

Beukel, Karin

Doctoral Thesis

The Determinants for Creating Valuable Inventions

PhD Series, No. 43.2013

Provided in Cooperation with:

Copenhagen Business School (CBS)

Suggested Citation: Beukel, Karin (2013) : The Determinants for Creating Valuable Inventions, PhD Series, No. 43.2013, ISBN 9788792977991, Copenhagen Business School (CBS), Frederiksberg, <https://hdl.handle.net/10398/8828>

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HANDELSHØJSKOLEN
SOLBJERG PLADS 3
DK-2000 FREDERIKSBERG
DANMARK

www.cbs.dk

ISSN 0906-6934

Print ISBN: 978-87-92977-98-4

Online ISBN: 978-87-92977-99-1

The Determinants for Creating Valuable Inventions

PhD Series 43.2013



**Copenhagen
Business School**
HANDELSHØJSKOLEN

The Determinants for Creating Valuable Inventions

Karin Beukel

The PhD School of Economics and Management

PhD Series 43.2013

The Determinants for Creating Valuable Inventions

Karin Beukel

Ph.D. School in Economics and Management
Copenhagen Business School

Karin Beukel
The Determinants for Creating Valuable Inventions

1st edition 2013
PhD Series 43.2013

© The Author

ISSN 0906-6934

Print ISBN: 978-87-92977-98-4

Online ISBN: 978-87-92977-99-1

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PREFACE

My aims in undertaking doctoral studies were to be challenged intellectually, and to conduct a deeper investigation of mechanisms of value creation, value capture, and appropriation for firms from an Intellectual Property Rights (IPR) perspective. Have I been successful – yes, absolutely. Academic study has been enlightening, and the methodologies and tools exploited during my doctoral training have been challenging and provided me with great enjoyment. In retrospect, during my period of PhD studies, I can honestly say that there were only a very few days when I did not feel inspired and eager to learn more; I look forward to a future of continuing to learn more as a more experienced academic researcher. I enjoy searching and acquiring knowledge, the people with whom I interacted, and the challenges encountered.

Although the process has been joyful it has been extremely challenging, but these two I feel are closely related. My experience before embarking on the PhD program was as an entrepreneur and an IP strategy consultant, which required me to be practical and solution oriented; I had to learn the ways of academia. I found that work experience outside of academia can be valuable, especially if it relates directly to one's PhD research topic, and that this practical knowledge can be drawn on to guide identification of research questions and also the methodologies and variables that are applicable and relevant to improve understanding in a particular area. I will therefore also in the future keep close connections to industry.

Three partners made my journey possible; they each sponsored a third of this PhD. They are H. Lundbeck A/S, Copenhagen University Faculty of Health and

Science, Molecular Disease Biology, and Copenhagen Business School. Not only did these sponsors provide financial help, individuals in all three organizations were great partners for sharing ideas and acting as sparring partners. I thank Nils Br  nner from Copenhagen University for his engagement and always positive and inspiring conversations, and the time he spent being interviewed during the case study (presented in Chapter 2 of this dissertation). At H.Lundbeck A/S there are several people to whom I owe thanks. First, members of the patent department; you were always welcoming and open in your conversations with me. Special thanks to Morten Rosted for discussions over the last years which helped my understanding about the details of patenting. The knowledge you imparted has been very valuable. I also thank Bo Kalum and Dorrit Bjerg Larsen for taking time to talk to me regularly over the last years, and Novozymes for the travel scholarship which allowed my participation in numerous conferences where I presented my ongoing research, and helped to fund a longer visit to Italy. At Novozymes I had several valuable discussions with Marianne Nonboe Weile for which I am grateful.

During my PhD study I visited LUISS Guido in Rome. Thanks to Francesco Rullani for welcoming me, and I look forward to working more intensively on the paper that we are coauthoring now that my writing of the dissertation is complete. In Chapter 2 I apply a new approach to estimating causal inferences in small N studies, which benefitted hugely from discussions with Peter Abell.

I want to thank all my distinguished colleagues at the department of Innovation and Organizational Economics (INO) where most my PhD period was spent. I benefitted from their open approach and detailed comments on my work. Special thanks to Lee Davis for discussing early drafts of my PhD proposal, to Toke Reichstein

who gave advice on econometrics, and Thomas Rønde for valuable input to the theorizing. I also want to thank my colleagues at the research center at Biotech Business, close colleagues such as Lars Alkærsig, Giancarlo Lauto, and Rasmus Vendelboe Lund Jensen – made this research more fun. My fellow PhD colleagues I also owe you many thanks – the PhD journey wouldn't have been the same without you.

Finally, I will be eternally grateful for the support from my excellent supervisors, Finn Valentin and Keld Laursen. Keld Laursen your wisdom and huge knowledge of research has been intriguing to try a dig into – thank you. Finn Valentin you taught me way beyond what one can expect from a supervisor, your wisdom and huge knowledge of life, academia, research, teaching, and program development is something I will build upon the rest of my life. In essence, dear supervisors you taught me more than I could have thought possible within the timeframe.

Finally, I want to thank my dear family and close friends for being there. There have been tough times due to my health during the last years which you have helped me through. To my girlfriends for being there and for the inspiration you bring to my life. Mum and dad thank you for your support, for listening and showing me how to believe in yourself. Lone, you are the best sister, I admire you, and I'm grateful for having you in my life. Frida you are the most wonderful daughter a mother could have, thank you for arriving just five months into the doctoral program. You were a wonderful diversion from my research and allowed me to remain (partly) sane during the process. I also thank Poul for our love and lives, for giving me the space for my all-important 'hobby' research, and for huge support which at times was a disruption to your own life.

ENGLISH SUMMARY

Empirical studies show that only a small number of all innovations created are valuable innovations. In spite of this, most innovation research focuses on identifying the determinants of innovation, rather than determining the factors influential in generating *valuable* innovations. The current knowledge therefore can guide organizations to increase innovation output, but not to increase the value of the innovation output.

The purpose of this PhD research is to contribute to our understanding of the determinants of valuable innovations by investigating how different intra-organizational factors and uncertainty influence organizations' abilities to generate valuable innovations. This thesis is comprised of four papers, a general introduction and a conclusion. The papers rely on both qualitative and quantitative research methods. One builds on interview data gathered at a Danish university and a firm, one relies on data from the Scandinavian biotech industry, and two papers rely on data from the global hydrocracking industry.

The first paper is an inductive grounded theory study of the transformation of twelve scientific inventions into patents, and an investigation of the micro-foundations that led to higher performance in terms of patent breadth. The results of the study point to three main mechanisms, interruption, cognitive variety, and abstraction, and highlight the role of patent experts in transforming science into patents.

The second paper is an inquiry into the effect of science on invention value. This paper asks when in the research and development (R&D) process scientific knowledge is beneficial for innovation value. A key finding is that the value generated

for innovation from search in science depends on the way it is balanced against technology search, and that the effects of this balance change across R&D stages. At the same time, this paper presents empirical evidence of a shift in how organizations rely on science versus technology for R&D. Innovations developed early in the R&D cycle rely more on science than innovations created later in R&D. On the contrary, for search in technologies, innovations developed early in the R&D cycle rely less on technologies than innovations created later in R&D.

The third paper investigates how organizations' knowledge bases affect their ability to generate complex innovations. In this paper we show that the degree of complexity of the organization's knowledge base is a determinant of the degree of complexity of the innovations the organization creates, therefore highlighting the importance of meta learning (vertical learning). At the same time this paper also investigates horizontal learning aspects, and finds that both related and unrelated learning are beneficial for complex innovations, while a specialized knowledge base has both indirect and direct negative effects on generation of complex innovations.

The fourth paper is an inquiry into strategizing for innovation, examining how rare and less rare innovative capabilities can benefit organizations developing valuable innovations, and how uncertainty moderates this relationship. A key finding is that not only rare capabilities, as emphasized in the literature, but also less rare capabilities are influential for creating valuable innovations. In addition this paper shows that the relationship between rarity and patent value is negatively moderated during periods characterized by low uncertainty.

The four contribution of this Phd research together provide significant insights into how organizations can optimize their development of valuable innovations.

DANISH SUMMARY

Empiriske studier viser at kun en lille andel af den samlede mængde af innovationer der bliver skabt er særligt værdifulde. Selv med dette i mente, har hovedparten af tidligere innovations studier fokuseret på at identificere de faktorer der har indflydelse på at skabe innovation, snarere end frembringelsen af *værdifulde* innovationer. På baggrund af dette, kan vi med vores nuværende viden om innovationer guide organisationer i at øge innovations output, men ikke i at øge værdien af disse innovationer.

Formålet med denne PhD er at bidrage til vores forståelse af determinanterne for værdifulde innovationer. Dette sker ved at undersøge hvordan forskellige organisatoriske faktorer samt usikkerhed i omgivelserne, har indflydelse på organisationers egnethed i at generere værdifulde innovationer. Denne PhD består af 4 artikler, en generel introduktion og en konklusion. Artiklerne varierer ved at både præsentere kvalitative og kvantitative studier. En artikel bygger på interview data indsamlet ved et dansk universitet og en virksomhed, en artikel tager afsæt i patent data og virksomheds data fra den skandinaviske biotek industri, medens de to sidste artikler beror på patent og virksomheds data fra den globale hydrocracking industri.

Den første artikel er et induktivt 'grounded theory' studie af tolv transformationer af forsknings til patent, mere præcist en undersøgelse af hvilke mikro-mekanismer der ledte til et bedre patent, udtrykt i patents teknologiske bredde. Studiet peger på tre væsentlige mekanismer at være opmærksom på; afbrydelse, kognitiv variation og abstraktion, og fremhæver den rolle patent eksperten spiller i at transformere forskning om til patenter.

Den anden artikel er en undersøgelse af videnskabens indflydelse på værdien af innovationer. Denne artikel spørger hvornår i en forsknings og udviklings (F&U) processen søgning efter viden i videnskaben vil være fordelagtig for skabelse af værdifulde innovationer. Studiet påpeger at værdien skabt ved at søge i videnskaben er afhængig af hvorledes det er balanceret mod teknologisk søgning, og at denne effekt af balancen ændrer sig henover en F&U proces. Samtidigt præsenterer denne artikel empirisk bevis for at hvorledes organisationer beror på videnskab og teknologi under F&U. Innovationer udviklet tidligt i F&U beror mere på videnskab end innovationer udviklet senere i F&U. For søgning i teknologier er det modsat, innovationer udviklet tidligt i F&U beror mindre på teknologi end innovationer udviklet senere i F&U.

Den tredje artikel undersøger hvordan organisationers videns base har indflydelse på deres evne til at generere komplekse innovationer. I denne artikel bevises det at graden af kompleksiteten i en organisations videns base har betydning for graden af kompleksiteten i de innovationer organisationen udvikler. Derved fremhæves vigtigheden af hvordan virksomheder lærer ved metalæring (vertikal læring). På samme tid undersøger denne artikel også horisontale lærings aspekter og finder at både relateret og ikke-relateret læring er fordelagtig for at generere komplekse innovationer. Derimod viser en specialiseret viden base både direkte og indirekte negative effekter på generering af komplekse innovationer.

Den fjerde artikel er en undersøgelse af innovations strategier, en udforskning af hvordan sjældne og mindre sjældne kapabiliteter kan fordelagtiggøre organisationer i deres udvikling af værdifulde innovationer, og hvordan usikkerhed modererer denne sammenhæng. Et vigtigt resultat er at ikke kun sjældne kapabiliteter,

men også mindre sjældne kapabiliteter har indflydelse på at udvikle værdifulde innovationer. Ydermere viser denne artikel at sammenhængen mellem sjældenhed og værdifulde innovationer er negativt modereret i perioder karakteriseret ved lav usikkerhed.

Bidraget fra denne PhD er fire individuelle artikler, som i sammenhæng, giver os væsentlig indsigt i hvorledes organisationer kan optimere deres arbejde med at udvikle værdifulde innovationer.

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CHAPTER 1

1 INTRODUCTION

Understanding the determinants of innovation is an important issue in the management literature. Starting from Schumpeter's early work on firm size and market structure as the primary determinants of innovation, scholars have complemented his work and contributed to a significant body of literature, emphasizing intra-organizational attributes, institutional influences, and other firm characteristics. Much of this research emphasizes the determinants of innovation, rather than the determinants of *valuable* innovation, even though the observed variations in the value of single inventions has for long been recognized. This thesis presents four essays related to *what determines the creation of valuable technological inventions* by analyzing intra-organizational and environmental determinants. Three of these pieces examine intra-organizational determinants of valuable inventions, first, how interruption, cognitive variety, and abstraction can enhance the value of single inventions, second how variation in firms' search processes towards science during different stages of R&D relate to creating valuable inventions, third, the relationship between types of learning and the degree of technological complexity of inventions. The fourth essay contributes to the market structure and firm innovation strategy literature by examining the relationship between rarity, uncertainty, and valuable inventions.

The central topic of this thesis is innovation, and *technological* inventions. This focus influences the methodological approaches applied, described in Section 'Novel

approaches to measuring valuable inventions' below, but limits the thesis in the sense that it does not include consideration and determinants of non-technical inventions, such as organizational or administrative innovations (e.g. Aiken and Hage 1971; Collins, Hage et al. 1988; Hage 1999; Ruef 2002), or innovations understood as diffusion, and adaptations of new behaviors in organizations (Hage 1999). This is not to suggest that these types of innovations are not important, however, their determinants can be expected to be significantly different and require a very different methodology to what is employed in this research. The words 'innovation' and 'technological innovation' are used synonymously as are 'invention' and 'technological invention'.

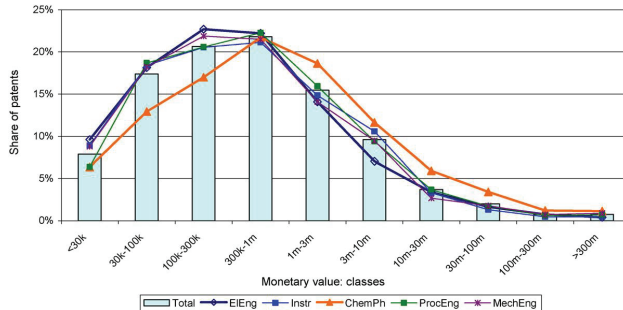
A sweetheart goes by many names, as do *valuable technological innovation*, for example, radical innovation, breakthrough innovation, complex innovation, and each type of 'more valuable innovation' is empirically measured differently. In the four essays in this thesis these dimension are examined, and linkages to types of more valuable invention are identified and measuring approaches are proposed for both large and small N-studies. This contributes to the innovation management literature in terms of how to measure innovation output at the level of single inventions. However, in essence the dependent variables in all four essays fall within the category of *inventions of higher value*.

Before examining the determinants of value in inventions, we need to specify the underlying properties of technological innovation per se. First, creating technological innovations is a journey into the unknown. Teece (1996) describes it as a search for technological and market opportunities, along a path characterized by uncertainty, path dependency, cumulativeness, irreversibility, technological interrelatedness, tacitness, and

inappropriability. Uncertainty in terms of both unpredictable changes (Koopmans 1957) and decision makers lack of knowledge of how agents in the market will act (Koopmans 1957), and as it arises from opportunistic behavior (Williamson 1975). Path dependence refers to the technological paradigm of technological innovations on technological trajectories (Dosi 1982). Cumulativeness refers to the relationship between new technological innovations and prior technologies, how new innovations ‘stand on the shoulders’ of prior technologies (Green and Scotchmer 1995; Scotchmer 2004). Irreversibility relates to the development of a new technological innovation introduced as a competing technology along a certain trajectory, in which the new technology outcompetes the old (Tushman and Anderson 1986). Interrelatedness refers to the subsystems in which the technological innovation is created which are important for outcomes, for example the way the different departments in a firm coordinate to co-develop a new technological innovation. Tacitness refers to the tacitness of the knowledge related to the technological innovation embedded in individual scientists and engineers, which it is difficult to codify (Polanyi 1962; Kogut and Zander 1993). Inappropriability refers to the effort injected into developing the a technical innovation which may not be rewarded appropriately due to imperfect assignment of intellectual property (IP) rights, for example in patents and/or copyrights, or lack of enforcement possibilities.

The properties of technological innovation mean that not all are successful, and empirical studies show that only few technological innovations really succeed to navigate this multifaceted and complex pathway of challenges. As a result the value of individual technological inventions follows a highly skewed distribution which approximates well to a log-normal distribution function, with most inventions having very little or no value, and very few

inventions being high value. Figure 1 shows the value of European patents across macro-technological classes, with less than 10 percent estimated at worth more than 10m EURO.



Source: Giuri, P., M. Mariani, et al. (2007). "Inventors and invention processes in Europe: Results from the PatVal-EU survey." *Research Policy* 36(8): 1107-1127.

Figure 1: The value of European patents across macro-technological classes in EUROS. Number of observations = 7752.

This distribution of valuable technological inventions has been confirmed in several studies (e.g. Jaffe 1986; Cockburn and Henderson 1996; Harhoff, Scherer et al. 2003; Giuri, Mariani et al. 2007; Harhoff and Hoisl 2007; Cassiman, Veugelers et al. 2008; Gambardella, Harhoff et al. 2008).

