x}\binom{K-n_i}{n_j-x}}{\binom{K}{n_j}} \qquad \text{(A.3)}$$

whit mean[43]:

$$\mu_{ij}=E(X_{ij})=\frac{n_i n_j}{K} \qquad \text{(A.4)}$$

[42] Since sample n_j was fixed as the number of inventions in class j, inventions assigned to class i in this quantity are *de facto* also assigned to class j.

[43] Since sample n_j was fixed as the number of inventions in class j, inventions assigned to class i in this quantity are *de facto* also assigned to class j.

[43]For intuition of the mean, assume that nj inventions in K have been assigned to class j. Now randomly assign inventions in K to class i. The probability that any one invention receives a class i assignment is $\frac{n_i}{K}$. Since there are nj inventions in K, each with probability $\frac{n_i}{K}$ of being assigned to class i, the expected number of inventions assigned to both class i and class j is $n_j\left(\frac{n_i}{K}\right)$.

and variance:

$$\sigma^2{}_{ij} = \mu_{ij}\left(1-\frac{n_i}{K}\right)\left(\frac{K-n_j}{K-1}\right) \tag{A.5}$$

The difference between J_{ij} and the expected value of the random variable, provides the basis for the final measure of conventionality in combinations:

$$\tau_{ij} = \frac{J_{ij}-\mu_{ij}}{\sigma_{ij}} \tag{A.6}$$

where the difference between the observed and the expected occurrence of the couple of classes (J_{ij}-μ_{ij}) is divided by the standard deviation of the observed incidence. When this difference is positive and large, it indicates that the combination of pairs of patent classes in multi-class inventions is systematic, typical or conventional. Thus, large values of the difference are associated to couple of classes-subclasses that are systematically recombined together and over-represented in the sample, hence based on local search strategies. On the other hand, small or even negative values of this difference indicates that unexpectedly few inventions have successfully combined the focal couple, suggesting that the combination thereof is not systematic, unconventional or unconventional pointing to search strategies that connect more distant pieces of knowledge.

From (A.5), we can derive the degree of conventionality of the patent *z*, a_z, as the simple average of the measure τ_{ij} for all combinations of technologies (*i*,*j*) whose the patent has membership.

$$InventionConventionality = a_z = \frac{1}{n}\sum_{i=1}^{m-1}\sum_{j=i+1}^{m}\tau_{ij} \quad , \tag{A.7}$$

where *n* is the number of the patent's subclass combinations and *m* is the combination index. For instance, if a patent has four subclasses, then *m* is equal to six, since this is the number of subclass combinations (4(4-1)/2). Hence, *m*=1, …, 6. We transform this measure by adding its minimum value and taking the natural log plus 1. We finally multiply this measure by (-1) so that higher value are associated to novel combination of knowledge.

A.2 Conventionality across years and technologicies

Appendix A.2 details the Table 2.2 and Table 2.3 reported in Chapter 2. The tables reported in this Appendix show the distribution of conventionality across applications years for several technological categories. Consistently with Table 2.2 in Chapter2, also these tables show a decrease in the level of conventionality over time.

Table A.7 reports the summary statistics of conventionality distinguishing for the frequency of combinations occurring at the level of all technologies recombined within a single patent. This table shows that conventionality is lower for combinations that are rarely recombined. The standard deviation associated to technologies frequently recombined decrease with the use. This summary statistics may suggest that combinations that rarely occur entail a higher level of risk that decreases with usage.

Table A. 8 shows the average tau for the most representatives technologies at dyadic level. In particular, it shows the average conventionality resulted from the recombination of these technologies, i.e. Drug technology recombined with communication has a conventionality of 14.5.

Table A.1: Conventionality over time in Drugs

appyear	mean	sd	N	appyear	mean	sd	N
1980	38.753	30.486	3,986	1991	29.026	23.425	7,941
1981	36.530	28.270	4,231	1992	28.884	22.047	9,138
1982	37.713	27.534	4,458	1993	32.727	28.661	10,872
1983	36.862	26.412	4,408	1994	35.249	31.244	14,850
1984	37.164	28.587	5,263	1995	39.507	35.379	22,989
1985	36.030	29.189	5,677	1996	24.365	20.976	13,921
1986	32.774	23.127	5,906	1997	29.615	26.635	17,417
1987	32.605	25.267	6,583	1998	26.697	22.937	16,844
1988	32.304	26.536	6,924	1999	28.439	24.967	19,220
1989	32.185	26.761	7,595	2000	32.275	29.086	20,569
1990	30.958	25.702	7,913	Tot	32.109	27.785	21,6705

Table A.2: Conventionality over time in Computer Hardware & Software

appyear	mean	sd	N	appyear	mean	sd	N
1980	60.131	40.057	2,618	1991	40.416	29.572	5,945
1981	57.551	39.645	2,884	1992	37.436	29.482	6,035
1982	58.140	43.561	3,059	1993	35.567	26.540	6,772
1983	51.605	39.039	2,888	1994	33.918	27.256	9,217
1984	52.560	39.474	3,232	1995	33.241	28.583	12,288
1985	51.014	38.060	3,282	1996	30.128	30.607	13,265
1986	48.342	35.540	3,594	1997	27.867	24.977	15,902
1987	48.471	33.889	4,318	1998	24.615	22.120	16,478
1988	46.880	33.607	4,973	1999	24.256	22.964	18,969
1989	45.810	32.123	5,213	2000	25.568	27.456	21,896
1990	42.732	31.091	5,816	Total	34.318	30.950	168,644

Table A.3: Conventionality over time in Information Storage

appyear	mean	sd	N	appyear	mean	sd	N
1980	50.878	37.195	1,910	1991	32.309	25.716	4,368
1981	49.308	35.254	2,038	1992	30.170	19.811	4,422
1982	46.710	35.181	2,244	1993	29.949	24.235	4,921
1983	43.543	34.797	1,978	1994	29.591	21.331	6,554
1984	43.369	38.403	1,920	1995	29.646	22.626	7,530
1985	39.738	32.967	2,272	1996	30.217	28.030	8,700
1986	39.840	29.660	2,628	1997	29.704	25.545	11,433
1987	39.873	28.519	2,967	1998	26.188	29.630	10,792
1988	38.783	32.944	3,511	1999	25.628	27.936	11,444
1989	37.312	30.315	3,536	2000	27.177	34.519	12,564
1990	34.229	28.606	3,737	Total	31.759	29.479	111,469

Table A.4: Conventionality over time Semiconductors

appyear	mean	sd	N	appyear	mean	sd	N
1980	45.314	26.277	1,269	1991	32.166	22.167	4,516
1981	47.253	28.401	1,104	1992	31.028	19.051	4,422
1982	45.261	26.849	1,182	1993	28.639	17.742	4,469
1983	43.166	22.153	1,385	1994	29.595	19.306	5,684
1984	44.217	28.556	1,638	1995	28.929	21.128	6,956
1985	42.037	23.944	1,665	1996	28.322	21.560	7,176
1986	41.281	23.610	1,812	1997	30.356	26.108	9,123
1987	42.830	29.11	2,300	1998	27.902	23.290	9,516
1988	40.805	25.218	3,212	1999	24.883	20.803	10,468
1989	35.891	20.227	3,488	2000	24.104	23.523	11,366
1990	32.721	19.249	3,963	Total	30.861	23.413	96,714

Table A.5: Conventionality over time in Material Processing & Handling

Table A.6. Conventionality over time inMaterial Processing & Handling							
appyear	mean	sd	N	appyear	mean	sd	N
1980	51.117	37.185	5,983	1991	46.005	37.927	7,533
1981	51.617	38.252	5,515	1992	45.935	39.840	7,247
1982	51.392	38.417	5,452	1993	46.337	39.869	6,909
1983	50.969	38.016	5,330	1994	48.794	40.848	7,148
1984	52.898	39.417	5,559	1995	49.858	43.519	7,294
1985	51.990	38.900	6,201	1996	52.338	43.796	7,360
1986	49.709	37.231	6,220	1997	55.185	47.758	8,294
1987	50.164	39.351	6,326	1998	54.303	49.084	7,759
1988	47.881	37.377	6,926	1999	54.740	48.461	8,373
1989	47.395	37.147	7,220	2000	55.632	53.123	8,607
1990	45.250	34.312	7,238	Total	50.522	41.838	144,494

Table A.6: Conventionality over time in Communications

appyear	mean	sd	N	appyear	mean	sd	N
1980	54.019	40.681	3,677	1991	38.350	28.650	7,310
1981	51.662	38.905	3,714	1992	36.604	27.544	7,696
1982	51.394	38.157	3,753	1993	35.398	26.485	8,229
1983	50.589	37.698	3,648	1994	33.889	27.291	10,563
1984	48.161	35.214	3,836	1995	32.073	26.737	12,876
1985	47.243	35.680	4,349	1996	30.026	25.499	14,737
1986	47.344	37.834	4,588	1997	28.506	25.491	17,944
1987	45.080	32.525	5,014	1998	26.562	24.877	19,054
1988	44.198	34.240	5,638	1999	27.443	27.260	21,282
1989	42.279	32.010	6,521	2000	28.570	31.718	23,108
1990	40.139	29.127	6,854	Total	34.621	30.684	194,391

Table A.7: Summary statistics of Conventionality distinguishing for the frequency of combinations occurring at the couple level

Frequency	N	Mean	Std. Dev.	Min	Max
≤ 5	29,190,002	44.08	62.355	-5.968	993.33
> 5	17,765,275	47.027	51.971	-5.398	993.33

This table shows that the average Conventionality is lower for combinations that are rarely recombined together.

Table A.8: Distribution of Conventionality for the combination between the most representative technologies

	Tecnology definition	1	2	3	4	5	6	7	8	9	10	11	
1	Agriculture, Food, Textiles	71.729	35.792	39.788	66.888	73.050	**32.064**	32.403	69.597	36.485	53.205	40.174	47.309
2	Organic Compounds	35.792	40.585	28.477	21.569	**17.502**	24.988	28.971	36.551	28.785	38.212	37.951	47.373
3	Resins	39.788	28.477	37.335	**16.681**	23.699	17.857	27.226	28.436	30.202	27.272	19.411	27.727
4	Communications	66.888	21.569	**16.681**	45.930	20.839	20.591	14.553	36.345	26.501	32.284	22.089	34.621
5	Computer Hardware & Software	73.050	17.502	23.699	20.839	34.854	17.181	**16.628**	30.112	27.921	42.513	18.227	34.318
6	Computer Peripherals	32.064	24.988	17.857	20.591	17.181	38.132	**15.955**	19.744	22.695	17.269	17.706	30.584
7	Drugs	32.403	28.971	27.226	**14.553**	16.628	15.955	35.894	36.560	15.634	18.347	18.494	32.109
8	Electrical Devices	69.597	36.551	28.436	36.345	30.112	**19.744**	36.560	61.261	36.716	37.674	27.971	44.266
9	Nuclear & X-rays	36.485	28.785	30.202	26.501	27.921	22.695	**15.634**	36.716	68.781	40.754	25.165	37.891
10	Power Systems	53.205	38.212	27.272	32.284	42.513	17.269	**18.347**	37.674	40.754	59.110	25.435	41.244
11	Semiconductor Devices	40.174	37.951	19.411	22.089	18.227	**17.706**	18.494	27.971	25.165	25.435	34.774	30.861
		47.309	47.373	27.727	34.621	34.318	30.584	32.109	44.266	37.891	41.244	30.861	

Note: in contrast with Table 2.1 and 2.2, this table shows the average Conventionality for the combination occurring among the most representative technologies taking a coupling perspective which is the base for the construction of the measure.
Lowest Conventionality among the combination of technologies are n bold. The last column and row report the average at the invention level.