The core question then is *what determines the creation of a valuable invention?* This is the core question examined in this thesis, and the four essays provide answers to what determines whether organizations create one of the few valuable technological inventions. The prior literature suggests that firm size is important for determining which firms are capable of creating valuable inventions. One strand of research suggests that large firms fail to introduce breakthrough inventions, because they become caught in familiarity traps with respect to

competence development and learning, which creates overly strong path dependency in their R&D (Henderson and Clark 1990; Henderson 1993; Ahuja and Lampert 2001). Yayavaram and Ahuja (2008) investigate path dependency in firms by studying the structure of their knowledge bases and the subsequent impact on valuable inventions, and find that a nearly decomposable knowledge bases increases the value of subsequent inventions. Another strand in the literature suggests that to counteract path dependency, firms should search beyond the firm's boundaries (Rosenkopf and Nerkar 2001), for example, by investing in R&D outside the firm's technological and organizational boundaries (Ahuja and Katila 2001; Kotha, Zheng et al. 2011). One source of external R&D might be university research, which is valuable for the science driven industries (Tijssen 2002; Ahuja and Katila 2004). The linkage to science and its effect on more valuable inventions is still being debated, Fleming and Sorenson (2004) identify science as the source of more complex inventions, whereas Cassiman, Veugelers et al. (2008) finds that science linkages to individual inventions are not significant for explaining more valuable inventions and that they affect only the scope of forward citations. Harhoff, Scherer et al. (2003) find that linkages to science at the level of the individual invention explain value for patents in the pharmaceutical sector but not in other industries.

In addition to the studies cited above investigating firm characteristics, there are some classical approaches that examine the link between the individual(s) behind an invention and the value it generates. The main determinants examined in these studies include scientist's productivity, age, education, experience, degree of and scientific excellence (see e.g. Zucker and Darby 1996; Harhoff, Narin et al. 1999; Marc Gruber, Dietmar Harhoff et al. 2013). In a recent study, Gruber, Harhoff and Hoisl (2013) examine the individual characteristics of scientists and engineers, and the breadth of their inventions, and find that higher education, such as a doctoral degree, is associated with greater breadth, and that inventors with a scientific background are

more likely than inventors with an engineering background, to generate inventions based on several technological areas. Czarnitzki, Hussinger, et al. (2009) find that the inventions of professors in academia constitute less valuable patents, and patents that are characterized by being more basic compared to corporate inventors. However, when university professors collaborate with industry the effect is less negative. Thus, science is not always beneficial for generating valuable inventions. One reason why professors working in universities may generate less valuable patents might be related to their different working logic which focuses on research rather than patenting. Gittelman and Kogut (2003) argue that the value captured from patented inventions seem to follow a different and even conflicting logic from valuable scientific inventions. Therefore, while there is a substantial literature on how firms develop more valuable inventions, it has some gaps which are outlined below.

1.1 Micro-foundations for creating more valuable inventions

The literature argues that micro-foundations can become a major contributor to our understanding of the performance of organizations in dynamic environments (Gavetti 2005; Teece 2007; Abell, Felin et al. 2008; Zahra and Wright 2011). It has been argued that superior firm performance depends on the ability of managers to resolve the fundamental tension between flexibility and efficiency (Tushman and Oreilly 1996; Brown and Eisenhardt 1997; Uzzi 1997; Martin and Eisenhardt 2010). Studies that draw on psychology literature have examined the micro-foundations enabling managers to resolve this tension between flexibility and efficiency. They suggest that solutions should encompass both flexibility and efficiency (Eisenhardt, Furr et al. 2010). Empirical studies of the micro-foundations to resolve this tension highlight the importance of heuristics (Bingham, Eisenhardt et al. 2007), mindfulness (Weick and Sutcliffe 2006), modular business unit structures (Karim 2006; Hill and Birkinshaw 2008;

Martin and Eisenhardt 2010), strategic alliances (Lin, Yang et al. 2007), and convergent attributions (Bingham and Halebian 2012). A recent theoretical contribution by Eisenhardt, Furr et al. (2010) suggests three more: cognitive variety, abstraction, and interruption, arguing that these dimensions are core to resolving the tension between flexibility and efficiency. This tension is present in the transformation of science into patented invention. The first essay in this thesis contributes to this stream of the literature on micro-foundations by exploiting a unique and detailed case study approach examining how 12 scientific inventions were transformed into patented inventions. It investigates the micro-foundations that influence the probability of generating more valuable inventions, and how the main stakeholders, patent experts, play a significant role in enabling both flexibility and efficiency in this particular process.

1.2 Search in science and its impact on the value of innovations at early vs. late stage R&D

A central issue in the organizational learning literature is *search* that is research that investigates which sources of knowledge that is utilized when for example creating new inventions. Much of literature in this area is founded on the fact that innovation is the result of organizational search and learning processes (March 1991; Levinthal and March 1993). Therefore, we need to understand how firms' search behavior influences their innovation output (Gupta, Smith et al. 2006; Laursen and Salter 2006). The mechanisms of search are discussed in several studies as a recombinatory process (Fleming 2001; Fleming and Sorenson 2004), or a cognitive and experiential process (Gavetti and Levinthal 2000). According to this literature, firms tend to search locally and close to the firm's technological area (e.g. Helfat 1994; Stuart and Podolny 1996). One way to overcome the firm's tendency to only search in familiar areas is science (Fleming and Sorenson 2004). Search in science is industry dependent; only a few sectors, such as biotech and life sciences, undertake systematic research based on new scientific discovery

(Cohen et al., 2002; Klevorick et al., 1995; Nelson 2003; Stankiewicz 2000). The benefits of science for innovation have been debated and some empirical studies show that the relationship is not straightforward (Harhoff, Scherer et al. 2003; Cassiman, Veugelers et al. 2008). However, none of this work takes account of the differences related to science search at different stages of the R&D cycle. The pattern of search between science and technology has been suggested to change along the R&D cycle (Kline and Rosenberg 1986; Iansiti and West 1997), however, these different focuses and the shift from science based cognitive maps to technology based cognitive maps has not been empirically tested. Because the value of search in science is dependent on the cognitive search pattern of the search process and the outcomes being sought, in some stages of the R&D cycle science search will be more positive than in others. The reasons for the variation in search in science at early versus late stages of R&D is the subject of the second essay in this thesis.

1.3 Types of learning and the effect on generating more complex innovations

The third essay examines another related theoretical part of the organizational learning literature that investigates how types of learning affect the degree of complexity of the innovations created. The emphasis in the contributions to the organizational learning literature on knowledge bases has changed since the early 1990s. The emphasis traditionally was on how specialization, i.e. experience in a narrow range of activities, was a driver of knowledge accumulation (Argote 1993; Argote 1999). More recent work argues that variation is more valuable than specialization (e.g. Schilling, Vidal et al. 2003; Boh, Slaughter et al. 2007; Eggers 2012) and that learning can be categorized into distinct concepts. Schilling et al. (2003) introduces the notion of learning viewed through the lenses of specialized, related, and unrelated learning. They find that variation is not always bad, and that related learning can enhance the learning process

significantly more than either specialization or unrelated learning. Majchrzak, Cooper et.al (2004) in a case study of innovators' search mechanisms to develop an instrument to detect and measure dust devils on Mars, highlight the importance of meta-knowledge for radical innovation, and more specifically that meta-knowledge is assessed differently at different levels in the process of reuse of the organizational knowledge base. These results suggest a more complex picture of learning than previously described. We draw on this literature and examine the types of prior learning that are favorable for generating inventions characterized by different levels of technological complexity. Complexity of innovation output has been shown in prior studies to be positively affected by external search in science (Fleming and Sorenson 2004); however, types of learning and complex inventions have been overlooked. We examine these elements in the third essay in this thesis.

1.4 The effect of technological rarity and uncertainty on invention value

Drawing on the Resource Based View in research on strategic management has been identified as problematic by several authors (Priem and Butler 2001a; Priem and Butler 2001b; Hoopes, Madsen et al. 2003; Lockett, Thompson et al. 2009; Kraaijenbrink, Spender et al. 2010; Wernerfelt 2013). The literature identifies shortcomings related to the concepts of competitive advantage (Powell 2001); the indeterminateness of the concept of value and resources (Priem and Butler 2001a; Priem and Butler 2001b); and the limited applicability of theory (Miller 2003; Gibbert 2006; Levitas and Ndofo 2006). In addition, one of the core concepts in the Resource Based View, i.e. the notion that rarity of a resource or a capability contributes to firm performance, has been questioned and empirically tested. It has been shown that firms benefit from rare *combinations* – rather than rare individual resources and capabilities (Kor and Leblebici 2005; Teece 2007; Newbert 2008), and that it is rarity of dynamic but not ordinary

capabilities that matters for firm performance (Drnevic and Kriauciunas 2011). These contributions emphasize the need for a better conceptualization and systematic empirical evidence of the propositions theorized in the Resource Based View. In this paper, we examine the concept of resource value by investigating a crucial function in sustainable competitive advantage: innovation management. We explore the relationships among the value of an invention, and the rarity of the technological capabilities upon which it builds. However, resource endowment is only part of the story; research on the dynamics of demand state explicitly that environmental uncertainty with respect to existing technological innovations on the market plays a major role in the appropriation of the returns from innovation (Ragatz, Handfield et al. 2002; Fontana and Guerzoni 2008). It has been identified also that environmental uncertainty tends to increase the value of more common technologies, particularly as uncertainty increases with technological complexity (Tushman and Rosenkopf 1992). However, the question of the rarity and value of inventions, as well as rarity when moderated by low or high uncertainty and value of inventions has not been empirically explored in a large-N study. The fourth essay in this thesis theoretically and empirically links rarity and uncertainty to the value of individual inventions, exploring how different innovation strategies in different environments influences innovation value.

1.5 Novel approaches to measuring valuable inventions

Research on the determinants of innovation use both innovative *output* and innovative *effort* as measures of innovation (Cohen and Levinthal 1989; Ahuja, Lampert et al. 2008). While innovative effort refers to ability and incentives (Tirole 1988), innovative output refers to R&D productivity (Kamien and Schwartz 1975). The four essays in this thesis contribute to this strand in the research.

Substantial debate in the empirical management literature is devoted to use the of patents as output measures, and how to identify more valuable inventions in large datasets. Early work by Carpenter, Narin et al. (1981) identifies how patents associated with important technological products, identified as outstanding products and award winners, are significantly more frequently cited than the control group of patents. Also, the firm's overall corporate technological strength, profits and sales have been shown to be associated with highly cited patents (Narin, Noma et al. 1987). Since these early contributions numerous studies have tried to measure more valuable patents using patent indicators.

This thesis contributes in three distinct ways by identifying more valuable patents using novel approaches. The second and fourth essays try to reduce the noise generated by using only a single estimator (e.g. forward citation). Patent value indicators are noisy (Harhoff, Scherer et al. 2003; Gambardella, Harhoff et al. 2008), Lanjouw and Schankerman (1999) suggest combining several estimators in order to overcome this problem. Two distinct patent value correlates, family size and forward citations, are combined in a measure, using the standardized values of each in combination. These two dimensions contribute to our understanding of patent value in different ways: Family size is a proxy for how important and core the firm finds the individual invention. If the patent is assessed by the firm as being core, the firm will apply for patent protection in more countries than in the case of non-core inventions. Forward citations are a proxy for technological importance of the patent because they measure the number of subsequent inventions that cite the focal patent. By utilizing these two measures in combination, family size and forward citations, and running robustness checks for each measurement individually, we demonstrate the strength of this method to measure

patent value, and examine this measure in relation to each estimate, which adds to our understanding of patent value measures.

In the third essay, the measure of complexity of a patent is used as dependent variable. Prior research utilizes IPC code counts to identify the complexity and breadth of patents, however, recent work indicates that counting IPC codes will lead to inaccurate results (Cohen, Nelson et al. 2002; Leydesdorff 2008). In this paper we apply a novel method to measure the complexity of inventions. With help from industry experts, we identify all potential patents belonging to an industry by utilizing a search string that includes number of IPC codes and specific wordings. We identify three distinct technological domains within the industry utilizing a specific list of IPC codes. This allows us to identify the outcome variable in terms of whether the invention created covers *one*, *two* or *three* of the possible technological domains in the industry, essentially providing a novel measure of the complexity of inventions based on the number of significant different technological domains included in each invention. Additional outcome of this Chapter is that in-depth work on IPC codes and search strings, conducted in corporation with industry IPC experts, inform future work on IPC codes as technological breadth indicators.

In the first essay, I link the measure of patent value to the theoretical patent literature in economics, which argues that patent breadth is an indicator of patent value (Gilbert and Shapiro 1990; Klemperer 1990; Scotchmer 2004). It has been argued that greater patent breadth equates with higher value since more competing products and processes will infringe the patent (Gilbert and Shapiro 1990; Merges and Nelson 1990). While the theoretical arguments are clear, empirical testing of the breadth of patents has proved difficult, and the results from utilizing IPC codes give contrasting results (Lanjouw and Schankerman 1997; Harhoff, Scherer

et al. 2003). In this first essay, which deals with patenting in a small-N study, the notion of patent breadth is disentangled in novel way. Patent breadth is determined as below, medium or high (exceeding) the technological scope of the scientific invention underlying the patent application.

This thesis proposes novel approaches for measuring valuable innovations, responding to challenges in the literature. In the next part a short overview of the questions raised in the four essays are presented, the method and data from which answers to the questions are sought, and the status of the individual papers.

Table 1: Overview of the Dissertation

Chapter	Title	Question	Data	Method	Status
2	How Patent Experts Create Patent Breadth	How is science transformed into patents, and what actions affect the generation of valuable innovations?	12 case studies of scientific inventions transformed into patents	Grounded theory & and novel algebraic interpretations based on Bayesian inferences	Submitted to Journal
3	How search in science impacts on the value of inventions at early versus late stages in the R&D cycle	How does search in science affect the value of innovations at different stages of R&D?	1,058 biotech patents.	Unique approach to identifying types of patented inventions by the usages of an algorithm. OLS, TOBIT and percentile regression	Submitted to Journal
4	Types of learning in complex technological innovations	How does horizontal and vertical learning affect organizations in generating more complex innovations?	936 hydro-cracking patents.	Ordered logit regressions and logit regressions	Presented at DRUID 2012 and AOM 2013.
5	The effect of rarity and uncertainty on innovation value	How does rarity and uncertainty affect organizations to generate valuable innovations?	934 hydro-cracking patents	OLS and TOBIT regressions	Submitted to Journal

1.6 References

- Abell, P., T. Felin, et al. (2008). "Building micro-foundations for the routines, capabilities, and performance links." Managerial and Decision Economics **29**(6): 489-502.
- Ahuja, G. and R. Katila (2001). "Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study." Strategic Management Journal **22**(3): 197-220.
- Ahuja, G. and R. Katila (2004). "Where do resources come from? The role of idiosyncratic situations." Strategic Management Journal **25**(8-9): 887-907.
- Ahuja, G. and C. M. Lampert (2001). "Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions." Strategic Management Journal **22**(6-7): 521-543.
- Ahuja, G., C. M. Lampert, et al. (2008). "Moving Beyond Schumpeter: Management Research on the Determinants of Technological Innovation." Academy of Management Annals **2**: 1-98.
- Aiken, M. and J. Hage (1971). "ORGANIC ORGANIZATION AND INNOVATION." Sociology-the Journal of the British Sociological Association **5**(1): 63-&.
- Bingham, C. B., K. M. Eisenhardt, et al. (2007). "WHAT MAKES A PROCESS A CAPABILITY? HEURISTICS, STRATEGY, AND EFFECTIVE CAPTURE OF OPPORTUNITIES." Strategic Entrepreneurship Journal **1**(1-2): 27-47.
- Bingham, C. B. and J. Halebian (2012). "How firms learn heuristics: Uncovering missing components of organizational learning." Strategic Entrepreneurship Journal **6**(2): 152-177.
- Boh, W. F., S. A. Slaughter, et al. (2007). "Learning from experience in software development: A multilevel analysis." Management Science **53**(8): 1315-1331.
- Brown, S. L. and K. M. Eisenhardt (1997). "The art of continuous change: Linking complexity theory and time-paced evolution in relentlessly shifting organizations." Administrative Science Quarterly **42**(1): 1-34.
- Carpenter, M. P., F. Narin, et al. (1981). "Citation rates to technologically important patents." World Patent Information **3**(4): 160-163.
- Cassiman, B., R. Veugelers, et al. (2008). "In search of performance effects of (in)direct industry science links." Industrial and Corporate Change **17**(4): 611-646.
- Cockburn, I. and R. Henderson (1996). "Public-private interaction in pharmaceutical research." Proceedings of the National Academy of Sciences of the United States of America **93**(23): 12725-12730.
- Cohen, W. M. and D. A. Levinthal (1989). "INNOVATION AND LEARNING - THE 2 FACES OF R-AND-D." Economic Journal **99**(397): 569-596.
- Cohen, W. M., R. R. Nelson, et al. (2002). "Links and impacts: The influence of public research on industrial R&D." Management Science **48**(1): 1-23.
- Collins, P. D., J. Hage, et al. (1988). "ORGANIZATIONAL AND TECHNOLOGICAL PREDICTORS OF CHANGE IN AUTOMATICITY." Academy of Management Journal **31**(3): 512-543.
- Czarnitzki, D., K. Hussinger, et al. (2009). "Why Challenge the Ivory Tower? New Evidence on the Basicness of Academic Patents*." Kyklos **62**(4): 488-499.