Appendix B

Appendix to Chapter 3

Appendix B: Additional analysis at firm level

Appendix B reports extra analysis at the level of the firm. Tables B.1 and B.2 show the trend in unconventionality at different lags of Real Output.

Table B.3 reports the estimators at the firm level of overall patent production. In Table B.4 and B.5 we focus on the patent production by differentiating between low and high financially constrained firms.

Table B.6 reports the estimations for the weighted unconventionality. This set of analysis has the objective to differentiate between intensive and extensive margins. Also in this set of analysis we differentiate between low and high financially constraints (Table B.8) and identify also firms that retrench from local search in innovation through a cut in R&D Table (B.7).

Table B indicates a cut in patent production during the contractive phases of the cycle (-0.262%). Table B.7 shows that firm that cut in R&D may have a different sensitivity to the contractive period of the cycle. Table B.6 details the finding based on patent level analysis suggesting that the decrease in unconventionality is not due to a general decline at the extensive margins but also at the intensive.

Table B.1: Estimations for technological search over the business cycle. OLS models for the degree of Unconventionality

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Real Output	0.0855***			0.0896***	0.0865***	0.0899***
	(0.0031)			(0.0032)	(0.0031)	(0.0032)
Expansion		0.0165		-0.8865***		-0.7923***
		(0.1461)		(0.1492)		(0.1522)
Contraction			0.8487**		1.6078***	1.2091***
			(0.3791)		(0.3793)	(0.3869)
Citations	-0.0103***	-0.0101***	-0.0101***	-0.0103***	-0.0103***	-0.0103***
	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
no Bwd Cits	-0.0171	0.0201	0.0199	-0.0173	-0.0180	-0.0179
	(0.0164)	(0.0163)	(0.0163)	(0.0164)	(0.0164)	(0.0164)
Components	0.2182***	0.2182***	0.2182***	0.2182***	0.2182***	0.2182***
	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)
Team	-0.0031***	-0.0045***	-0.0045***	-0.0031***	-0.0031***	-0.0030***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Experience	0.0000	0.0001	0.0001	-0.0000	0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Concentration	-0.1675***	-0.2139***	-0.2144***	-0.1715***	-0.1675***	-0.1711***
	(0.0358)	(0.0359)	(0.0359)	(0.0358)	(0.0358)	(0.0358)
Assignee Size	0.0007	0.0184***	0.0182***	0.0005	0.0002	0.0002
	(0.0023)	(0.0022)	(0.0022)	(0.0023)	(0.0023)	(0.0023)
Constant	-4.8803***	-4.0632***	-4.0622***	-4.9167***	-4.8876***	-4.9184***
	(0.0894)	(0.0844)	(0.0844)	(0.0896)	(0.0894)	(0.0896)
N	166168	166168	166168	166168	166168	166168
R^2	0.1728	0.1690	0.1690	0.1730	0.1729	0.1730

Standard errors in parenthes* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
The models report the results of the Ordinary Least Square on the median value of the degree of novelty in patents. Models include 20 year, 36 technology and sector dummies. Models also include controls (dummies) for missing information about backward citations. All models include firm fixed effects.

Table B.2: Estimations for technological search over the business cycle.

	Model 1	Model 2	Model 3	Model 4	Model 5
Real Output	0.0925***			0.0956***	0.0935***
	(0.0033)			(0.0033)	(0.0033)
Expansion t-2		-0.3280**		-0.9230***	
		(0.1414)		(0.1426)	
Contraction t-2			1.6834***		2.2731***
			(0.3938)		(0.3933)
Citations	-0.0103***	-0.0100***	-0.0101***	-0.0101***	-0.0103***
	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
no Bwd Cits	-0.0178	0.0208	0.0199	-0.0170	-0.0185
	(0.0164)	(0.0163)	(0.0163)	(0.0164)	(0.0164)
Components	0.2182***	0.2182***	0.2183***	0.2181***	0.2182***
	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)
Team	-0.0030***	-0.0045***	-0.0045***	-0.0030***	-0.0030***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Experience	-0.0000	0.0001	0.0001	-0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Concentration	-0.1724***	-0.2158***	-0.2133***	-0.1759***	-0.1710***
	(0.0358)	(0.0359)	(0.0359)	(0.0358)	(0.0358)
Assignee	0.0002	0.0187***	0.0182***	0.0005	-0.0002
	(0.0023)	(0.0022)	(0.0022)	(0.0023)	(0.0023)
Constant	-4.9450***	-4.0624***	-4.0614***	-4.9722***	-4.9522***
	(0.0898)	(0.0844)	(0.0844)	(0.0899)	(0.0898)
N	166168	166168	166168	166168	166168
R^2	0.1730	0.1690	0.1691	0.1732	0.1732

Standard errors in parenthes * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.3 : Estimations for Patent Production over the business cycle.

	Model 1	Model 2	Model 3
	ln_pat	ln_pat	ln_pat
Real Output	0.2979***	0.3015***	0.2984***
	(0.0200)	(0.0196)	(0.0200)
Expansion	0.2108		0.6397
	(0.7732)		(0.8024)
Contraction		2.8418*	3.1839**
		(1.5399)	(1.5986)
Concentration	-0.6384***	-0.6360***	-0.6371***
	(0.0649)	(0.0649)	(0.0649)
R&D Intensity	0.0001	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)
No R&D Intensity	0.1370*	0.1327*	0.1314
	(0.0804)	(0.0804)	(0.0804)
Size	0.6914***	0.6931***	0.6932***
	(0.0323)	(0.0323)	(0.0323)
KZ	0.0244	0.0252	0.0250
	(0.0205)	(0.0205)	(0.0205)
Cons	-3.5944***	-3.6327***	-3.6062***
	(0.2727)	(0.2706)	(0.2727)
N	6080	6080	6080
R^2	0.8616	0.8617	0.8617

Standard errors in parentheses; * p<0.1, ** p<0.05, *** p<0.01

The models report the results of the OLS on the natural logarithm of the patent count by firm and Year. Models include 20 year and sector dummies including also controls (dummies) for missing information on the number of employees, sales and R&D. Standard errors are clustered by firm. This analysis is built on the same dataset used in the main set of regressions but the observations have been now collapsed by firm and Year. Drawing on Fabrizio and Tsolmon (2014) we use the Ln Real Output at time *t* and $_{t-1}$. Results show a pro-cyclical trend.

Table B.4: Estimations for patent production based on R&D cut.

	Cut in R&D	Non Cut in R&D
	Model 1	Model 2
	ln_pat	ln_pat
Real Output	0.4015***	0.2700***
	(0.0378)	(0.0247)
Expansion	-0.6989	1.5572
	(1.3076)	(1.0321)
Contraction	3.8692*	2.1455
	(1.9827)	(2.8301)
Concentration	-0.7114***	-0.6107***
	(0.1089)	(0.0812)
R&D Intensity	-0.0000	0.0001
	(0.0003)	(0.0001)
No R&D Intensity	0.3023***	-0.0284
	(0.1164)	(0.1124)
Size	0.7065***	0.7042***
	(0.0480)	(0.0449)
KZ	0.0454	0.0012
	(0.0305)	(0.0280)
Constant	-3.0960***	-3.3312***
	(0.4563)	(0.3178)
N	2567	3513
R^2	0.8666	0.8566

Standard errors in parentheses; * p<0.1, ** p<0.05, *** p<0.01

The models report the results of the OLS on the natural logarithm of the patent count by firm and Year. Models include 20 year and sector dummies including also controls (dummies) for missing information on the number of employees, sales and R&D. Standard errors are clustered by firm. Drawing on Fabrizio and Tsolmon (2014) we use the Ln Real Output at time *t* and $_{t-1}$. Results show a pro-cyclical trend.

Table B.5: estimations for patent production bases on Kaplan Zingales.

	Low KZ	High KZ
	Model 1	Model 2
	ln_pat	ln_pat
R Output	0.2374***	0.4245***
	(0.0273)	(0.0340)
Expansion	-0.0795	0.3833
	(0.9944)	(1.5021)
Contraction	2.7977	4.7082*
	(2.0786)	(2.7169)
Concentration	-0.5903***	-0.7097***
	(0.0859)	(0.1145)
R&D Intensity	0.0001	0.0007**
	(0.0003)	(0.0003)
No R&D Intensity	0.3686***	-0.2714**
	(0.1292)	(0.1323)
Size	0.7848***	0.4861***
	(0.0423)	(0.0606)
Constant	-3.3013***	-3.1532***
	(0.3355)	(0.4284)
N	3973	2107
R^2	0.8781	0.8739

Standard errors in parentheses; * p<0.1, ** p<0.05, *** p<0.01

The models report the results of the OLS on the natural logarithm of the patent count by firm and Year. Models include 20 year and sector dummies including also controls (dummies) for missing information on the number of employees, sales and R&D. Standard errors are clustered by firm. Drawing on Fabrizio and Tsolmon (2014) we use the Ln Real Output at time *t* and $_{t-1}$. Results show a pro-cyclical trend.

Table B.6: Estimation for the weighted conventionality.

	Model 1	Model 2	Model 3
Real Output	0.3351***	0.3351***	0.3354***
	(0.0252)	(0.0247)	(0.0252)
Expansion	-0.4312		-0.0615
	(0.9728)		(1.0098)
Contraction		2.7773	2.7444
		(1.9379)	(2.0119)
Concentration	-0.9587***	-0.9577***	-0.9575***
	(0.0817)	(0.0817)	(0.0817)
R&D Intensity	0.0001	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)
No R&D Intensity	0.1538	0.1488	0.1489
	(0.1011)	(0.1012)	(0.1012)
Size	0.7575***	0.7590***	0.7590***
	(0.0406)	(0.0406)	(0.0406)
KZ	0.0335	0.0340	0.0340
	(0.0259)	(0.0258)	(0.0259)
Constant	-5.7054***	-5.7130***	-5.7156***
	(0.3432)	(0.3406)	(0.3432)
N	6080	6080	6080
R^2	0.8417	0.8418	0.8418

Standard errors in parentheses; * p<0.1, ** p<0.05, *** p<0.01

Table B.7: Estimations for the weighed conventionality based on tut in R&D.

	Cut in R&D	Non Cut in R&D
	Model 1	Model 2)
Real Output	0.4596***	0.2980***
	(0.0477)	(0.0311)
Expansion	-1.5236	0.9264
	(1.6509)	(1.2957)
Contraction	4.1415*	0.3262
	(2.5032)	(3.5531)
Concentration	-1.0719***	-0.9118***
	(0.1375)	(0.1019)
R&D Intensity	-0.0000	0.0001
	(0.0004)	(0.0001)
No R&D Intensity	0.3694**	-0.0533
	(0.1469)	(0.1412)
Size	0.7689***	0.7739***
	(0.0606)	(0.0564)
KZ	0.0556	0.0081
	(0.0385)	(0.0352)
Constant	-5.5354***	-5.3852***
	(0.5761)	(0.3990)
N	2567	3513
R^2	0.8421	0.8409

Standard errors in parentheses; * p<0.1, ** p<0.05, *** p<0.01

Table B.8; Estimations for the weighed conventionality based on .