- Dosi, G. (1982). "TECHNOLOGICAL PARADIGMS AND TECHNOLOGICAL TRAJECTORIES - A SUGGESTED INTERPRETATION OF THE DETERMINANTS AND DIRECTIONS OF TECHNICAL CHANGE." Research Policy **11**(3): 147-162.
- Drnevich, P. L. and A. P. Kriauciunas (2011). "CLARIFYING THE CONDITIONS AND LIMITS OF THE CONTRIBUTIONS OF ORDINARY AND DYNAMIC CAPABILITIES TO RELATIVE FIRM PERFORMANCE." Strategic Management Journal **32**(3): 254-279.
- Eggers, J. P. (2012). "All experience is not created equal: learning, adapting, and focusing in product portfolio management." Strategic Management Journal **33**(3): 315-335.
- Eisenhardt, K. M., N. R. Furr, et al. (2010). "Microfoundations of Performance: Balancing Efficiency and Flexibility in Dynamic Environments." Organization Science **21**(6): 1263-1273.
- Fleming, L. (2001). "Recombinant uncertainty in technological search." Management Science **47**(1): 117-132.
- Fleming, L. and O. Sorenson (2004). "Science as a map in technological search." Strategic Management Journal **25**(8-9): 909-928.
- Fontana, R. and M. Guerzoni (2008). "Incentives and uncertainty: an empirical analysis of the impact of demand on innovation." Cambridge Journal of Economics **32**(6): 927-946.
- Gambardella, A., D. Harhoff, et al. (2008). "The value of European patents " European Management Review **5**(2): 69-84.
- Gavetti, G. (2005). "Cognition and hierarchy: Rethinking the microfoundations of capabilities' development." Organization Science **16**(6): 599-617.
- Gavetti, G. and D. Levinthal (2000). "Looking forward and looking backward: Cognitive and experiential search." Administrative Science Quarterly **45**(1): 113-137.
- Gibbert, M. (2006). "Generalizing about uniqueness - An essay on an apparent paradox in the resource-based view." Journal of Management Inquiry **15**(2): 124-134.
- Gilbert, R. and C. Shapiro (1990). "OPTIMAL PATENT LENGTH AND BREADTH." Rand Journal of Economics **21**(1): 106-112.
- Giuri, P., M. Mariani, et al. (2007). "Inventors and invention processes in Europe: Results from the PatVal-EU survey." Research Policy **36**(8): 1107-1127.
- Green, J. R. and S. Scotchmer (1995). "ON THE DIVISION OF PROFIT IN SEQUENTIAL INNOVATION." Rand Journal of Economics **26**(1): 20-33.
- Gupta, A. K., K. G. Smith, et al. (2006). "The interplay between exploration and exploitation." Academy of Management Journal **49**(4): 693-706.
- Hage, J. T. (1999). "Organizational innovation and organizational change." Annual Review of Sociology **25**: 597-622.
- Harhoff, D. and K. Hoisl (2007). "Institutionalized incentives for ingenuity - Patent value and the German employees' inventions act." Research Policy **36**(8): 1143-1162.
- Harhoff, D., F. Narin, et al. (1999). "Citation frequency and the value of patented inventions." Review of Economics and Statistics **81**(3): 511-515.
- Harhoff, D., F. Scherer, et al. (2003). "Citations, family size, opposition and the value of patent rights." Research Policy **32**(8): 1343-1363.
- Helfat, C. E. (1994). "EVOLUTIONARY TRAJECTORIES IN PETROLEUM FIRM RESEARCH-AND-DEVELOPMENT." Management Science **40**(12): 1720-1747.
- Henderson, R. (1993). "UNDERINVESTMENT AND INCOMPETENCE AS RESPONSES TO RADICAL INNOVATION - EVIDENCE FROM THE PHOTOLITHOGRAPHIC

- ALIGNMENT EQUIPMENT INDUSTRY." Rand Journal of Economics **24**(2): 248-270.
- Henderson, R. M. and K. B. Clark (1990). "ARCHITECTURAL INNOVATION - THE RECONFIGURATION OF EXISTING PRODUCT TECHNOLOGIES AND THE FAILURE OF ESTABLISHED FIRMS." Administrative Science Quarterly **35**(1): 9-30.
- Hill, S. A. and J. Birkinshaw (2008). "Strategy-organization configurations in corporate venture units: Impact on performance and survival." Journal of Business Venturing **23**(4): 423-444.
- Hoopes, D. G., T. L. Madsen, et al. (2003). "Guest editors' introduction to the special issue: Why is there a resource-based view? - Toward a theory of competitive heterogeneity." Strategic Management Journal **24**(10): 889-902.
- Iansiti, M. and J. West (1997). "Technology integration - Turning great research into great products." Harvard Business Review **75**(3): 69-&.
- Jaffe, A. B. (1986). "TECHNOLOGICAL OPPORTUNITY AND SPILLOVERS OF RESEARCH-AND-DEVELOPMENT - EVIDENCE FROM FIRMS PATENTS, PROFITS, AND MARKET VALUE." American Economic Review **76**(5): 984-1001.
- Kamien, M. I. and N. L. Schwartz (1975). "MARKET STRUCTURE AND INNOVATION - SURVEY." Journal of Economic Literature **13**(1): 1-37.
- Karim, S. (2006). "Modularity in organizational structure: The reconfiguration of internally developed and acquired business units." Strategic Management Journal **27**(9): 799-823.
- Klemperer, P. (1990). "HOW BROAD SHOULD THE SCOPE OF PATENT PROTECTION BE." Rand Journal of Economics **21**(1): 113-130.
- Kline, S. J. and N. Rosenberg (1986). "An Overview of Innovation" in Landau, R. and Rosenberg, N.: The Positive Sum Strategy. Washington D. C. 1986, excerpt pp. 285 - 298.
- Kogut, B. and U. Zander (1993). "KNOWLEDGE OF THE FIRM AND THE EVOLUTIONARY-THEORY OF THE MULTINATIONAL-CORPORATION." Journal of International Business Studies **24**(4): 625-645.
- Koopmans, T. (1957). Three essays in the state of economic science, McGraw-Hill, NY.
- Kor, Y. Y. and H. Leblebici (2005). "How do interdependencies among human-capital deployment, development, and diversification strategies affect firms' financial performance?" Strategic Management Journal **26**(10): 967-985.
- Kotha, R., Y. F. Zheng, et al. (2011). "ENTRY INTO NEW NICHES: THE EFFECTS OF FIRM AGE AND THE EXPANSION OF TECHNOLOGICAL CAPABILITIES ON INNOVATIVE OUTPUT AND IMPACT." Strategic Management Journal **32**(9): 1011-1024.
- Kraaijenbrink, J., J. C. Spender, et al. (2010). "The Resource-Based View: A Review and Assessment of Its Critiques." Journal of Management **36**(1): 349-372.
- Lanjouw, J. and M. Schankerman (1997). "Stylized facts of patent litigation: value, scope, ownership, ." NBER Working Paper No. 6297. National Bureau of Economic Research, Cambridge, MA.
- Lanjouw, J. O. and M. Schankerman (1999). "THE QUALITY OF IDEAS: MEASURING INNOVATION WITH MULTIPLE INDICATORS." NBER Working Paper 7345.
- Laursen, K. and A. Salter (2006). "Open for innovation: the role of openness in explaining innovation performance among U.K. manufacturing firms." Strategic Management Journal, John Wiley & Sons, Inc. / Business. **27**: 131-150.

- Levinthal, D. A. and J. G. March (1993). "THE MYOPIA OF LEARNING." Strategic Management Journal **14**: 95-112.
- Levitas, E. and H. A. Ndofo (2006). "What to do with the resource-based view - A few suggestions for what ails the RBV that supporters and opponents might accept." Journal of Management Inquiry **15**(2): 135-144.
- Leydesdorff, L. (2008). "Patent classifications as indicators of intellectual organization." Journal of the American Society for Information Science and Technology **59**(10): 1582-1597.
- Lin, Z., H. Yang, et al. (2007). "The performance consequences of ambidexterity in strategic alliance formations: Empirical investigation and computational theorizing." Management Science **53**(10): 1645-1658.
- Lockett, A., S. Thompson, et al. (2009). "The development of the resource-based view of the firm: A critical appraisal." International Journal of Management Reviews **11**(1): 9-28.
- Majchrzak, A., L. P. Cooper, et al. (2004). "Knowledge reuse for innovation." Management Science **50**(2): 174-188.
- Marc Gruber, Dietmar Harhoff, et al. (2013). "Knowledge Recombination Across Technological Boundaries: Scientists vs. Engineers " Management Science **59**(4).
- March, J. G. (1991). "EXPLORATION AND EXPLOITATION IN ORGANIZATIONAL LEARNING." Organization Science **2**(1): 71-87.
- Martin, J. A. and K. M. Eisenhardt (2010). "REWIRING: CROSS-BUSINESS-UNIT COLLABORATIONS IN MULTIBUSINESS ORGANIZATIONS." Academy of Management Journal **53**(2): 265-301.
- Merges, R. P. and R. R. Nelson (1990). "ON THE COMPLEX ECONOMICS OF PATENT SCOPE." Columbia Law Review **90**(4): 839-916.
- Miller, D. (2003). "An asymmetry-based view of advantage: Towards an attainable sustainability." Strategic Management Journal **24**(10): 961-976.
- Narin, F., E. Noma, et al. (1987). "PATENTS AS INDICATORS OF CORPORATE TECHNOLOGICAL STRENGTH." Research Policy **16**(2-4): 143-155.
- Newbert, S. L. (2008). "Value, rareness, competitive advantage, and performance: A conceptual-level empirical investigation of the resource-based view of the firm." Strategic Management Journal **29**(7): 745-768.
- Polanyi, M. (1962). Personal knowledge: Toward a post critical philosophy, New York, Harper and Row.
- Powell, T. C. (2001). "Competitive advantage: Logical and philosophical considerations." Strategic Management Journal **22**(9): 875-888.
- Priem, R. L. and J. E. Butler (2001a). "Is the resource-based "view" a useful perspective for strategic management research?" Academy of Management Review **26**(1): 22-40.
- Priem, R. L. and J. E. Butler (2001b). "Tautology in the resource-based view and the implications of externally determined resource value: Further comments." Academy of Management Review **26**(1): 57-66.
- Ragatz, G. L., R. B. Handfield, et al. (2002). "Benefits associated with supplier integration into new product development under conditions of technology uncertainty." Journal of Business Research **55**(5): 389-400.
- Rosenkopf, L. and A. Nerkar (2001). "Beyond local search: Boundary-spanning, exploration, and impact in the optical disk industry." Strategic Management Journal **22**(4): 287-306.
- Ruef, M. (2002). "Strong ties, weak ties and islands: structural and cultural predictors of organizational innovation." Industrial and Corporate Change **11**(3): 427-449.

- Schilling, M. A., P. Vidal, et al. (2003). "Learning by doing something else: Variation, relatedness, and the learning curve." Management Science **49**(1): 39-56.
- Scotchmer, S. (2004). Innovation and Incentives, Cambridge, Massachusetts: The MIT Press.
- Stuart, T. E. and J. M. Podolny (1996). "Local search and the evolution of technological capabilities." Strategic Management Journal **17**: 21-38.
- Teece, D. J. (1996). "Firm organization, industrial structure, and technological innovation." Journal of Economic Behavior & Organization **31**(2): 193-224.
- Teece, D. J. (2007). "Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance." Strategic Management Journal **28**(13): 1319-1350.
- Tijssen, R. J. W. (2002). "Science dependence of technologies: evidence from inventions and their inventors." Research Policy **31**(4): 509-526.
- Tirole, J. (1988). The theory of industrial organization, Cambridge, MA: MIT Press.
- Tushman, M. L. and P. Anderson (1986). "TECHNOLOGICAL DISCONTINUITIES AND ORGANIZATIONAL ENVIRONMENTS." Administrative Science Quarterly **31**(3): 439-465.
- Tushman, M. L. and C. A. O'Reilly (1996). "Ambidextrous organizations: Managing evolutionary and revolutionary change." California Management Review **38**(4): 8-&.
- Tushman, M. L. and L. Rosenkopf (1992). "ORGANIZATIONAL DETERMINANTS OF TECHNOLOGICAL-CHANGE - TOWARD A SOCIOLOGY OF TECHNOLOGICAL EVOLUTION." Research in Organizational Behavior **14**: 311-347.
- Uzzi, B. (1997). "Social structure and competition in interfirm networks: The paradox of embeddedness." Administrative Science Quarterly **42**(1): 35-67.
- Weick, K. E. and K. A. Sutcliffe (2006). "Mindfulness and the quality of organizational attention." Organization Science **17**(4): 514-524.
- Wernerfelt, B. (2013). "Small forces and large firms: Foundations of the RBV." Strategic Management Journal **34**(6): 635-643.
- Williamson, O. E. (1975). Market and Hierarchies, Free Press, NY.
- Yayavaram, S. and G. Ahuja (2008). "Decomposability in knowledge structures and its impact on the usefulness of inventions and knowledge-base malleability." Administrative Science Quarterly **53**(2): 333-362.
- Zahra, S. A. and M. Wright (2011). "Entrepreneurship's Next Act." Academy of Management Perspectives **25**(4): 67-83.
- Zucker, L. G. and M. R. Darby (1996). "Star scientists and institutional transformation: patterns of invention and innovation in the formation of the biotechnology industry. ." Proceedings of the National Academy of Sciences of the United States of America **93** (23), 12709-12716.

CHAPTER 2

2 HOW PATENT EXPERTS CREATE PATENT BREADTH

By Karin Beukel

ABSTRACT

Science as an input to patented inventions is a fundamental of economic growth. However, our understanding of *how* science is transformed into patents is limited. In the present paper I seek to fill this gap by examining the micro-foundations of science-patent transformations. Using an inductive, grounded theory approach to study the transformation of 12 scientific discoveries into patents I recast the relationship between science and patents: I show it as a particular process that affects patent breadth. Exploiting surplus patent breadth depends on the processes of abstraction and cognitive variety, which can be mobilized by patenting experts. The theory is tested using a recently published algebraic interpretive method for examining causal relationships in small-N studies.

Keywords: science & technology; patent expertise; micro-foundations, cognitive variety & abstraction; patent breadth

2.1 Introduction

A central debate in the innovation literature is the relationship between science and patents in the innovation exploitation process. Research suggests that science is an input to technological innovation (Rosenberg and Nelson 1994; Tijssen 2002; Ahuja and Katila 2004), and that its contribution is more important in certain sectors, such as science based industries (Dosi 1988; Pavitt 1991; Klevorick 1995; R 2000; Cohen 2002; Nelson. R R 2003). However, even in these industries there is no consensus on the importance of science as an input. There is a stream of studies that argues that the contribution of science to technological progress is limited (Kline and Rosenberg 1986), while other authors argue that the contribution of science has increased (Bonaccorsi and Thoma 2007) and that *'science does remain an important condition and component of technological progress, and one that is fundamental in science-based industries'* (p.6 Balconi, Brusoni et al. 2010). Other research at the level of individual inventions suggests that the relationship between science and patents is not straightforward (Murray 2002; Gittelman and Kogut 2003; Murray and Stern 2007; Cassiman, Veugelers et al. 2008). Assessing the links to science at firm level is more informative than at the individual invention level (Cassiman, Veugelers et al. 2008). There are distinctive scientific and technological networks that provide evidence of the overlaps between licensing, founding, and consultancy, but not citations and co-publishing (Murray 2002). Patent-paper pair analysis shows that granting of patents affect result of scientific publication negatively, as citations received to scientific publication declines after the granting of a patent on the same scientific knowledge (Murray and Stern 2007). Also Gittelman and Kogut (2003) point out that scientific inventions are not simple inputs to patented inventions, and that the value captured by patented inventions seems to follow a different and even conflicting logic to valuable scientific inventions. Their research also show that important

science does not always transform into valuable patents, and the most valuable patents are not necessarily based on more important science (Gittelman and Kogut 2003). These complementary lines of research add to our understanding of the commercialization of science as occurring not through simple translation but rather *transformation*. This transformation from science to patents however, represents a black box with respect to the mechanisms that explain the differences observed in patent breadth outcome.

The current study addresses this issue where research is rather scarce. We adopt a grounded theory building approach (Eisenhardt 1989; Strauss and Corbin 1990), guided by structures originating in sequence analysis (Abbott 1995) essentially to develop a theory of how surplus patent breadth is created during the process of transforming science to patents. We test the results of our proposed theory exploiting the algebraic method suggested by Abell (2009) for testing causal inferences in small-N studies. I examine how the transformation of science to patented inventions is conducted, and what causes patent breadth to exceed the technological breadth originally identified by the scientist. The process from science to patent is likely to involve conflicting agendas; solving conflicting agendas is fundamental for high performance (Brown and Eisenhardt 1997; He and Wong 2004; Smith and Tushman 2005). The conflicts expected in the transformation process are related to differences in the motivations and goals related to the process: The networks that play a role in the transformation process overlap, and there are also many different stakeholders involved in the process (Murray 2002). Venture capitalists can influence the choice of exploitation strategy in certain directions (Hsu 2006), while scientists may be focused on their research and be willing to accept a lower financial return in order to retain the autonomy to conduct their scientific research (Stern 2004). Also, research and development (R&D) personnel might find it difficult to evaluate the true value of their inventions (Moran and Ghoshal 1999), and scientists may be unable to abstract the value

from the scientific inventions they have created or to understand how their scientific invention can be transformed into valuable patents. They may lack the ability to assess the market and technological opportunities and limitations. So how are patented inventions created? We can answer this in part by examining the role of a set of actors who are often overlooked by the innovation literature, i.e. patent experts or those responsible for creating, defining, and formulating the patented invention.