	Low KZ	High
	Model 1	Model 2
Real Output	0.2763***	0.4579***
	(0.0341)	(0.0441)
Expansion	-0.8714	-0.3420
	(1.2426)	(1.9454)
Contraction	2.1975	4.3100
	(2.5975)	(3.5188)
Concentration	-0.9171***	-1.0209***
	(0.1073)	(0.1483)
R&D Intensity	-0.0000	0.0010**
	(0.0004)	(0.0004)
No R&D Intensity	0.4571***	-0.3295*
	(0.1615)	(0.1713)
Size	0.8618***	0.5124***
	(0.0529)	(0.0784)
Constant	-5.4371***	-5.4096***
	(0.4193)	(0.5548)
N	3973	2107
R^2	0.8603	0.8527

Standard errors in parentheses; * p<0.1, ** p<0.05, *** p<0.01

Appendix C

Appendix to Chapter 4

This section presents additional regression tables that validate the findings discussed in Chapter 4 and rule out alternative explanations.

Table C.1 uses the same model specification of Table 4.10 but includes firm dummies in order to exclude potential trends at the level of the firm. This specification was not preferred as our base model because the inclusion of firm fixed effects leads to the necessary omission of firms with only one project in the sample. The number of observations drops by about 1000. The results on the learning variables are consistent with findings reported in Chapter 4. All in all, citing previous failure (Self and Non Self) increases the incidence of failure with the coefficient of Self being larger. A contrasting pattern is shown for building further on previous Success. The coefficient of citing others' success and failure and ongoing projects, significant at $p<0.1$ in Table 4.10 is not significant when we include firm dummies.

Table C.2 uses the same specification of Table 4.11 with the inclusion of timing restriction on the citation patterns. Overall results are consistent with what shown in Table 4.11 although with smaller coefficients and lack of significance for the variables of citing previous ongoing projects.

Table C.3 provides insights into the effects of the reuse of the same patent on the likelihood of success. In this model specification learning derive from previous R&D projects and from prior started same-patent projects (set of dummies for Prior Self/Non Self with same Family). We also include a control for the number of projects sharing the same patent that are initiated simultaneously *Num. Sim. Projs*. Overall the results are consistent with learning generated from building on previous projects only. In particular Self Failure and Self Ongoing in prior same family reduce the chances of success of the focal projects. Prior Success in the same Family instead increase the likelihood of success especially for prior Success by other firms. The coefficients for prior failures by other firms is statistically significant and is positively associated with success of the focal projects.

Table C.4 uses the same specification of Table C.3 but the independent variables are built on the restricted version that, for the set of independent variables of focal building on previous projects, doesn't consider the links to previous projects terminated after the focal. These cases are captured by the dummy "*focal terminated before cited*". Also the restricted models give to an important extent similar results for prior projects using the same family. These results emphasize that building on multiple patents having similar characteristics reduces the likelihood of success. This patterns may also suggest that firms may use previous similar patents to reduce costs.

Table C.5 reports results of a multinomial logit model that includes the category of ongoing project in the dependent variable. In particular, our dependent variable includes the following categories: Success and Failures as defined in Section 4.3 and Ongoing projects. For Ongoing project we note that 31.63% of these projects didn't reported any update regarding the development process for more than 10 years. Hence, we also treat the different ongoing projects separately by making a distinction between real ongoing projects (11.32%), reporting a recent update on status, and Suspicious ongoing whose last update on the development phase is before 1995. Results show that for the Success category, showed in the last column, the incidence of success is driven by building on previous success (self/Non Self) while failures decrease this incidence. The coefficients have similar magnitude to those showed in our baseline logit models.

Table C.6 reports the frequencies in the three models that are used in the supplementary regression analysis reported in Table C.7. This set of regressions employs several different timing of citations patterns to ensure robustness of inferences to different time window and to check possible variations and different learning mechanisms.

In particular, as shown in Figure C.1, in Model 1 we consider the citations to projects that have reached their outcome before the starting date of the focal project. In Model 2 the focal project starts before the outcome date of the cited project but ends after, whereas in Model 3 the focal project starts and reaches its final status before the outcome date of the cited. Since a focal project can cite multiple related projects the inclusion of the focal in one of the timing restriction is not exclusive. As it is possible to note the likelihood of success from building on previous related success increase in Model 1 when the focal project relies on at least one related projects that has been marketed, knowing in this way the final outcome before starting the experimentation. Also citing previous failure (Self/Non Self) has a smaller negative coefficient in Model 1 compared to Model 3.

In non reported analysis, we also account for potential learning from collaboration with other firms by controlling for potential other firms (licensors and licensees) involved in the project. Results for the main variable of interest remain, while the involvement of other firms increased the likelihood of success in line with prior studies stressing the role of alliances in increasing the probability of project success (Danzon et al., 2005; Hoang et al., 2010).

Table C.1:: Estimations for experiential and vicarious learning on project status fixed effect

	Model 1	Model 2
Cites Self Failure		-0.8338**
		(0.3304)
Cites Others' Failure		-0.5545**
		(0.2215)
Cites Self Success		0.6542*
		(0.3473)
Cites. Others' Success		0.4876**
		(0.2095)
Cites Self Succ.&Failure		0.0055
		(0.2991)
Cites Others' Sucs.&Failure		-0.3107
		(0.2604)
Cites Self Ongoing		-0.7137
		(0.4975)
Cites Others' Ongoing		-0.3820
		(0.2999)
Num Indication	0.2994***	0.2986***
	(0.0350)	(0.0359)
Num ATC classes	0.6092	0.7442
	(0.5935)	(0.6166)
Num Patent Family	0.7780***	0.8353***
	(0.1459)	(0.1496)
Shared patent Family	-0.2617	-0.2344
	(0.1598)	(0.1643)
Focal Patent originality	-1.4995**	-1.2391**
	(0.6138)	(0.6222)
Focal Patent Number of Comp.	-0.0014*	-0.0013*
	(0.0008)	(0.0008)
Focal Lead= Focal Pat	-0.4782***	-0.4568***
	(0.1512)	(0.1530)
Citing NPL Scientific	0.2416	0.2344
	(0.1674)	(0.1703)
Bwd cits	0.4835***	0.4847***
	(0.0846)	(0.0925)
fwd cited	0.0023	0.0012
	(0.0091)	(0.0093)
Cited Patent Originality	-0.3821	-0.4892

	(0.6824)	(0.6874)
Num. Comp. of cited Patent	-0.0010	0.0000
	(0.0018)	(0.0019)
Focal Lead-Cited Patent	0.1876	0.4042
	(0.2120)	(0.2524)
Same ATC focal-cited	0.2982**	0.3246*
	(0.1366)	(0.1729)
Succ in ATC	1.5248***	1.3410***
	(0.3551)	(0.3663)
R&D competition in ATC	-0.0071	0.0245
	(0.0741)	(0.0752)
Failure Ratio	3.2947***	3.3365***
	(0.5355)	(0.5411)
Breadth of firm activities	5.7370	6.2945
	(18.1048)	(18.0917)
Constant	-4.0579	-4.9941
	(15.4220)	(15.4074)
Observations	2721	2721
Pseudo R^2	0.4163	0.4286
log Lik.	-1058.8472	-1036.5508
Chi squared	1510.4974	1555.0901

Standard errors in parentheses; * p<0.1, ** p<0.05, *** p<0.01
Logit model for Success and Failures. Models include 25 year, 87 ATC classes and Firm dummies.

Table C.2: Estimations for experiential and vicarious learning on project status fixed effect. Time restriction.

	Model 1	Model 2
Cites Self Failure		-0.6571*
		(0.3462)
Cites Others' Failure		-0.2636
		(0.2357)
Cites Self Success		1.3381***
		(0.4533)
Cites. Others' Success		0.7567***
		(0.2373)
Cites Self Success and Failure		0.2692
		(0.3136)
Cites Others' Success and Failure		-0.1553
		(0.2747)
Cites Self Ongoing		-0.5849
		(0.4998)
Cites Others' Ongoing		-0.2340
		(0.3099)
Project before cited outcome	-1.1175***	-1.0284***
	(0.2212)	(0.2600)
Num Indication	0.2966***	0.2961***
	(0.0349)	(0.0356)
Num ATC classes	0.4833	0.5903
	(0.5887)	(0.6073)
Num Patent Family	0.7676***	0.7930***
	(0.1465)	(0.1491)
Shared patent Family	-0.2702*	-0.2958*
	(0.1615)	(0.1663)
Focal Patent originality	-1.4609**	-1.2494**
	(0.6140)	(0.6212)
Focal Patent Number of Comp.	-0.0013*	-0.0013
	(0.0008)	(0.0008)
Focal Lead=Focal Pat	-0.4795***	-0.4428***
	(0.1529)	(0.1548)
Citing NPL Scientific	0.2078	0.1859
	(0.1688)	(0.1707)

Bwd cits	0.4519***	0.4214***
	(0.0852)	(0.0937)
fwd cited	0.0017	0.0004
	(0.0091)	(0.0093)
Cited Patent Originality	-0.4562	-0.4367
	(0.6870)	(0.6937)
Num. Comp. of cited Patent	-0.0012	-0.0003
	(0.0018)	(0.0018)
Focal Lead=Cited Patent	0.2102	0.2800
	(0.2152)	(0.2511)
Same ATC focal-cited	0.4639***	0.4211**
	(0.1418)	(0.1784)
Succ in ATC	1.5526***	1.4107***
	(0.3578)	(0.3671)
R&D competition in ATC	-0.0405	-0.0124
	(0.0749)	(0.0761)
Failure Ratio	3.3817***	3.4071***
	(0.5377)	(0.5427)
Breadth of firm activities	2.4790	1.8724
	(18.5782)	(18.3691)
Constant	-0.8002	-0.6359
	(15.8819)	(15.6773)
Observations	2721	2721
Pseudo R^2	0.4239	0.4360
log Lik.	-1045.1413	-1023.1270
Chi squared	1537.9092	1581.9378

Standard errors in parentheses; * $p<0.1$, ** $p<0.05$, *** $p<0.01$
Logit model for Success and Failures. Models include 25 year, 87 ATC classes and Firm dummies

Table C.3:: : Estimations for experiential and vicarious learning on project status. PATENT REUSE

	Model 1	Model
Cites Self Failure		-0.6007**
		(0.2620)
Cites Others' Failure		-0.4933**
		(0.2006)
Cites Self Success		1.0581***
		(0.2504)
Cites. Others' Success		0.3006*
		(0.1716)
Cites Self Succ.&Failure		0.2686
		(0.2494)
Cites Others' Succ. & Failure		-0.3530
		(0.2185)
Cites Self Ongoing		-0.6985**
		(0.3478)
Cites Others' Ongoing		-0.4236*
		(0.2378)
Prior Self Fail Same Fam		-0.4258
		(0.3558)
Prior No Self Fail Same Fam		0.7721**
		(0.3630)
Prior Self Succ Same Fam		1.2523**
		(0.6258)
Prior No Self Succ Same Fam		1.8612***
		(0.5124)
Prior Self Ong.Same Fam		-0.8870**
		(0.4171)
Prior No Self Ong. Same Fam		0.9178**
		(0.3960)
Num Sim Proj	-0.8801***	-1.1482***
	(0.2609)	(0.2517)
Num Indication	0.2624***	0.2551***
	(0.0262)	(0.0258)
Num ATC classes	0.9589**	1.0174**
	(0.4711)	(0.4864)
Num Patent Family	0.6257***	0.6395***