The research on the role of patent experts is quite limited (eg. Fox 1998; Somaya, Williamson et al. 2007; Reitzig and Wagner 2010; Harrison and Sullivan 2012; Somaya 2012). Research shows that there is a hidden cost to outsourcing patent expert work (Reitzig and Wagner 2010), and that R&D output (measured by number of patents) is dependent not only on R&D activity but also on patenting expertise (Somaya, Williamson et al. 2007). However, to my knowledge, the link between patent expertise with transformation of individual scientific inventions has been overlooked. The existing research mostly links patents directly to the characteristics of the inventors behind the invention (Zucker, Darby et al. 2002; Gittelman and Kogut 2003; Giuri, Mariani et al. 2007) rather than considering the patent as something that is created on the basis of a transformation of the scientific invention developed by a scientist (inventor), and a scientific invention which requires a transformation process, orchestrated by patent experts, to become a patented invention. This transformation process requires the scientific invention to be positioned and developed along the broadest possible technological scope in order to occupy the maximum patent breadth in the patent landscape, to secure the freedom to operate in relation to future developments, and potentially to identify technological applications and ways of exploitation not the focus of the inventor's original scientific invention. Creating patent breadth results in more competitors for the technology and a more valuable patent (Gilbert and Shapiro 1990; Klemperer 1990; Scotchmer 2004).

This study makes three important contributions. First, the findings show that creating additional patent breadth is dependent on three main micro-foundations: interruption, cognitive variety, and abstraction. This study is in line with the literature that argues that examining the micro-foundations of organizations should improve our understanding of organizational performance (Gavetti 2005; Teece 2007; Abell, Felin et al. 2008; Zahra and Wright 2011). Second, I highlight that the transformation of science into patents is orchestrated by patent experts rather than the scientists, and that the outcomes of the transformation are related to the success of this particular process. This view of the transformation of science into patented inventions has implications for innovation theory. Our findings confirm that science is an input to technology (Tijssen 2002; Ahuja and Katila 2004), and that science is fundamental to science based industries as argued by (Balconi, Brusoni et al. 2010). I contribute to this work by proposing a specific relationship between science and patents in terms of technological breadth. Third, to address the specific research questions we adopt an innovative research method which combines established inductive qualitative research approaches (Eisenhardt 1989; Strauss and Corbin 1990) with more recent deductive algebraic methods to study narratives (Abell 2009). This is a unique contribution and proposes a research design that could be used for other very complex, small N studies.

The paper is organized as follows: First, I describe the theory building and the multiple case study method which is based on sequence studies, semi-structured interviews, observation studies, and secondary data. I next describe the research sample and the data collected. I review the findings from the data analysis and their implications for understanding the transformation of science into patented inventions, and formulate four propositions related to predicted performance in terms of patent breadth. I present the analytical techniques on which basis I can perform likelihood estimations of the causal inferences proposed. I conclude by

discussing the broader implications of this study for understanding the micro-foundations of the transformation of science into patented inventions.

2.2 Methods

The research design used in this study is grounded theory building (Eisenhardt 1989; Strauss and Corbin 1990) combined with an algebraic and mathematical approach to narrative data analyses suggested by Abell (2009). I chose the grounded theory approach because of the lack of prior theory and research on the role of scientists and patent experts in the transformation of scientific discoveries into patented inventions. The setting is the pharmaceutical industry, which is a leader in systematic commercialization of scientific discoveries (Cohen et al. 2002; Klevorick et al. 1995). I use a multiple case study in order to allow ‘replication logic’. I treat each scientific discovery that has been transformed into a patented invention as a series of experiments, with each transformation serving to confirm or reject the inferences drawn from the other cases (Yin 1989). Thus, the findings are deeply grounded in varied empirical evidence, which makes the results more valid and generalizable compared to single-case studies (Eisenhardt and Graebner 2007).

The study design involves 12 transformations of science into patented inventions (see Table 1 for a description of the scientific inventions and patented inventions). The selection of cases was based on accessibility and a number of criteria. In order to increase generalizability, the 12 scientific discoveries are split between university and private firm inventions. Prior research suggests that the timing of R&D influences the degree to which a new technology is based on science: early in the process there is an emphasis on science-based discoveries; in the later stages of R&D, the emphasis tends to be on technological knowledge (Cassiman et al. 2010; Iansiti and West 1999). To create generalizable findings with respect to

the timing of the R&D process, the sample includes three innovation processes that had been ongoing for around 10 years. During this period, several scientific discoveries had been made and transformed into patents. In order to avoid the likelihood of respondents having a misperception of the innovation process due to extreme success or failure, I chose only active innovation projects yet to be commercialized (or closed down) at the time of the interviews. Another criterion was to include only R&D projects where respondents were available who had been involved in the early stages of the process. Some interviewees had up to 15 years experience on the project. Thus, the research includes retrospective and concurrent data, allowing in-depth exploration of how the innovation process has evolved over time (Leonard-Barton 1990). Since the innovation process was ongoing, the project development process was fresh in the minds of the interviewees. In total three innovation processes, two in one firm and one university project, were included in the research.

Insert Table 1 here

Respondents were identified through the snowballing and pyramiding methods (Von Hippel 2009; Poetz and Prugl 2010) and included both the scientists responsible for the inventions, the patent experts engaged in the transformation process, and other stakeholders in the drug development teams, such as project managers, clinicians, regulatory personnel, marketing personnel, biostatisticians, technology transfer officers, and R&D managers.

2.2.1 Data collection and analysis

I used three main data sources: 1) interviews, 2) participant observation of innovation process meetings, and 3) archival data, both public and non-public, including patents, scientific publications, and other material provided by respondents. The primary data source was more

than 50 interviews and observations of more than 30 meetings. Data collection extended over three years. For a total of more than 12 months, I visited the firm once a week. Prior to the main data collection period, I conducted nine pilot interviews to get some preliminary insights into the transformation process I wanted to study, to identify an appropriate method to access highly sensitive knowledge, and to test the more general questions in the interview guide. The pilot interviews were conducted with university scientists, biotech entrepreneurs, R&D managers, patent engineers in biotech firms, and patent experts hired at patent consultant bureaus. During the pilot interviews it became clear that patent experts were the main drivers of this transformation. To learn more about this group I identified all patent experts working in Danish drug discovery biotech firms via online CV databases, and contacted the Danish drug discovery firms to confirm the identified patent experts' engagement in the individual firms (further information on the methods applied is available from the author). The results of this initial investigation showed that, of the 122 patent experts identified, almost half had a science PhD (e.g. in Biochemistry, Chemistry, Molecular Biology, Human Biology), and in addition over two thirds of this population had a European Patent Attorney degree. The requirements for studying for a European Patent Attorney degree are a degree in science and practical intellectual property work experience. Thus, patent experts have a thorough education in their field of expertise, combining deep scientific insights with patenting. The natural science background is similar to that of the inventors of European Patent Office (EPO) patents. Giuri, Mariani et al. (2007) show that 59.1 percent of inventors in Chemicals and Pharma are doctoral graduates.

The data analysis method involved analysis of each individual case and then comparison of cases to construct a conceptual framework (Eisenhardt 1989), based on within-case and cross-case analysis (Miles and Huberman, 1984). In analyzing the cases, I focused on generating constructs of the transformation from science to patented invention to understand

how it had been achieved. This involved an iterative process of refining questions and reinterviewing the respondents. Quotes relating to how each action led to an event were collected and examined using sequence analysis. For the sequence analysis I first established a separate chronology of events for each of the three innovation processes. During the selection of events for the chronology to be presented in the case study, I conducted theoretical sampling. I focused on events that were related to: a) a change of direction in innovation and/or product breadth, and b) patent initiatives, such as patent applications and changes in the patent filing focus. The preliminary chronology of the *events* collected took the form of E denoting a point in time. For each of the events investigated, a range of different *actions* (A_n) led to a certain *event* (E_n) occurring in a certain *context* (C_1). The actions are not necessarily time constrained and the context changes over time, following Abbots (1990; 1995) approach to sequence patterning based on the relationships between patterns, independent variables, and dependent variables. Figures 1, 2 and 3 depict the innovation processes for the patented inventions.

Insert Figure 1, 2 and 3 here

To identify the actions (A_n) leading to the events (E_n) happening in a certain context (C_1), I interviewed stakeholders in three innovation processes (Interview guide available from author). The information provided by interviewees is sensitive and relates to potentially highly profitable drugs still under development. Therefore, the firm did not allow recording of interviews, and only some of the interviews at the university were recorded and transcribed. This required extensive note taking, and requests to the respondents to wait while I wrote down a quote (which I anonymized) and excluded specific details, e.g. relating to indications, substances, compounds, diseases, persons, firms, and cooperators. The quotes were subsequently checked by the firm for anonymization. Some respondents/key stakeholders were

interviewed several times – some more than five times - in order to clarify quotes or to gain further insight.

2.2.2 The dependent variable patent breadth

The theoretical economics patent literature focuses on two different measures as determinants of patent value: patent length (Nordhaus 1969; Scherer 1972) and patent breadth (Gilbert and Shapiro 1990; Klemperer 1990; Scotchmer 2004). The literature on patent breadth argues that broader patent breadth results in a higher number of competing products and processes that will infringe the patent; therefore, a higher value is associated with broader patents (Gilbert and Shapiro 1990; Merges and Nelson 1990). Building on this, empirical studies have used International Patent Codes (IPC) as measures of technology breadth (Lerner 1994). Lerner (1994) finds a correlation between number of IPCs (the measure of patent breadth) and the value of patents in the biotechnology industry. However, these results may be specific to the biotech industry because they have not been confirmed in other empirical studies in other contexts (Lanjouw and Schankerman 1997; Harhoff, Scherer et al. 2003). Thus, the notion of patent breadth might be too complex to be measured by counting IPCs. Merges and Nelson (1990) describe elements related to the complexity of patent breadth: patent breadth is linked to both the decision process related to claims handled by (national) patent offices, which take account of local legal principles as well as the individual invention proposed by the applicant. The individual invention as described in the patent application provides the greatest opportunity for increased value (increased patent breadth) for patent applicants. Therefore, we measure this outcome variable.

The present study is the first to demonstrate that the individual scientific invention can have three different patent breadth outcomes – low, medium, or high (excess) - defined by

the breadth of the technological scope of the patent. *Low technological breadth* refers to those innovations where the patent does not provide protection of the scientific invention. *Medium technological breadth* describes patent applications that cover only the technological breadth of the scientific invention. *Excess technological breadth* describes patent applications where the protection applied for exceeds the technological breadth of the initial scientific invention. An example might be where the initial scientific invention refers to only *one type* of sulphur for example, and a certain effect, but where during discussions (leading perhaps to additional work in the lab) lead to a patent application for *all types* of sulphur, potentially providing broader scope technological protection. For the assessment of the individual patent applications in this study in to low, medium or excess, two specialists with the relevant expert knowledge (e.g. the scientist behind the invention or the patent expert) are assigned to conduct an evaluation.

The benefits of achieving additional patent breadth differ depending on the conditions under which the patent has been developed. I would argue that excess patent breadth is equally important for scientists working in firms and in universities. There are increasing numbers of academic scientists who commercialize their scientific discoveries (Henderson, Jaffe et al. 1998; Thursby and Thursby 2002; Meyer, Sinilainen et al. 2003; Breschi, Lissoni et al. 2008), and university patenting has been shown to be a channel for technology transfer (Archibugi 1992; Jaffe, Trajtenberg et al. 2000). University scientists may patent an invention in order to sell it by transferring the priority patent application and leaving the process of further development of the invention (e.g. a drug) to a commercial firm, or may develop it to an extent through the means of a university spin-out. Thus the broader the technology breadth of a university patent, the greater the number of possible applications of the technology in the market and the greater the number of potential buyers. The situation is different for firm scientists (at least those working in large pharmaceutical firms) who are focused on achieving the freedom to

operate in the product's intended market in the future. They are less likely to reap the benefits of broad technology coverage as soon as university scientists. Because technological innovation is highly uncertain by nature (Koopmans 1957; Williamson 1975; Teece 1996), creating the broadest possible breadth minimizes the need for firms to in-license competing technologies and to penetrate the market without infringing third-party rights. It enables anticipation of potential 'minefields' (e.g. patents the inventor might infringe in the future) that the R&D process must circumvent. The inventor (together with the patent expert) is able to identify means to avoid them upfront instead of later after time-consuming and costly innovation. The notion of creating excess technological breadth links to discussions in the literature on patent strategizing for appropriability (Cohen, Nelson et al. 2000; Granstrand 2000; Ziedonis 2004) by explicitly providing examples of what Pisano (2006) describes as patent appropriability that is not exogenous or automatically assigned but is created endogenously by firms' strategies and conscious actions.

2.3 Making patent breadth exceed the technological breadth of the scientific invention

The distribution of patent breadth in our samples shows that among the 12 cases, two patents (one firm and one university patent) have excess breadth. Two university but no firm patents were assessed as low patent breadth; six patents were assessed as partly excess partly medium. Two patents were assessed as medium patent breadth. The timing of the R&D phase matters for the patent breadth the patent agent can create. In each of the three innovation processes examined the initial patents were assessed as excess breadth (#1 and #12, referring to Table 1) or excess/medium (#3) and excess/medium patent breadth (#7, #8, #9 and #10). This might indicate that early in the R&D process there is more room for the patent agent to make improvements. With the exception of one university patent which was assessed as 'most basic

science' by the patent expert, all patents were assessed as based on applied science. In the case of the university patent assessed by the patent expert as basic science, the inventor identified it as based on applied science. By definition, patenting requires industrial applicability in order to meet the patent requirements and this is why patenting of basic science can be problematic.

Analyzing the assessment of patent breadth via general patent indicators, IPC codes, forward and backward citations, and number of inventors provides some interesting results. These should be interpreted with some caution since the sample studies only 12 observations. In terms of forward citations, an indicator of patent value (Trajtenberg 1990; Harhoff, Narin et al. 1999; Harhoff, Scherer et al. 2003) the patents in our sample show a different distribution to the results from large scale studies. In the present study only one-third of patents did not receive any forward citations, with a mean of 5.3 citations and a standard deviation of 7.19, showing a less skewed distribution towards zero than expected. This indicates that the patents examined in this small sample are higher value compared to the distributions observed in large N-studies (see for example Gambardella, Harhoff et al. 2008). A Fisher exact test shows that there is no statistically significant relationship between forward citations and the mean of the specialist assessments of the patent breadth created in the transformation process ($p=0.661$). This indicates that the surplus patent breadth created by patent experts is not necessarily related only to more valuable patents. Lerner (1994) shows that number of IPC classifications (indicating patent breadth) is correlated with value; we analyze each patent with respect to the number of IPC classifications at the four, seven, and nine digit level, and find a significant relationship between IPC codes at the nine digit level and forward citations ($p=0.083$ Fisher exact test), whereas both four and seven digit IPC codes are insignificant. None of the other patent indicators, number of inventors, patents cited by examiner, NPLs (non patent literature citations) cited by examiner, patents cited by inventor or NPLs cited by inventor shows significant correlations with the mean

of the assessments. This might indicate that the work done by the patent expert is not reflected in available patent indicators. The results of the assessments of individual patents and patent indicators are summarized in Table 2.

Insert Table 2 here

Why do some transformation processes from scientific discoveries to patented inventions create new value in the form of extended patent breadth, and others do not? In this study using grounded theory I identify three distinct mechanisms that influence whether excess patent breadth is generated in the process after scientific invention, the mechanisms are interruption, cognitive variety and abstraction. The cognitively psychology literature discusses these mechanisms separately (Neisser 1976; Piaget 1985; Carroll 1993), while in recent management literature the three micro-foundations identified are described as mechanisms for how managers control the tension between efficiency and flexibility in dynamic organizations (Eisenhardt, Furr et al. 2010). The micro-foundations identified, support a single solution to achieve a balance between flexibility and efficiency as opposed to the dual solutions proposed in the ambidexterity literature (Tushman and O'Reilly 1996; Adler, Goldoftas et al. 1999; He and Wong 2004). The three main mechanisms identified have an influence on patent breadth created in the process of transformation from science to patent, are interruption, cognitive variety and abstraction, each presented below.

2.3.1 Interruption

The drivers of technological breadth are distinct, yet patent experts play a critical role in each of them. Medium technological breadth is realized when patent experts are included in early in the process, and ensure an *interruption* to the scientific research. The effect of interruption upon flexibility and efficiency is described by Eisenhardt, Furr *et.al* (2010, p. 1269) as

'Interruption enables flexibility because it creates a pause in the flow of activity that can trigger reassessment and change of direction. Yet interruption simultaneously allows for efficiency because it also enables leaders to avoid wasting time on inappropriate paths.'

In an experimental study Okhuysen and Eisenhardt (2002) identify interruption as a significant mechanism to increase the performance of both novel and ambiguous assignments. However, in management studies that examine interruption at the level of individuals, the results are different. Tushman and Rosenkopf (1996) examine how CEO succession influences performance and find a positive effect in stable contexts, and a negative effect in turbulent contexts. Another study (Boeker 1997) of top managers, associates interruption with mobility of top managers across organizations which results in subsequent changes in product-market entries, with the effects moderated by experience. In the present study a range of types of interruptions are identified, one being a patent expert assigned to identify a new way of protecting substance X_1 against disease Z_1 if product is brought to the market (see E12 in Figure 2). A patent application should entail an inventive step, novelty, and industrial applicability, why the particular assignment the patent expert were requested to do was creating a new patentable invention, relying on input from R&D staff. In this process the interruption was initiated by management because the patent which allowed 20 years protection was expiring. This meant that the invention would not be protected against generics or competitors beyond the time period provided by regulatory data protection (the time period varies across countries: US is 5 years for pharmaceutical chemical entities, EU 10 years, and Japan 8 years). During the interruption the patent expert interviews the innovation project stakeholders to obtain information. The patent expert handling the process (patent #8, #9 and #10) explained the interruption as:

'I talked to many different persons, several persons had really good ideas, some of the ideas was old ideas that we have implemented now, and some new ideas. There

was surprisingly a lot of information which needed to be shared in the organization, so it was a really good catch.'

During the interruption innovation project members also met and discussed the ideas generated. The innovation project team members describe the meeting (see Figure 2):

'At the meeting (E15) it was kind of a health check on the ideas that was gathered during the interviews (E14), but new ideas was also generated' and

'During E15 we had ideas generated which we together build to be a sort of realization, then we could see the future perspectives of things (E16).'

However, while the process –interruption mobilized by the patent expert - provides evidence enabling project team members to identify directions for the future, and suggest inventions that could be patented (in our case three), the chemist interviewed described it thus:

'The chemical considerations the patent expert had made contained identifying IP opportunities in the chemical structure, IP opportunities in the production and process considerations and so on, it means that the ideas are more of a defensive character. They did not influence the chemical structure of the innovation it was more to keep the others away'.

The description and assessment of the patents created as a result of interruptions in the cases indicate that interruption can lead to medium patent breadth. In formal terms, this finding suggests the following relationship:

Proposition 1; Patented inventions will be more likely to achieve medium technological breadth if patent experts perform 'interruption' during the transformation phase from scientific invention to patented invention.

It was clear that without an interruption there could not have been a patent application. In the above example the interruption was initiated by management, but implemented by the patent expert, as one stakeholder in the process explained: *'The patent experts needed to live up to his management's expectations, I think that is why he needed to find*

alternative IP routes'. The patent expert explained that his approach was outside the firm's formal structures:

'How do we organize this process? It was my colleagues' idea to interview all stakeholders of the project prior the meeting. This was a very good idea this removed the pressure as everybody had the opportunity to say what they wanted on beforehand. And then I could structure the results from the interviews in a way which we could use at the meeting.'

The above quotes identify the patent expert as a main driver in the 'patent' interruption in the firm. The firm had structures that allowed patent experts to scrutinize new ideas coming out of its R&D. This did not apply to the universities. A professor interviewed explained:

'Here the interaction with TTO (Tech Transfer Office) happen ad-hoc or actually it is not present, we never see our contact person, there is no work internally in the organization (referring to the tech transfer office mainly conducting external to the university activities). They (TTO) never come here, they do not make any arrangements for us, nothing happens. It is like we do not exist, only when we send them an invention disclosure, or else we do not exist. And that even though we are a group of scientists where there have been several discoveries, it would have suited if they had come to visit occasionally.'

The literature describes how structures in organizations improve reliability of actions, and that less structure allows more room for unintended actions (Gibson and Birkinshaw 2004). It calls for moderate structures to increase organizational performance (Galunic and Eisenhardt 1996; Tripsas 1997; Gilbert 2005). This study suggests that the relationship between structure and interruption is a parallel one to an extent. In the university, lack of interruption (or a structure that ensured a visit from a Technology Transfer Office (TTO)/patent expert) resulted in no patents being applied for. The scientist behind the scientific inventions that were not transformed into patents explained it thus:

'Then we did the tests, and the first time we tried it we saw that it was a general tendency, then we also tried other markers. It was extremely interesting. However, we could not patent it, because of prior art, or maybe we could actually have

patented it, if we had known more about patenting then, but that was not something we knew at that point'.

The scientist refers to results prior E2 (see Figure 1). The patent expert (externally hired by the TTO), who participated in parts of the innovation process at the university explained the situation as follows:

'The process is, that the scientists comes very late. I do not recall that we had an interaction, in which we sat down and planned. The scientist came as a sorcerer out of a box and told that 'now this invention had been made, and by the way I should be at a conference in 14 days'. So there was no red thread in the process. It was all led by when the scientists thought it was time. And always in last minute – so you just throw everything you have in your hands and start to put things together.'

In an innovation process where scientists manage the process of engaging patent experts, the *interruption* can be forgotten or omitted due to lack of interest in patenting or lack of knowledge about how to identify patentable elements in scientific developments. In formal terms, this finding suggests the following relationship:

Proposition 2; Inventions will be more likely to result in low technological breadth patents or no patents, if there is no structure in place to involve (patent experts to mobilize) an interruption as part of the innovation process.

2.3.2 Cognitive Variety

While cognitive variety overlaps with interruption, there are distinct differences: cognitive variety goes a step further by initiating a reassessment that includes a combination of several lenses used during the interruption. The cognitive psychology literature argues that a cognitive map is required to suggest an orientation of the current situation in relation to the environment (Neisser 1976; Piaget 1985; Carroll 1993). The management literature Daft and Weick (1984) proposes that organizations that find it difficult to understand their complex environment benefit from a mapping of the situation to assess its uncertainty and complexity. Organizational

stakeholders are able to make better decisions about directions for future work, which leads to a more balanced organization with flexibility for future actions and the possibility of achieving goals efficiently. Eisenhardt, Furr et al. (2010, p.1269) advocate that the focus on cognitive variety creating value due to contradictions (Brown and Eisenhardt 1997; Smith and Tushman 2005) should be replaced by an emphasis on synergies and *‘cognitive variety that enables flexible recombination of individually efficient mental templates.’* Synergies generate positive outcomes rather than contradictions through convergent rather than divergent attributions. Recent research shows, that convergent attributions lead to greater organizational learning, since convergent attributions are more accurate representations of firm experiences, which can be transformed into heuristics to guide future work (Bingham and Halebian 2012). In line with these arguments this research shows that to transform scientific inventions into greater patent breadth cognitive variety is beneficial. A lead scientist from a firm involved in a process that led to patents with excess breadth explained the process as follows:

‘The process is normally this way, I put up some ideas... and then the patent expert considers how it can be protected and the value. And after that we become sparring partners. I use many hours in testing ways to circumvent our patents, because we would like to have very strong patents.’

Another scientist explained cognitive mapping:

‘I know the chemistry, they know the IP, and together we figure out how to protect the innovation. They (patent experts) look at the innovation and tries to structure it in ‘boxes’, and then they say ‘maybe we can get better protection if...’

This research suggests that the scientist and the patent expert take on different roles, represented by the different mental maps they use, and that when mapping the future of the innovation together, they can create additional patent breadth. Thus the science based map is complemented by a patent/market related map. The science based map is described by Fleming and Sorenson (2004 p.909) who explain how using science as a map can guide researchers / inventors *‘science alters inventors’ search processes, by leading them more directly to useful*

combinations, eliminating fruitless paths of research, and motivating them to continue even in the face of negative feedback'. Similarly, searching with a patent based mental map can result in fruitful solutions to how to access a market that is not populated by competitors, and inspiration for additional couplings. Cognitive variety requires both types of mental maps to be available to obtain surplus patent breadth. I argue that it is the convergence between these two mental modes that drives this surplus. This can be hypothesized as:

Proposition 3; Patented inventions will be more likely to exceed technological breadth if patent experts mobilize 'cognitive variety' during the transformation phase from scientific invention to patented invention.

2.3.3 Abstraction

Abstraction is the ability to generalize and conceptualize thinking. Examples of abstraction in management literature are limited. However, Eisenhardt, Furr et al. (2010) offer the example of managers in a Finnish firm that fails to hire US graduates due to the heuristics of the firm's online hiring process, which was changed to include both online and local applicants. In the present research we find examples of abstraction processes which led to surplus patent breadth. The abstraction process is enacted by patent experts in cooperation with the inventing scientists. For example when transforming the scientific invention into a patent, the patent expert creates patent breadth by identifying a higher level of the substance, such as a chemical structure, biomarker, etc. than that in the original scientific invention. Thus both the original substance identified during the scientific research is protected by the patent application and the whole group of substances to which the original substance belongs. A patent expert (referring to Patent #6) described it as: *'Patent covers a group where the invention only is a part of.'* In one of the university patent cases the scientist described the invention as the result of the abstraction

process (referring to Patent #1): *'The patent expert made an invention on top of our invention'*, and one of the patent experts involved in the patent drafting process explained patent breadth as follows (referring to Patent #1): *'Because the way the patent was constructed with a graph showing the different estimates of thresholds of specificity and sensitivity. This increased technological breadth.'* In these examples the process leading to surplus patent breadth was related to the abstraction process. We also identified an example of an abstraction process which led to a solution that had no positive effect on the efficiency or flexibility of patent breadth. A scientist explained how useless abstraction can occur if expertise and understanding of the business area is too limited (referring to Patent #4): *'Algorithms were inserted in the invention, however, it did not give any additional value ...'*

Another way of creating value from abstraction mobilized by patent experts is exemplified in the way patent experts anticipate potential future situations and ensure that they are included in the patent application. The lead scientist in the university described the abstraction conducted by the patent expert in the following way:

'If you are good at chemistry and biology, then you will be capable in understanding our invention. Then when you on top of this knowledge have an enormous knowledge of intellectual property rights, then you can make a 'world map' for us and say 'listen friends we should go this way, haven't you done that? No? Then go home and do so. Because if we get that as well, then we will be much stronger if we face this challenge in the future.'

Excess patent breadth calls for patent experts to act to apply abstraction to the process of transforming the scientific invention into a patented invention. Scientific inventions are often a product of extremely challenging abstraction processes, in which scientists develop the invention over several years. However, patent experts are uniquely qualified to conduct additional abstraction processes, from a market perspective, based on the inventor's scientific findings, because the patent expert has a deep understanding of both the scientific invention and

the opportunities offered by the patent system and patent landscape. This knowledge allows the patent expert to navigate the relevant environment to identify the *excess* potential of the scientific invention. In formal terms, these findings suggest the following relationship:

Proposition 4; Patented inventions will be more likely to exceed the original technological breadth if patent experts perform 'abstraction' during the transformation phase from scientific invention to patented invention.

The individual patent expert's ability to mobilize cognitive variety and abstraction was mentioned by respondents as being conditional on the patent expert's experience and creativity. This might indicate that the role of patent expert is highly specialized and that part of this job relates to craftsmanship, which involves learning by doing. In the next part I present the quantitative evidence supporting the claims made in the propositions formulated.

2.4 Small N, narratives and causal inferences

Examining the case studies through several lenses can be enlightening. Eisenhardt (1989, p.533) suggests that utilizing cross-case pattern search by applying divergent techniques is appropriate to ensure that the investigator '*look[s] beyond the initial impressions and see[s] evidence through multiple lenses*'. To my knowledge, the present study is the first to operationalize Abell's (2009) method as a supporting technique to analyze the qualitative evidence gathered and the propositions. In practical terms this means that besides using the 12 cases inductively to develop a theory that predicts the transformation of scientific inventions into patented inventions, I use the narratives gathered related to each of the events in the case studies to examine causal inferences between each event. This type of data analysis is not applicable for developing theory, but can help to provide assessments in the form of likelihoods for the proposed causal inferences by showing support or rejection of the propositions. The approach

was chosen because the transformation process studied in this research is a highly complex phenomenon and a sensitive topic. It would not be possible to test the theory proposed using a large N study. Analyzing the assessment of patents with available indicators does not show that we can rely on these for testing the proposed relationships (referring to results presenting in Table 2).

We provide a brief introduction to the reasoning behind this data analysis method; for an in-depth explanation see Abell (2009). Narratives (gathered in a sequence study) can be structured as presentations of evidence for each linkage in an event study. For example, if we have two events, E1 and E2, then a narrative (b) collected to explain the actions (A1) that demonstrate a linkage between E1 and E2 can be analyzed as evidence for the causal link between E1 and E2. Therefore, if one statement (b), presented as an explanation of (A1), is proposed as evidence for the causal linkage between E1 and E2, then according to Bayes's Law, the probability of the causal inference would be:

$$P(b) \cdot P(A|b) = P(b) \cdot P(b|A) \text{ and } P(b) \cdot P(\neg A|b) = P(\neg A) \cdot P(b|\neg A)$$

where $P(A)$ is the probability of A, $P(b)$ is the probability of b , and $P(b|A)$ is the probability of b given A, and $P(b|\neg A)$ is the probability of b given $\neg A$. Furthermore, based on Good (1983):

$$\log L_b = \log \text{odds}((A: \neg A)|b) - \log \text{odds}(A: \neg A)$$

it is possible to provide a measure of evidence b in support of the causal link A. If more than one piece of evidence (b) is present, the probability of L_b is found by multiplying the odds ratios of each item, which for n items of evidence can be expressed as:

$$L_b = L_{b1} \cdot L_{b2/b1} \cdot L_{b3/b2 \cdot b1} \cdot \dots \cdot L_{bn/b1 \cdot b2 \cdot \dots \cdot b(n-1)}$$

In practice, this means that if a number of assessments of each quote (b) are obtained, the likelihood of a causal inference (A) can be estimated. Using this method allows a jury to assess the evidence for the causal relationships proposed.

In line with the approach suggested by Abell (2009), I had a number of jury members assess the likelihood ratios for each piece of evidence linked to a certain causal inference. The jury consisted of three or four members, one or two stakeholders in the original transformation process being examined, and two social science PhD students who were not familiar with the cases, events, narratives, or evidence. The constitution of the jury (internal and external to the innovation process) allowed analysis of whether being a stakeholder influences jury members' estimations of probative force. The jury members were given explicit guidelines about how to assign likelihoods. The process entailed a number of steps (detailed description of process is available from author). First, I introduced the jury to the research topic. Second, the jury members' assignment of likelihood ratios in the perspective of the research was outlined. Third, in response to the difficulties jury members experienced in assigning likelihoods during pilot testing, I included an example. Fourth, the context of the cases was introduced. Fifth, the entire innovation process, including all actions (A_n) and events (E_n), was introduced together with the 'evidence' (b) connected to it. Most often there were several pieces of evidence (both counterfactuals and other narratives: b_1 , b_2 , b_3 etc.) to present to the jury members. Finally, the jury was asked to estimate the probative force of each piece of evidence in respect to the hypothesis presented. Thus, each jury member analyzed each piece of evidence (b) and assigned it a likelihood ratio. Since I knew (from the pilot testing) that jury members found it difficult to use infinite numbers when assigning likelihood ratios, jury members were asked to assign likelihood ratios between 2 to 10, where 10 was almost certain. In total, 42 relationships (A) were investigated with more than 100 pieces of evidence (b), resulting in 383 individual

likelihood assessments. Table 3, 4, 5 and 6 presents the jury ratings for all the pieces of evidence.

Insert Tables 3, 4, 5 and 6 here

Figure 4 and Tables 4 and 5 provide examples of how the jury's results were analyzed. I provide an overview of the results of selected six actions (A1, A2, A3, A4, A5, and A6) based on 23 pieces of evidence (b_1 , b_2 , b_3 etc) – relating to Figure 2 (E11 to E17), patent no #8, #9 and #10. Each hypothesized relationship was assessed by analyzing the results of the likelihood ratios for each of the pieces of evidence; between two to five pieces of evidence for each relationship. In Tables 4 and 5, jury members '1' and '2' were the PhD candidates and jury members '3' and '4' were representatives of the innovation process. The results presented in Table 4 show the likelihood ratios of the hypothesized relationships. A closer examination of the data shows that 14 out of 23 quotes were assessed by at least one jury member to justify the causal links presented beyond all reasonable doubt ($b=10$), divided as follows: eight quotes by one jury member, five quotes by two jury members and one quote by three jury members. Eight out of 23 quotes were not assessed by any jury members as being supportive or contradictory beyond all reasonable doubt. Eleven out of 23 quotes were not assessed by any jury members as being neither supportive nor contradictory. All of the 23 quotes were assessed to be supportive to some degree. In addition, the differences between types of stakeholders in the innovation process were analyzed (see example in Table 5). For example, the patent expert who had been part of the innovation process (jury member 3) made a higher average assessment of likelihoods than the three other jury members. In general, jury members that were also representatives of the innovation process, gave higher assessments than the external jury (PhD candidates). The

external jury members selected the assessment value of ‘1’ (neither supportive nor contradictory) much more often than the internal experts (see Table 4 and Table 5).

Insert Figure 4 here

In addition to these examples, pieces of evidence evaluating different (high standard deviation) or similar (low standard deviation) were investigated in terms of the content of the evidence. For example, questions such as is one of the persons assessing the evidence the person behind the evidence? Or are they an observer of the linkage? Is the wording mainly positive or negative? Does the quote refer to the ‘departure’ event or the ‘arrival’ event? Are there personnel characteristics included in the quote, or are there linguistics terminology: many adjectives/attributives that could be leading the different assessments? In this way the likelihood ratios and especially high standard deviations, inform the analysis of the narratives.