	(0.1446)	(0.1423)
Shared patent Family	-0.3987**	-0.5978***
	(0.1611)	(0.2104)
Focal Patent originality	-1.7542***	-1.3435***
	(0.4453)	(0.4327)
Focal Patent Number of Comp.	-0.0006	-0.0005
	(0.0006)	(0.0006)
Focal Lead=Focal Pat	-0.6130***	-0.5380***
	(0.1450)	(0.1446)
Citing NPL Scientific	0.0996	0.1023
	(0.1157)	(0.1191)
Bwd cits	0.4230***	0.3973***
	(0.0609)	(0.0685)
fwd cited	0.0021	0.0017
	(0.0059)	(0.0059)
Cited Patent Originality	0.2571	0.1690
	(0.4833)	(0.4784)
Num. Comp. of cited Patent	0.0004	0.0012
	(0.0016)	(0.0015)
Focal Lead= Cited Patent	0.0620	0.0767
	(0.1840)	(0.2129)
Same ATC focal-cited	0.3731***	0.4062***
	(0.1016)	(0.1228)
Succ in ATC	1.2555***	1.1719***
	(0.2598)	(0.2862)
R&D competition in ATC	-0.0761	-0.0407
	(0.0645)	(0.0655)
Failure Ratio	-1.0135***	-1.0434***
	(0.2301)	(0.2311)
Breadth of firm activities	0.7932**	0.7906**
	(0.3368)	(0.3353)
Constant	-1.8176**	-2.2249***
	(0.7736)	(0.7634)
Observations	3568	3568
Pseudo R^2	0.3304	0.3549
log Lik.	-1585.1867	-1527.2433
Chi squared	2036.1545	2174.7218

Standard errors in parentheses; * p<0.1, ** p<0.05, *** p<0.01. Logit model for Success and Failures. Models include 25 year, 87 ATC classes and Firm dummies

Table C.4: : Estimations for experiential and vicarious learning on project status. PATENT REUSE. Time restriction

	Model 1	Model 2
Cites Self Failure		-0.4935*
		(0.2721)
Cites Others' Failure		-0.3355
		(0.2062)
Cites Self Success		1.6130***
		(0.3880)
Cites. Others' Success		0.5077***
		(0.1952)
Cites Self Success and Failure		0.4685*
		(0.2593)
Cites Others' Success and Failure		-0.2649
		(0.2294)
Cites Self Ongoing		-0.6764*
		(0.3522)
Cites Others' Ongoing		-0.3547
		(0.2434)
Prior Self Fail Same Fam		-0.5034
		(0.3532)
Prior No Self Fail Same Fam		0.6893*
		(0.3649)
Prior Self Succ Same Fam		1.1394*
		(0.6640)
Prior No Self Succ Same Fam		1.7342***
		(0.5353)
Prior Self Ong.Same Fam		-0.9475**
		(0.4234)
Prior No Self Ong. Same Fam		0.8429**
		(0.3904)
Num Sim Proj	-0.8916***	-1.1459***
	(0.2595)	(0.2503)
Num Indication	0.2611***	0.2563***
	(0.0262)	(0.0257)
Num ATC classes	0.9392**	0.9611*
	(0.4745)	(0.4948)
Num Patent Family	0.6114***	0.6196***
	(0.1467)	(0.1406)
Shared patent Family	-0.3838**	-0.5510**
	(0.1635)	(0.2176)
Focal Patent originality	-1.7445***	-1.3669***
	(0.4527)	(0.4533)

Focal Patent Number of Comp.	-0.0006	-0.0004
	(0.0006)	(0.0006)
Focal Lead=Focal Pat	-0.6335***	-0.5565***
	(0.1434)	(0.1435)
Citing NPL Scientific	0.0786	0.0797
	(0.1173)	(0.1175)
Bwd cits	0.3987***	0.3493***
	(0.0615)	(0.0671)
fwd cited	0.0018	0.0010
	(0.0061)	(0.0058)
Cited Patent Originality	0.2854	0.2219
	(0.4796)	(0.4789)
Num. Comp. of cited Patent	0.0002	0.0009
	(0.0015)	(0.0015)
Same Company Lead-Patent	0.0776	0.0177
	(0.1799)	(0.2098)
Same ATC focal-cited	0.5030***	0.4925***
	(0.1116)	(0.1324)
Succ in ATC	1.2748***	1.2315***
	(0.2713)	(0.2919)
R&D competition in ATC	-0.0921	-0.0585
	(0.0656)	(0.0665)
Failure Ratio	-0.9972***	-1.0176***
	(0.2292)	(0.2294)
Breadth of firm activities	0.8026**	0.7760**
	(0.3367)	(0.3333)
Project before cited outcome	-0.8727***	-0.7763***
	(0.1574)	(0.1928)
Constant	-1.6786**	-2.0898***
	(0.7874)	(0.7881)
Observations	3568	3568
Pseudo R^2	0.3360	0.3603
log Lik.	-1571.9455	-1514.5365
Chi squared	2013.0377	2071.2262

Standard errors in parentheses; * p<0.1, ** p<0.05, *** p<0.01. Logit model for Success and Failures. Models include 25 year, 87 ATC classes and Firm dummies