Nevertheless their analysis requires some caution. In addition to acting as an indication of which narratives to be particularly cautious with when analyzing, the objective in utilizing Abell’s (2009) approach is also to investigate the causal inferences between the case study events. The results in this respect are convincing: 383 individual likelihood assessments by jury members were conducted, of which only six percent were identified as not supportive. Considering all jury members’ assessments, the average result was that they were supportive. More specifically, five pieces of evidence were assessed on average as being contradictory (b16, b28 and b29 in Table 3, b19 in Table 4 and b46 in Table 6) and were investigated more in-depth, by taking other pieces of evidence concerning with the same action into account. The remaining evidence showed stronger positive likelihoods (see last rows in Tables 3, 4 and 6, presenting total likelihood assessments for each causal inference aggregated at the level of individual actions). It is reasonable to state that, according to the quantitative evidence for causal inferences, they

support our contention of the linkages between the proposed case study events which are the basis for our propositions according to the theoretical framework presented.

2.5 Discussion and conclusions

The findings from this study contribute to the psychology based management literature and the innovation literature by proposing a model for the transformation of science to patents whose breadth exceeds that of the original scientific invention. A scientific invention is often a product of extremely abstract knowledge processes, created by a scientist with in-depth scientific knowledge of the technological area in which it resides. Patents that exceed the breadth of the original scientific invention are those patents that contain new insights leading to greater technological breadth generated after the creation of the scientific invention and before the patent is granted. I showed that this surplus depends on processes related to abstraction and cognitive variety mobilized by patent experts who have in-depth understanding of the scientific discovery based on their educational background in life sciences, and knowledge about the legal framework related to patenting. This allows the patent experts to adopt a cognitively different approach to scientific invention than the scientists (inventors), and to implement cognitive variety in which additional opportunities for exploitation are identified which extends the invention farther than foreseen by the inventor. Extending technological breadth secures the freedom to operate in order to conduct further work on the invention and to secure patent protection that will provide adequate returns from a future product launch based on the scientific invention. I showed that the struggle for technological breadth in the examination process for individual patents is a time-consuming process that extends over several years and is orchestrated by the patent expert and influenced by his/her knowledge of a given invention might be exploited. The direction of exploitation must be determined early in the process,

immediately after scientific discovery, in order to guide the inventor and owner (e.g. university or firm) through the patent examination process. I identified this iterative process between business, IP, and science as part of the transformation process for the cases originating the firm but found them to be mostly absent in relation to inventions created at the university. More specifically, the findings reveal previously unreported aspects of the transformation of academic science at universities into patents, and particularly in relation to how university scientists take a fragmented approach to the patenting process. This compares to firm scientists who are able to reap the benefits of close interaction with patenting experts, and patent experts potentially assume responsibility for searching new directions for development if challenges of exploitation arise with regard to the scientific invention.

Taken together the findings in this paper recast the relationship between science and patents as a process in which the transformation treatment the scientific invention receives affects the patent breadth of the patented invention. To unleash the full patent breadth potential, the innovation process must incorporate certain developments. First, an interruption is needed. If no organizational structures of interruption are in place, then 'lost' patent breadth will likely occur. Second, iterations between scientists and patent experts are needed to unlock the potential for greater patent breadth. These include actions mobilizing the effects of abstraction and cognitive variety, which have been identified as central to generating excess patent breadth. These findings highlight how the micro-foundations of interruption, cognitive variety, and abstraction, previously identified as important for balancing flexibility and efficiency (Eisenhardt, Furr et al. 2010), also help to boost the value of science for patent breadth through the transformation process. Real life examples of distinct situations of interruption, cognitive variety, and abstraction are provided related to the drug discovery processes. They give insights

into the innovation processes that normally are kept confidential by inventors to avoid creating material for future patent battles.

This study contributes also to method development in offering a first attempt to apply the case study method proposed by Abell (2009). Abell (2009) suggests that narratives add paths of causal links to a chronology of events and actions. This perspective enabled me to study the links identified in the cases as Bayesian inferences generating Bayesian narratives, and to examine them through a lens that dictates that the causal paths in a narrative have a Boolean structure. This makes it possible to conduct an analysis of the cases in which narratives are presented and assessed by a jury as evidence of causal links in order to estimate the posterior odds, conditional on the evidence, by explicitly investigating the causal inferences in each of the cases. Furthermore, applying this method offers a distinct opportunity to investigate the narratives through the lenses of both internal and external stakeholders in the innovation process. This highlighted where I should be cautious in interpreting the linkage proposed, but also provided me with estimates of posterior odds of the event study.

The view I present here of the transformation of science into patented inventions has implications for innovation theories. The findings confirm the linkage between science and technologies (Tijssen 2002; Ahuja and Katila 2004), support the findings in Gittelman and Kogut (2003) and Murray (2002), and provide further explanations for the outcomes of their studies. It extends the organizational literature, which highlights the importance of an exploitative and explorative organizational nature for creating high performing firms (March 1991), by identifying and testing the micro-foundations presented by Eisenhardt, Furr et al. (2010) and how they influence the complex process of transforming science into patented inventions. In addition, this study shows the role played by patent experts, and stakeholders in the invention process which are somewhat overlooked in management literature (Somaya,

Williamson et al. 2007), highlighting how patenting strategies are created in firms. The paper proposes a specific relationship between science and patents in terms of patent breadth.

Finally, this study, off course, has its limitations. First of all not being able to tape and transcribe interviews is an issue. I tried to minimize the negative effect by conducting all interviews and observation studies on my own, and writing down extensive notes, in this way I continuously went through data collected and tried to, especially by asking counterfactual questions, challenge the understanding of the data that was developing while interviews were ongoing. Another way of overcoming the issue was by observing the processes in action, in this way, what was explained in the interviews were also identified in actual meetings. The focus on a single industry could also be seen as a limitation, but the single-industry does allow us to keep contextual factors more or less constant, and thereby gain an in-depth understanding of the drivers of patent breadth heterogeneity. A follow-up to this study would perhaps involve innovation processes from other high-tech industries, thereby also investigating their patenting processes, or maybe also less patenting active firms (e.g. firms within furniture, lighting, clothes), where focus could be on the breadth of other types of intellectual property rights, such as designs rights, to see whether same micro-foundation actions have influence on IP outcome in general.

2.6 Tables and figures

Table 1: Description of cases: The scientific discovery and the patented invention

Scientific invention	Patented invention	Case
It is possible to predict whether it is blood from a healthy or a sick person with TIMP-1	Detection of cancer with TIMP-1 (#1)	University
Level of * in a person changes over time dependent on whether the person is sick from cancer or in a well period at the time	Patent on monitoring via TIMP-1(#2)	University
TIMP-1 and PAI-1 inhibit programmed cell death, two usages: predicative biomarker or as part of treatment	Patent covering TIMP-1 and PAI-1 as predictive biomarker and treatment (#3)	University
Enhanced predicative analysis	Patent covering prognostic stratification of colorectal cancer (#4)	University
TIMP-1 as a prediction is shown to be different in populations	TIMP-1 and TOP2 (#5)	University
Substance X_1 against disease Z_1	Patent focusing on substance X_1 (#6)	Firm
Substance X_1 against disease Z_1 and phase 2 results	Patent focusing on substance X_1 with 'transporter' (#7)	Firm
Interview and brainstorming outcome (Invention 1)	Patent filing on new product strategy, patent 1 (#8)	Firm
Interview and brainstorming outcome (Invention 2)	Patent filing on new product strategy, patent 2 (#9)	Firm
Interview and brainstorming outcome (Invention 3)	Patent filing on new product strategy, patent 3 (#10)	Firm
Invention X for disease Z	Patent focusing on X_1 as mono therapy against disease Z (#11)	Firm
Invention on X for disease Z	Divisional patent application, Patent focusing on X_1 as add on against disease Z (#12)	Firm

Table 2: Cases- Assessment: low, medium or exceeding technological breadth and Citations data

To ensure confidentiality of patents categories identifying number of inventors, citations and IPC codes are inserted, using the following categorization: 0) 0; 1) 1-3; 2) 4-6; 3) 7-10; 4)>10; Min, Max, mean and std.dev. are based on real numbers.

Patented invention	Assessment		Forward citations	IPC classes			Inventors	Backward citations			
	Assessment total	1 2		nine digit	seven digit	four digit		Patents cited by examiner	NPLs cited by examiner	Patents cited by inventor	NPLs cited by Inventor
#1	Exceeding	3 ¹ 3 ²	1	1	1	1	2	1	2	0	0
#2	Medium	2 ³ 2 ⁴	1	4	2	1	2	2	3	1	3
#3	Exceeding/medium	2 ⁵ 3	1	4	4	1	3	3	3	0	0
#4	Medium / Low	2 1 ⁶	0	3	2	2	1	1	1	0	0
#5	Medium / Low	2 1 ⁷	0	3	2	2	1	1	1	0	1
#6	Exceeding/medium	3 ⁸ 2	4	2	2	1	1	4	4	0	0
#7	Exceeding/medium	3 ⁹ 2	4	4	4	2	3	4	4	0	0
#8	Exceeding/medium	2 3 ¹⁰	1	2	2	1	1	1	1	2	1
#9	Exceeding/medium	2 ¹¹ 3 ¹⁰	0	1	1	1	1	1	0	2	1
#10	Exceeding/medium	2 3 ¹⁰	0	2	1	1	1	1	1	1	4
#11	Medium	2 ¹² 2	3	4	3	1	1	1	4	0	0
#12	Exceeding	3 ¹³ 3	3	4	3	1	2	1	4	0	0
Min		2 1	0	1	1	1	1	1	0	0	0
Max		3 3	23	36	16	5	10	49	79	5	16
Mean		2.3 3.2	5.3	14.3	6.08	3	3.58	9	13.16	1.25	2.5
std. Dev		0.49 0.77	7.19	13.9	4.33	1.27	2.96	15.4	21.9	2.00	4.96

¹Because the way the patent was constructed with a graph showing the different estimates of thresholds of specificity and sensitivity. (1 because we simply forgot to write 'saliva' in the patent app. Which turned out to be important for (patent #2) this was only identified later when applying for patent (#2))

²The patent expert made an invention on top of our invention.

³The patent later turned out to be in trouble from prior art due to prior academic publication from the inventor team.

⁴Nothing added

⁵The patent was not well-made from the beginning, there were problems with fist five claims

⁶Algorithms were inserted in the invention, however, it did not give any additional value, and they simply forgot areas.

⁷The patent experts could have been more active in understanding the invention

⁸Patent covers a group where the invention is only a part of.

⁹The transformer of the invention was the core of, however the technological breadth also covers intermediary and the manufacturing process

¹⁰ Evaluation based on added value generated by initiating and leading a brain storming.

¹¹ The method of precipitate, Utility patent, very narrow, patent expert together with scientists sat down and identified the invention to be protected in the data received from screening.

¹² Late in invention process so not much room to go for. Patent application based on extra clinical studies.

¹³ This patent was very closely drafted in accordance to the invention doneAss1) In this patent application the group of substances the invention Z to was eventually included in the application.

Table 3: Overview, likelihood assessments from jury members, Case 1-5 (referring to innovation process in Figure 1)

Patent	#1										#5																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																					
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*The star marks the patent expert which has been in charge of scoping the patent. **The minus in front of the numeric value indicates contradictory relationship.

Table 6 Overview, likelihood assessments from jury members, Case 11-12 (referring to innovation process in Figure 3)

Patent	#11, #12											
	a1	a1	a1	a2	a2	a2	a2	a2	a2	a2	a2	a2
	b1	b2	b3	b4	b5	b6	b7	b8	b9	b10	b11	b12
External 1	6	3	2	10	3	3	3	5	5	-4	4	1
External 2	8	5	8	10	4	8	3	8	2	3	1	4
Internal 1	9	2	9	8	9	10	7	7	4	1	5	2
Internal 2*	10	8	5	5	7	4	2	5	5	1	10	8
Total assessment	33	18	24	33	23	25	20	20	22	0	22	15
Average	8.3	4.5	6	8.3	5.8	6.3	5	5	5.5	0	5.5	3
std. Dev.	1.7	2.6	3.16	2.4	2.8	3.3	2.9	1.6	1.7	2.7	3.1	3.4
Analysis Actions												
	a1			a2			a3			a4		
	Exf1:360			Exf1:687			Exf1:48			Exf1:5		
	Exf2:3.200			Exf2:12.288			Exf2:3			Exf2:128		
	Inf1:1.296			Inf1:17.640			Inf1:60			Inf1:18		
	Inf2:2.000			Inf2:1.400			Inf2:240			Inf2:16		
Total												
Patent	a6	a6	a7	a8	a8	a8	a8	a8	a8	a9	a9	a9
	b27	b28	b29	b30	b31	b32	b33	b34	b35	b36	b37	b38
External 1	5	1	-4	8	-3	1	1	3	6	3	3	5
External 2	2	2	3	4	5	2	5	2	-2	2	4	3
Internal 1	5	6	5	7	4	6	8	5	4	6	8	2
Internal 2*	1	5	8	10	10	4	3	9	1	1	10	10
Total	13	14	11	28	15	14	12	25	14	6	21	27
Average	3.3	3.5	5	7	3.8	3.5	3	6.3	3.5	1.5	5.3	6.8
std. Dev.	2.1	2.4	2	2.9	5.3	1.7	2.2	2.8	2.4	2.6	3.6	2.8
Analysis Actions												
	a6			a7			a8			a9		
	Exf1:5			Exf1:144			Exf2:600			Exf1:45		
	Exf2:4			Exf2:107.520			Exf2:1.535			Exf2:1.920		
	Inf1:30			Inf1:107.520			Inf1:9.216			Inf1:12.500		
	Inf2:5			Inf2:10.800			Inf2:5.000			Inf2:2.560		
Total												
Patent	a10	a10	a11	a12	a12	a12	a12	a12	a12	a12	a12	a12
	b49	b49	b49	b49	b49	b49	b49	b49	b49	b49	b49	b49
External 1	5	1	-5	123	5	188	5	5	5	5	5	5
External 2	2	2	3	4	5	2	-2	2	4	1	3	-5
Internal 1	5	5	7	4	6	8	5	4	6	8	2	4
Internal 2*	1	5	8	10	10	4	3	9	1	1	10	-5
Total	13	14	11	28	15	14	12	25	14	6	21	18
Average	3.3	3.5	5	7	3.8	3.5	3	6.3	3.5	0	-0.3	4
std. Dev.	2.1	2.4	2	2.9	5.3	1.7	2.2	2.8	2.4	2.5	6.3	3.9
Analysis Actions												
	a10			a11			a12			a12		
	Exf1:0.4			Exf1:1.920			Exf1:12.500			Exf1:2.560		
	Inf1:12.500			Inf1:12.500			Inf1:12.500			Inf1:12.500		
	Inf2:2.560			Inf2:2.560			Inf2:2.560			Inf2:2.560		
Total												

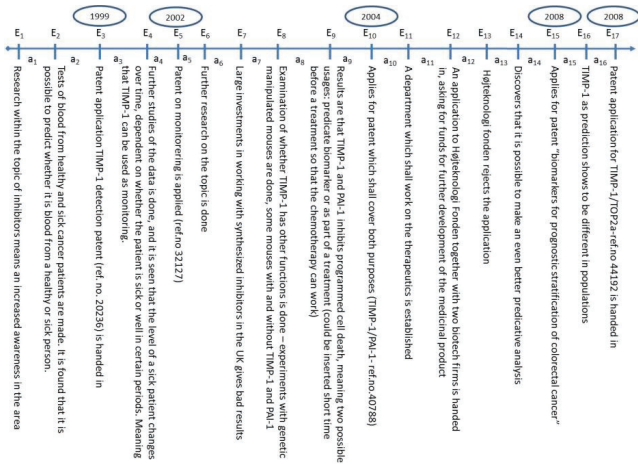


Figure 1: Case 1 to 5: Chronology of events at the University



Figure 2: Case 6-10, Innovation process at firm

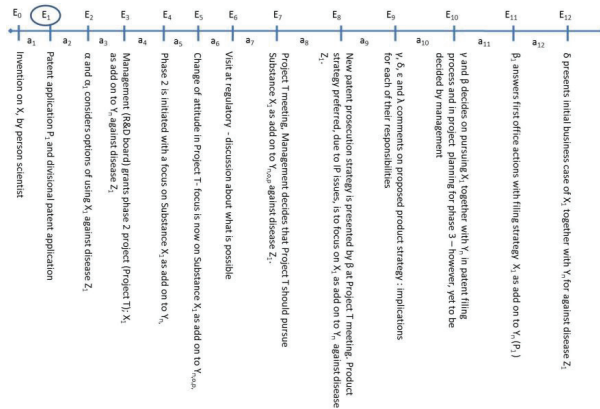


Figure 3, Case 11 and 12: Innovation process at firm

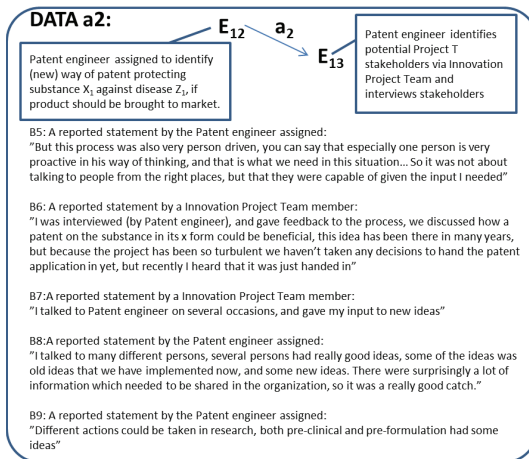


Figure 4, Example of quotes as evidence

2.7 References

- Abbott, A. (1990). "A PRIMER ON SEQUENCE METHODS." *Organization Science* **1**(4): 375-392.
- Abbott, A. (1995). "SEQUENCE-ANALYSIS - NEW METHODS FOR OLD IDEAS." *Annual Review of Sociology* **21**: 93-113.
- Abell, P. (2009). "A Case for Cases Comparative Narratives in Sociological Explanation." *Sociological Methods & Research* **38**(1): 38-70.
- Abell, P., T. Felin, et al. (2008). "Building micro-foundations for the routines, capabilities, and performance links." *Managerial and Decision Economics* **29**(6): 489-502.
- Adler, P. S., B. Goldoftas, et al. (1999). "Flexibility versus efficiency? A case study of model changeovers in the Toyota production system." *Organization Science* **10**(1): 43-68.
- Ahuja, G. and R. Katila (2004). "Where do resources come from? The role of idiosyncratic situations." *Strategic Management Journal* **25**(8-9): 887-907.
- Archibugi, D. (1992). "Patenting as an indicator of technological innovation: a review." *Science and Public Policy* **19**: 357-368.
- Balconi, M., S. Brusoni, et al. (2010). "In defence of the linear model: An essay." *Research Policy* **39**(1): 1-13.
- Bingham, C. B. and J. Halebian (2012). "How firms learn heuristics: Uncovering missing components of organizational learning." *Strategic Entrepreneurship Journal* **6**(2): 152-177.
- Boeker, W. (1997). "Executive migration and strategic change: The effect of top manager movement on product-market entry." *Administrative Science Quarterly* **42**(2): 213-236.
- Bonaccorsi, A. and G. Thoma (2007). "Institutional complementarity and inventive performance in nano science and technology." *Research Policy* **36**(6): 813-831.
- Breschi, S., F. Lissoni, et al. (2008). "University patenting and scientific productivity: a quantitative study of Italian academic inventors " *EUROPEAN MANAGEMENT REVIEW* **5**(2): 91-109.
- Brown, S. L. and K. M. Eisenhardt (1997). "The art of continuous change: Linking complexity theory and time-paced evolution in relentlessly shifting organizations." *Administrative Science Quarterly* **42**(1): 1-34.
- Carroll, J. B. (1993). *Human Cognitive Abilities: A Survey of Factor-Analytic Studies.*, Cambridge University Press, New York.
- Cassiman, B., R. Veugelers, et al. (2008). "In search of performance effects of (in)direct industry science links." *Industrial and Corporate Change* **17**(4): 611-646.
- Cohen, M., R. Nelson, et al. (2000). "Protecting their intellectual assets: Appropriability conditions and why US manufacturing firms patent (or not). " *National Bureau of Economic Research*.
- Cohen, W. M., Nelson, R.R., Walsh, J.P (2002). "Links and impacts: The influence of public research on industrial R&D." *Management Science* **48**(1): 1-23.
- Daft, R. L. and K. E. Weick (1984). "TOWARD A MODEL OF ORGANIZATIONS AS INTERPRETATION SYSTEMS." *Academy of Management Review* **9**(2): 284-295.
- Dosi, G. (1988). "SOURCES, PROCEDURES, AND MICROECONOMIC EFFECTS OF INNOVATION." *Journal of Economic Literature* **26**(3): 1120-1171.
- Eisenhardt, K. M. (1989). "BUILDING THEORIES FROM CASE-STUDY RESEARCH." *Academy of Management Review* **14**(4): 532-550.
- Eisenhardt, K. M., N. R. Furr, et al. (2010). "Microfoundations of Performance: Balancing Efficiency and Flexibility in Dynamic Environments." *Organization Science* **21**(6): 1263-1273.
- Eisenhardt, K. M. and M. E. Graebner (2007). "Theory building from cases: Opportunities and challenges." *Academy of Management Journal* **50**(1): 25-32.
- Fleming, L. and O. Sorenson (2004). "Science as a map in technological search." *Strategic Management Journal* **25**(8-9): 909-928.

- Fox, S. P. (1998). Intellectual property management: From theory to practice. *Profiting from Intellectual Capital*, P. Sullivan, John Wiley & Sons, New York.; 142-156.
- Galunic, D. C. and K. M. Eisenhardt (1996). "The evolution of intracorporate domains: Divisional charter losses in high-technology, multidivisional corporations." *Organization Science* 7(3): 255-282.
- Gambardella, A., D. Harhoff, et al. (2008). "The value of European patents " *European Management Review* 5(2): 69-84.
- Gavetti, G. (2005). "Cognition and hierarchy: Rethinking the microfoundations of capabilities' development." *Organization Science* 16(6): 599-617.
- Gibson, C. B. and J. Birkinshaw (2004). "The antecedents, consequences, and mediating role of organizational ambidexterity." *Academy of Management Journal* 47(2): 209-226.
- Gilbert, C. G. (2005). "Unbundling the structure of inertia: Resource versus routine rigidity." *Academy of Management Journal* 48(5): 741-763.
- Gilbert, R. and C. Shapiro (1990). "OPTIMAL PATENT LENGTH AND BREADTH." *Rand Journal of Economics* 21(1): 106-112.
- Gittelman, M. and B. Kogut (2003). "Does good science lead to valuable knowledge? Biotechnology firms and the evolutionary logic of citation patterns." *Management Science* 49(4): 366-382.
- Giuri, P., M. Mariani, et al. (2007). "Inventors and invention processes in Europe: Results from the PatVal-EU survey." *Research Policy* 36(8): 1107-1127.
- Good, I. J. (1983). *Good thinking: The foundations of probability and its applications*., Minneapolis: University of Minnesota Press.
- Granstrand, O. (2000). "Corporate management of intellectual property in Japan." *International Journal of Technology Management* 19(1-2): 121-148.
- Harhoff, D., F. Narin, et al. (1999). "Citation frequency and the value of patented inventions." *Review of Economics and Statistics* 81(3): 511-515.
- Harhoff, D., F. Scherer, et al. (2003). "Citations, family size, opposition and the value of patent rights." *Research Policy* 32(8): 1343-1363.
- Harrison, S. and P. Sullivan (2012). *Edison in the Boardroom: How Leading Companies Realize Value from Their Intellectual Assets*, John Wiley & Sons.
- He, Z. L. and P. K. Wong (2004). "Exploration vs. exploitation: An empirical test of the ambidexterity hypothesis." *Organization Science* 15(4): 481-494.
- Henderson, R., A. B. Jaffe, et al. (1998). "Universities as a source of commercial technology: A detailed analysis of university patenting, 1965-1988." *Review of Economics and Statistics* 80(1): 119-127.
- Hsu, D. H. (2006). "Venture capitalists and cooperative start-up commercialization strategy." *Management Science* 52(2): 204-219.
- Jaffe, A. B., M. Trajtenberg, et al. (2000). "Knowledge spillovers and patent citations: Evidence from a survey of inventors." *American Economic Review* 90(2): 215-218.
- Klemperer, P. (1990). "HOW BROAD SHOULD THE SCOPE OF PATENT PROTECTION BE." *Rand Journal of Economics* 21(1): 113-130.
- Klevorick, A. K., Levin, R.C., Nelson, R.R., Winter, S.G., (1995). "On the sources and significance of interindustry differences in technological opportunities." *Research Policy*: 185-205.
- Kline, S. J. and N. Rosenberg (1986). "An Overview of Innovation" in Landau, R. and Rosenberg, N.: *The Positive Sum Strategy*. Washington D. C. 1986, excerpt pp. 285 - 298.
- Koopmans, T. (1957). *Three essays in the state of economic science*, McGraw-Hill, NY.
- Lanjouw, J. and M. Schankerman (1997). "Stylized facts of patent litigation: value, scope, ownership, ." *NBER Working Paper No. 6297*, National Bureau of Economic Research, Cambridge, MA.
- Leonard-Barton, D. (1990). "A DUAL METHODOLOGY FOR CASE STUDIES: SYNERGISTIC USE OF A LONGITUDINAL SINGLE SITE WITH REPLICATED MULTIPLE SITES." *Organization Science* 1(3): 248-266.

- Lerner, J. (1994). "THE IMPORTANCE OF PATENT SCOPE - AN EMPIRICAL-ANALYSIS." Rand Journal of Economics **25**(2): 319-333.
- March, J. G. (1991). "EXPLORATION AND EXPLOITATION IN ORGANIZATIONAL LEARNING." Organization Science **2**(1): 71-87.
- Merges, R. P. and R. R. Nelson (1990). "ON THE COMPLEX ECONOMICS OF PATENT SCOPE." Columbia Law Review **90**(4): 839-916.
- Meyer, M., T. Siirilainen, et al. (2003). "Towards hybrid Triple Helix indicators: A study of university-related patents and a survey of academic inventors." Scientometrics **58**(2): 321-350.
- Moran, P. and S. Ghoshal (1999). "Markets, firms, and the process of economic development." Academy of Management Review **24**(3): 390-412.
- Murray, F. (2002). "Innovation as co-evolution of scientific and technological networks: exploring tissue engineering." Research Policy **31**(8-9): 1389-1403.
- Murray, F. and S. Stern (2007). "Do formal intellectual property rights hinder the free flow of scientific knowledge? An empirical test of the anti-commons hypothesis." Journal of Economic Behavior & Organization **63**(4): 648-687.
- Neisser, U. (1976). Cognition and Reality: Principles and Implications of Cognitive Psychology., W. H. Freeman, San Francisco.
- Nelson, R. R. (2003). "On the uneven evolution of human know-how." Research Policy **32**(6): 909-922.
- Nordhaus, W. (1969). Invention, Growth, and Welfare: A Theoretical Treatment of Technological Change, Cambridge.
- Okhuysen, G. A. and K. M. Eisenhardt (2002). "Integrating knowledge in groups: How formal interventions enable flexibility." Organization Science **13**(4): 370-386.
- Pavitt, K. (1991). "What makes basic research economically useful?" Research Policy **20**: 109-199.
- Piaget, J. (1985). The Equilibration of Cognitive Structures: The Central Problem of Intellectual Development., University of Chicago Press, Chicago.
- Pisano, G. (2006). "Profiting from innovation and the intellectual property revolution." Research Policy **35**(8): 1122-1130.
- Poetz, M. K. and R. Prugl (2010). "Crossing Domain-Specific Boundaries in Search of Innovation: Exploring the Potential of Pyramiding." Journal of Product Innovation Management **27**(6): 897-914.
- R, S. (2000). The concept of 'design space'. Technological Innovation as an Evolutionary Process. J. Ziman, Cambridge University Press, Cambridge: 234-247.
- Reitzig, M. and S. Wagner (2010). "THE HIDDEN COSTS OF OUTSOURCING: EVIDENCE FROM PATENT DATA." Strategic Management Journal **31**(11): 1183-1201.
- Rosenberg, N. and R. R. Nelson (1994). "AMERICAN UNIVERSITIES AND TECHNICAL ADVANCE IN INDUSTRY." Research Policy **23**(3): 323-348.
- Scherer, F. M. (1972). "NORDHAUS THEORY OF OPTIMAL PATENT LIFE - GEOMETRIC REINTERPRETATION." American Economic Review **62**(3): 422-427.
- Scotchmer, S. (2004). Innovation and Incentives, Cambridge, Massachusetts: The MIT Press.
- Smith, W. K. and M. L. Tushman (2005). "Managing strategic contradictions: A top management model for managing innovation streams." Organization Science **16**(5): 522-536.
- Somaya, D. (2012). "Patent Strategy and Management: An Integrative Review and Research Agenda." Journal of Management **38**(4): 1084-1114.
- Somaya, D., I. O. Williamson, et al. (2007). "Combining patent law expertise with R&D for patenting performance." Organization Science **18**(6): 922-937.
- Stern, S. (2004). "Do scientists pay to be scientists?" Management Science **50**(6): 835-853.
- Strauss, A. and J. Corbin (1990). Basics of Qualitative Research - grounded theory procedures and techniques., Sage Publications, London.
- Teece, D. J. (1996). "Firm organization, industrial structure, and technological innovation." Journal of Economic Behavior & Organization **31**(2): 193-224.

- Teece, D. J. (2007). "Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance." *Strategic Management Journal* **28**(13): 1319-1350.
- Thursby, J. G. and M. C. Thursby (2002). "Who Is Selling the Ivory Tower? Sources of Growth in University Licensing." *Management Science* **48**(1): 90-104.
- Tijssen, R. J. W. (2002). "Science dependence of technologies: evidence from inventions and their inventors." *Research Policy* **31**(4): 509-526.
- Trajtenberg, M. (1990). "A PENNY FOR YOUR QUOTES - PATENT CITATIONS AND THE VALUE OF INNOVATIONS." *Rand Journal of Economics* **21**(1): 172-187.
- Tripsas, M. (1997). "Unraveling the process of creative destruction: Complementary assets and incumbent survival in the typesetter industry." *Strategic Management Journal* **18**: 119-142.
- Tushman, M. L. and C. A. Oreilly (1996). "Ambidextrous organizations: Managing evolutionary and revolutionary change." *California Management Review* **38**(4): 8-&.
- Tushman, M. L. and L. Rosenkopf (1996). "Executive succession, strategic reorientation and performance growth: A longitudinal study in the US cement industry." *Management Science* **42**(7): 939-953.
- Von Hippel, E., Franke, N., and Pru gl, R. (2009). "Pyramiding: Efficient Search for Rare Subjects." *Research Policy* **38**: 1397-1406.
- Williamson, O. E. (1975). *Market and Hierarchies*, Free Press, NY.
- Yin, R. (1989). *Case Study Research: Designs and Methods*.
- Zahra, S. A. and M. Wright (2011). "Entrepreneurship's Next Act." *Academy of Management Perspectives* **25**(4): 67-83.
- Ziedonis, R. H. (2004). "Don't fence me in: Fragmented markets for technology and the patent acquisition strategies of firms." *Management Science* **50**(6): 804-820.
- Zucker, L. G., M. R. Darby, et al. (2002). "Commercializing knowledge: University science, knowledge capture, and firm performance in biotechnology." *Management Science* **48**(1): 138-153.

Acknowledgements

I would like to thank H. Lundbeck A/S, Copenhagen University: Faculty of Health and Science, Molecular Disease Biology and Copenhagen Business School for sponsoring my PhD research, during which this study was conducted. I also acknowledge the generosity of anonymous informants who participated in this study, my PhD colleagues: Rasmus Toft-Kehler and Marcus Møller Larsen, who participated as jury members, and the useful feedback from Peter Abell, Stijn Kelchtermans, Keld Laursen, Finn Valentin, Theresa Veer, Jacob Rubæk Holm, Christian Sternitzke, Dietmar Harhoff, Hans Christian Kongsted, Ulrich Kaiser, participants at the PhD Workshop Leuven 2013, DRUID winter 2013 (PhD conference), DRUID summer 2013, EURAM 2013, PhD seminar at CBS at the department of Innovation and Organizational Economics, and AOM anonymous reviewers.

CHAPTER 3

3 HOW SEARCH IN SCIENCE IMPACTS ON THE VALUE OF INVENTIONS AT EARLY VERSUS LATE STAGES IN THE R&D CYCLE

By Karin Beukel, Finn Valentin and Rasmus Lund Jensen

ABSTRACT

The literatures on innovation and organizational learning have identified search in prior science and technology as critical inputs to industrial R&D. Efforts to distinguish the contributions - separately and combined - of these two search orientations are scarce, and quantitative estimates offer contradictory results. The contributions to R&D from science are particularly elusive. To achieve some transparency on these issues we study R&D in biotech drug discovery, where the role of science is pervasive and structured into a recurrent sequence of inventions required to build a drug candidate. The patents filed on these inventions offer, through their citations to prior art, a fine-grained view of the role of science along the R&D cycle. Applying a unique text-mining algorithm we categorize a set of 1,058 patents from Scandinavian drug discovery firms into six types of drug-related inventions. Tests confirm a significantly decreasing presence of science vis a vis technology over the R&D cycle. Effects of the composition of search on the value of single inventions show notable differences. In early R&D increasing predominance of search in science detracts from invention value. In late R&D, inventions increase in value when search includes a scientific orientation. Science-based R&D is cognitively heterogeneous and builds value in forms requiring sophisticated R&D management. Our results add to the theoretical understanding of search and the role of science in innovations. They also explain why an aggregate view, as presented in prior literature, on the value produced by science in R&D leads to contradictory or insignificant findings.

Keywords: organizational learning, science and technology, cumulative inventions, patent value

3.1 Introduction

Differences in the sources of the knowledge exploited in Research and Development (R&D) influence firm productivity and economic growth (Mansfield 1972; Rosenberg 1974; Griliches 1984; Griliches 1986). The organizational learning literature shows that both explorative and exploitative search is needed to enable good firm performance (March 1991; Tushman and Oreilly 1996; Brown and Duguid 2001; Katila and Ahuja 2002; Benner and Tushman 2003; Gupta, Smith et al. 2006), and that both science and technology are potentially valuable sources of knowledge for the development of innovations (Rosenberg 1990; Brooks 1994; Tijssen 2002; Jensen, Johnson et al. 2007). However, search in science and search in technology are fundamentally different, and therefore respond to different problem solving processes during innovation. Search in science is aimed at understanding phenomena while search in technologies is directed to exploiting existing solutions in further innovations (Brooks 1994; Rosenberg and Nelson 1994). Despite these essential differences between science and technology, the literatures on innovation and on organizational learning provide strong empirical support for their combined role in the process of innovation. However, little is known about the patterns of these combinations and their effects on innovation value.