Table C.5: : Multinomial Logit

	Model 1		Model 2		Model 3	
Self Failure		-0.4416**		-0.6190**		-0.7297***
		(0.2235)		(0.2834)		(0.2509)
Others' Failure		0.1888*		0.2776*		-0.4969***
		(0.1067)		(0.1625)		(0.1830)
Self Success		0.1236		0.2913		1.0141***
		(0.3194)		(0.3477)		(0.2438)
Others' Success		0.1165		0.0029		0.3329**
		(0.1335)		(0.1956)		(0.1596)
Self Succ.&Fail		0.0417		-0.3501		0.0259
		(0.2522)		(0.3614)		(0.2687)
Others' Succ.&Fail		-0.0888		0.0776		-0.3141
		(0.1847)		(0.2164)		(0.1958)
Self Ongoing		0.9029***		0.4039		-0.8348**
		(0.2686)		(0.3619)		(0.3744)
Others' Ongoing		0.0472		0.1603		-0.4045*
		(0.1513)		(0.2055)		(0.2198)
Num Indication	-0.1619***	-0.1632***	0.1013***	0.1031***	0.2573***	0.2537***
	(0.0268)	(0.0273)	(0.0266)	(0.0269)	(0.0262)	(0.0263)
Num ATC classes	0.4753	0.5059	1.1707**	1.1827*	0.8493**	0.8947**
	(0.5890)	(0.5848)	(0.5958)	(0.6162)	(0.4127)	(0.4166)
Num Patent Family	-0.3210*	-0.3156*	0.8092***	0.8200***	0.5521***	0.5875***
	(0.1681)	(0.1673)	(0.1515)	(0.1508)	(0.1393)	(0.1372)
Shared patent Family	0.3963***	0.4040***	-0.2127	-0.1801	-0.6151***	-0.5837***
	(0.0935)	(0.0929)	(0.1566)	(0.1616)	(0.1532)	(0.1455)
Focal Patent originality	-0.1827	-0.2181	-0.2855	-0.3757	-1.5536***	-1.3892***
	(0.3554)	(0.3668)	(0.6347)	(0.6321)	(0.3694)	(0.3667)
Focal Number of Comp.	-0.0011**	-0.0011**	-0.0004	-0.0005	-0.0005	-0.0003
	(0.0005)	(0.0006)	(0.0007)	(0.0007)	(0.0006)	(0.0005)
Focal Lead= Focal Pat	0.0690	0.0644	-0.0462	-0.0606	-0.5859***	-0.5859***
	(0.1107)	(0.1081)	(0.1327)	(0.1326)	(0.1332)	(0.1337)
Citing NPL Scientific	0.1801*	0.1818*	0.5257**	0.5303**	0.0701	0.0595
	(0.0949)	(0.0942)	(0.2062)	(0.2087)	(0.1135)	(0.1148)
Bwd cits	-0.1402***	-0.1270**	-0.1035	-0.1005	0.3866***	0.4018***
	(0.0507)	(0.0539)	(0.0704)	(0.0753)	(0.0568)	(0.0640)
fwd cited	0.0055	0.0050	-0.0058	-0.0065	0.0040	0.0039
	(0.0049)	(0.0049)	(0.0070)	(0.0072)	(0.0059)	(0.0057)
Cited Patent Originality	-0.4224	-0.3710	0.6516	0.7077	-0.1853	-0.1904
	(0.3186)	(0.3113)	(0.7109)	(0.7087)	(0.4287)	(0.4220)
Num. Comp. of	-0.0001	0.0000	-0.0007	-0.0007	0.0004	0.0009

cited						
	(0.0010)	(0.0011)	(0.0015)	(0.0015)	(0.0015)	(0.0014)
Focal Lead=Cited Patent	-0.0527	-0.0599	-0.1916	-0.0270	0.0020	0.0821
	(0.1679)	(0.1883)	(0.2064)	(0.2279)	(0.1744)	(0.2175)
Same ATC focal-cited	0.0439	0.0042	0.0640	0.0399	0.3620***	0.3707***
	(0.0818)	(0.1006)	(0.1214)	(0.1373)	(0.0961)	(0.1156)
Succ in ATC	-1.0005***	-1.0340***	0.9042**	0.9420**	1.1622***	0.9508***
	(0.2778)	(0.2777)	(0.4570)	(0.4614)	(0.2698)	(0.2686)
R&D competition in ATC	-0.2723***	-0.2761***	0.3697***	0.3743***	-0.0724	-0.0458
	(0.0686)	(0.0671)	(0.0987)	(0.0978)	(0.0640)	(0.0631)
Failure Ratio	-0.8413***	-0.8087***	-1.0340***	-0.9905***	-1.1033***	-1.0536***
	(0.1906)	(0.1845)	(0.2075)	(0.2070)	(0.2058)	(0.2054)
Breadth of firm activities	-0.1522	-0.1660	-0.8482***	-0.8517***	0.9126***	0.8747**
	(0.2545)	(0.2534)	(0.2869)	(0.2888)	(0.3492)	(0.3448)
Constant	10.202	0.9875	-5.3671***	-5.3898***	-1.4224*	-1.6788**
	(0.8942)	(0.8904)	-10.590	-10.639	(0.7284)	(0.7178)

Multinomial Logit. All models includes 7350 observations. The Pseudo R^2 of Model 1 is 0.2450, of Model 2 is 0.2531. The base group is Failure. Standard errors clustered by Firm. No restriction applied on timing of citations.

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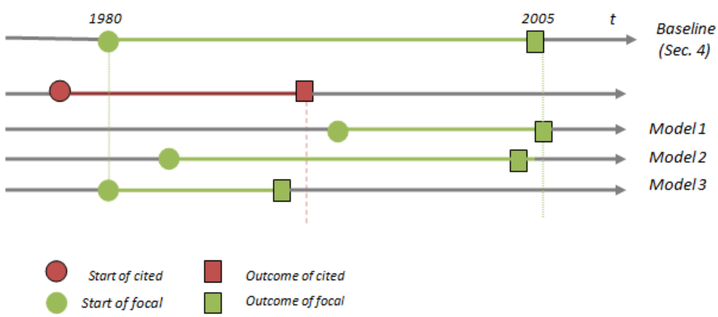
Figure C.1: Models taking into account different timing



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