Empirical studies of science-based firms differ regarding the role they attribute to science in the context of other sources of knowledge applied in R&D (Fleming and Sorenson 2004; Bruno Cassiman and Zuniga 2007). For individual innovations, the orientation of search - towards science vs. technology - may shift across the R&D cycle (Iansiti, 1997; Kline and Rosenberg, 1986). Often the final product is the result of multiple cumulative inventions, whose origins in relation to science and technology search differ. Rosenberg and Nelson (1994) suggested that early in the R&D cycle inventions rely on science search while later innovation

stages rely on search in technology. This pattern presents a challenge for the management of science-based innovations. Although different search patterns predominate in different stages, a *balanced configuration of search* across the R&D cycle may be matter more for innovation performance. This paper investigates questions related to differences in the role of science search across the R&D cycle, and the effects on the value of innovations of the balance between science and technology search. To our knowledge, these issues have not been addressed in the existing literature.

Following a tradition in the organizational learning literature (Fleming and Sorenson 2004; Yayavaram and Ahuja 2008) we conceptualize search as an expression of the distinct knowledge sources exploited for problem solving. Drawing on work by Rosenberg and Nelson (1994) and Brooks (1994) on the fundamental difference between science and technology, we propose that search through the lens of science provides answers to questions such as '*why an effect appears*', while search through the lens of technological application provides answers to '*how an effect appears*'. In the science based industries, a core objective of R&D is to transform a scientific discovery providing a solution to a fundamental question, into a commercial invention (Stankiewicz 2000). Search in science and technology are different approaches applied by firms to inform this innovation task.

Previous studies use backward citations in patents as footprints of the prior science and technology relating to the focal invention. We argue that these footprints also demonstrate how science and technology can be used as *search lenses* to generate inventions. Search based on science is expressed in backward citations in the focal patent, to the scientific literature (referred to as non-patent literature citations) (Harhoff, Scherer et al. 2003; Fleming and Sorenson 2004;

Cassiman, Veugelers et al. 2008). Search based on technology is expressed in backward citations to prior patents (Lanjouw and Schankerman 1997; Harhoff, Scherer et al. 2003).

Although most innovation studies assume that search in science is predominant in early R&D while search in technology prevails later in the R&D cycle, this fundamental difference has not been demonstrated empirically in a large N-sample. Identifying individual inventions at early versus late stages of R&D is problematic in large scale empirical studies. To the best of our knowledge, the present study is the first to suggest a method to resolve this issue. To identify individual inventions from a string of cumulative inventions requires in-depth knowledge of the types of inventions created during R&D and a method for identifying them. We focus on the biotech industry where types of inventions emerging from R&D are identified in the literature along with their most prevalent sequences. By developing a unique algorithm based on semantic structures and International Patent Codes (IPCs), we can identify different invention types from a large number of patent observations on which basis we can test our hypotheses in an empirical study utilizing unusually detailed data on 1,058 biotech patents.

Our results support our expectation; search in science gradually becomes less predominant across the R&D cycle and search in technologies become significantly more prevalent during late R&D. Second, we show that invention value is correlated with search in science, however, the sign differs depending on the stage of R&D. With separate tests of invention created early vs. late in R&D we find that in early R&D search in technologies is infrequent in comparison to late R&D processes, but one-sided search in science has a penalizing effect on invention value. At the opposite end, in late stage R&D, search in science is less frequent but nevertheless is associated with increased invention value. We therefore

highlight the importance of considering individual stages in the R&D cycle when examining the value and disadvantages associated with search in science.

Our findings add several insights to the management of innovation and organizational learning literatures. First, we empirically demonstrate how, in an intensive science-based industry, search in science varies from the early to the late stages in the R&D cycle. Second we demonstrate how the value generated for innovation from search in science depends on the way it is balanced against technology search, and that the effects of this balance change across R&D stages. Third, on this basis we resolve the contradictions in the previous literature. Studies have demonstrated the value that research-based firms extract from inflows of strong science vary (Gittelman and Kogut 2003). But pursued at the level of single inventions the relationship is either negative or absent (Cassiman, Veugelers et al. 2008). Our findings related to changes in the effects of inputs across the R&D cycle mostly resolve this paradox. Fourth, our findings are based on a novel methodology for advanced profiling of large numbers of patented inventions.

The remainder of the paper is organized as follows: In the first section, we discuss the mechanisms of search in both early and late R&D processes. We develop hypotheses related to the declining role of search in science across the R&D cycle, associated with increases in technology search. We develop hypotheses related to the effects of innovation value. We present the data and methods and the empirical findings. In the final section we discuss the results and their implications, limitations, and extensions of the research.

3.2 Changes in search across the R&D cycle

Since its origins, the innovation literature has recognized both science and technology as sources of novelty, and examined how innovations emerge from their interaction and iteration

(Schumpeter 1939; Gibbons and Johnston 1974; Kline and Rosenberg 1986). A few sectors including biotech and life sciences, carry out systematic in-house research as the basis for their innovations (insert ref to: Cohen et al., 2002, Klevorick et al 1995; Nelson 2003; Stankiewicz 2000), and in these sectors the relationship between scientific and technological advances allows firms to compete on the basis of their ability to extract innovations directly from research (Pavitt, 1991). In these science-based industries, inventions originate from conversations with nature about “why” questions. In this context we expect early stage R&D to be strongly oriented to science. In complex technologies (Cohen, Nelson et al. 2000) innovations emerge from the accumulation of separately patentable elements. As R&D work progresses, problem-solving shifts to issues that are increasingly technological in nature (Iansiti, 1997; Kline and Rosenberg, 1986). Case studies of the R&D cycle in science-based firms demonstrate this shift from early science-based discovery toward subsequent stages of development and an increased emphasis on technological knowledge (Iansiti and West 1999; Cassiman 2010). There is a change of scientific “why” questions to technological questions about “how” to make things work, e.g. secure stable functionality and compatibility with other technologies.

A powerful conceptualization of these differences in cognitive direction of search and problem solving in R&D has emerged in the notion of *cognitive maps*. In the psychological literature, cognitive maps refer to the constructs allowing people to perceive and interpret the current situation in relation to its environment, in their search for suggestions of which orientation to follow (Neisser 1976; Piaget 1985; Carroll 1993). In the management literature, Gavetti and Levinthal (2000) build on this conceptualization of maps: They develop a distinction between two different cognitive problem solving approaches associated with innovations, in the *forward looking* approach, cognitive mapping is concerned with linkages

between choice of action and subsequent impact. This type of problem solving centers on the development of hypotheses related to identification of potential causal relationships. Search in the *backward looking* approach is exploitative and uses existing knowledge. We suggest that these two approaches correspond to two different R&D-related search lenses. The forward looking approach is closely associated with science-based search for explanations of ‘why an effect appears’. The backward looking approach corresponds to which existing technologies are exploited and define the context.

This correspondence between forward/backward looking cognitive maps and search lenses and science/technology is effectively demonstrated by (Yayavaram and Ahuja 2008) in their study of the discovery of high-temperature superconductivity in copper-oxide based materials. This discovery led inventors to apply a forward looking cognitive approach to the search for a theoretical model offering a scientific explanation of ‘why this effect appeared’. A different experiential approach was applied to gain alternative and more exploitative insights. Applying a backward looking cognitive approach involves experiments with related materials to answer questions about ‘how the effect appears in different settings’. The forward looking science-based approach is critical for understanding the underlying causal mechanisms of high-temperature superconductivity in copper-oxide based materials. A backward exploitative view of existing technological knowledge is required to stabilize and enable industrial applicability, but offers no overall guidance on the critical cause-effect relationships in this new area of technology. Therefore, drawing on Gavetti and Levinthal (2000) and Yayavaram and Ahuja (2008) we relate search in science and search in technology to two distinct different cognitive maps guiding problem solving processes in different directions.

With reference to science-based industries we conjecture that:

Hyp. 1: Inventions in early stage R&D are based on search in science more than are inventions in late stage R&D

Hyp. 2: Inventions in late stage R&D are based on search in technology more than are inventions in early stage R&D.

3.3 Invention value and shifts in the composition of search

Although the composition of search shifts across the R&D cycle the most valuable innovations may not arise from taking these shifts to extremes. Theory suggests that innovation performance is enhanced by cognitive variety. In the present context that implies R&D search based on a combination of the two cognitive maps with scientific and technological orientations. Management research demonstrates that more valuable problem solving emerges from combining different mental models (Brown and Eisenhardt 1997; Smith and Tushman 2005), partly because it enables flexible recombination of individual cognitive maps (Eisenhardt, Furr et al. 2010).

However, based on the theory underpinning Hypotheses 1 and 2, we expect cognitive variety to affect innovation performance based on *different configurations* of scientific and technological search at the opposite ends of the R&D cycle. In early stage R&D, the predominant pattern of search is based on the cognitive map of science. At the same time, the learning loops required by the chain-linked nature of R&D (Kline and Rosenberg 1986) suggest that innovations will be more valuable if they anticipate technological conditions appearing in later R&D stages. Also, search in technologies provides a window on prior related learning in other firms, and combines the focal inventions with proven principles incorporated in previous

technologies, which increases their value by reducing the underlying uncertainty (Nemet and Johnson 2012) and economizing by reusing knowledge (Langlois 1999).

To reap these benefits the cognitive map of early R&D must maintain a technological orientation, suggesting that a search pattern that relies predominantly on science-based search will detract from the value of early stage R&D. The logic of this argument suggests that this penalty will increase particularly if science-based search begins to dominate inventive search. Hence we propose:

Hyp 3: Early stage R&D decreases in value when search in science increasingly predominates search in technology

The circumstances in the later stages of R&D are different. The input to these stages of R&D is not “raw” scientific opportunity but ‘well-developed’ invention, which has progressed through the pipeline for several years. Drug development takes around 8-12 years (Mansfield 1991; Mansfield 1998; Achilladelis and Antonakis 2001; DiMasi 2001; Chandy, Hopstaken et al. 2006). The aim in the later processes of R&D is to further modify and optimize the invention to ease its progress through the Food and Drug Administration (FDA) process, to ensure no or small side effects, to prove the drug to be more efficient than the drugs already available on the market, and to create new patent protection to extend the patent protected life of the drug. In this setting the experiential knowledge accumulated by firms is based on problem-solving using technology based cognitive maps (Pisano 1996). The risks of falling into familiarity traps (Ahuja and Lampert 2001) are particularly acute in this phase of the cycle, and finding an effective balance among different mental models by applying cognitive variety involves securing inflows of new information and knowledge (Leonard-Barton 1992; Tuahene-Gima

2005). Prior research shows that a science based cognitive map is a powerful way to avoid familiarity traps (Fleming 2001). Therefore, we propose, in line with the arguments about cognitive variety, that in the late stages of R&D where technology search predominates, inserting in the technology based cognitive map elements of a science based cognitive map will enhance the value of inventions.

Hyp 4: Late stage R&D increases in value if an orientation towards science is part of the search underpinning inventions.

3.4 Data and Methods

3.4.1 Differences in patenting across the R&D cycle

We draw on research on innovation and focus on the level of the individual patent as the unit of analysis. Prior research has applied this strategy to map the firm's knowledge base (Katila and Ahuja 2002; Yayavaram and Ahuja 2008), and to characterize its science search (Fleming and Sorenson 2004) and the effects on innovation value. We contribute to these methodological approaches by a) identifying the constituent inventions that ultimately combine to form a single marketable innovation (in our case a drug), and b) by categorizing these constituent inventions into recurrently appearing types, related to either the early exploratory stages of R&D or the later exploitative stages. To these solutions we add methodologies proposed in the literature such as characterizing each invention in terms of its reliance on search in science, prior technologies, and value. The drug discovery segment of the biotech industry has a pattern of R&D, and paper trails that allow us to apply these methodological approaches. The final dataset consists of 1,058 patents applied by 110 Scandinavian drug discovery firms established between 1987 and 2003.

In the biotech industry, patents are critical for effective appropriability (Levin, Klevorick et al. 1987). In drug discovery, different types of patented inventions are created during distinct stages of discovery and development of drug candidates. We identify six patent types as relevant for biopharmaceutical drug discovery inventions. They tend to appear in a distinct sequence in the R&D cycle (Gupta and Bansal 2002; Kaushal and Garg 2003; Yoo, Ramanathan et al. 2005; Norman 2007; Sternitzke 2010; Sternitzke 2013): 1) patents protecting the *method of identifying new products*. In the biotech industry, these are *platform patents* (Yoo, Ramanathan et al. 2005) which cover inventions created through very early and explorative problem solving on industrialized high-throughput screening platforms (Nightingale 2000); 2) patents that protect *the core structure of a product* in the biotech industry, or *composition of matter/compound patents* (Norman 2007); 3) patents protecting *methods of utility*. In the biotech industry, these are *utility patents* (Norman 2007), (note that in the US utility patents also have a broader meaning referring to the “normal” invention type of patents, as distinct from for example plant or design patents); 4) patents protecting *the specific application* of the core structure of the product. In the biotech industry, or *formulation patents* (Norman 2007); 5) patents protecting the *method of manufacturing (process patents* (Norman 2007)); and 6) patents protecting the *method of delivery (instrument patents* (Gupta and Bansal 2002; Kaushal and Garg 2003)). Different patented inventions take a certain form and focus that is contingent on the phase of R&D in the invention process. Fig. 1 provides a visualization of four selected patent types, which are the most common inventions brought together to form a drug candidate.

 Insert Figure 1 here

3.4.2 Identifying inventions in early vs. late R&D

This paper uses a text mining methodology developed by the authors to identify six patent types in Derwant patent abstracts, using semantic structures, keywords, and IPC codes. The text-mining method was developed in three phases: 1) generating a text-mining algorithm, 2) testing and adjusting the text-mining method, and 3) validating the results of the text-mining algorithm with industry players. Each step is described below [a separate report with in-depth details on the text-mining algorithm is available from authors upon request].

3.4.3 Generating a text-mining algorithm

First, a literature review of patent types in the biotech industry was conducted. Since the biotech industry developed out of the pharmaceutical industry (Hopkins, Martin et al. 2007), the patent types utilized are closely related to both industries. After identifying patent type, we interviewed industry stakeholders to ensure that our patent type identifications were in line with industry praxis. To develop the text mining method, we first randomly selected 85 biotech patents and categorized them “manually” into the six types. Iterations allowed identification of differentiating semantic structures (keywords and sentence pieces) and IPC codes. A range of prior biotech patent related studies helped us to identify keywords and IPC codes and categorize the patents: the OECD methodology for identifying biotechnology patents (OECD 2005), the results of the biotechnology comparative study on patent rights by EPO, USPTO, and JPO (EPO, USPTO et al. 1998), the patent search literature focused on bioscience (Yoo, Ramanathan et al. 2005), and Dimberger’s (2011) case of the human recombinant insulin patent landscape.

In total, 608 semantic structures were identified as belonging to a patent type: Platform (142), Compound (129), Process (98), Formulation (87), Instrument (77), and Utility (75). A further 255 IPCs were identified as belonging to a patent type: Compound (98), Formulation

(10), Instrument (29), Platform (28), Process (87), and Utility (3). Each patent was examined to see how it matched the 608 semantic structures and 255 IPCs, frequencies of ‘hits’ for each patent type were noted for number of semantic structures and IPCs. The frequencies of IPCs and semantic structures were then weighted. The highest score indicated the type of patent. Approx. 10 % of patent scores were equally high in several categories and were assigned to a ‘mixed-patent’ category.

3.4.4 Testing the automatic text-mining method

The above categorization was translated into an algorithm to allow patent type categorization to be handled automatically by a script. Two tests were performed to check whether the machine method categorization (the algorithm) produced the same result as manual categorization. First, a test of the 1,079 patents from 107 biotech firms was conducted. The 1,079 patents were read and categorized manually into patent types and the results were compared with the results of the automatic machine coding: In 91% of cases the classifications were the same. Second, we tested patents from a large biopharmaceutical company, Novo Nordisk: 5% of their patent portfolio (1,937 patents) was randomly selected and manually classified; for 92% of these patents manual and automatic categorizations were the same.

3.4.5 Validating the text-mining method with industry experts

To ensure that the results of the automatic text mining method correspond to what the industry experts would identify as certain patent types, three external tests with two small biotech firms and one large pharmaceutical firm were conducted. In biotech firm A, the firm’s IP counsel’s categorization matched the automatic categorization in 9 out of 11 patents. In biotech firm B, the firm’s IP counsel’s categorization matched the automatic categorization in 9 out of 13 patents. In the large pharmaceutical firm, H. Lundbeck A/S, 50 patents – representing one-sixth of the

total patent portfolio – were randomly chosen for the test; 35 patents were categorized similarly using the automatic categorization. Thus the output from the machine patent type categorization is satisfactory.

3.5 Variables

Identifying valid proxies for search behavior and the firms' underlying cognitive maps in the process of creating new inventions is difficult; Thus, management researchers have relied on observing the innovative outcomes of a given search behavior, patents, and related the search process, to those from the backward citations inserted in patents (Benner and Tushman 2002; Katila and Ahuja 2002; Laursen, Leone et al. 2010; Phelps 2010; Laursen 2011). In depth research in the U.S. exploring the validity of backward citations, focusing on the examiners inserted backward citations, as well as all backward citations, has been shown to be noisy when backward citations are used as proxies for search behavior in innovation (Jaffe, Trajtenberg et al. 2000; Alcacer and Gittelman 2006; Alcacer, Gittelman et al. 2009; Roach and Cohen 2012). Since backward citations are handled differently in the European and U.S. contexts (Criscuolo and Verspagen 2008), the validity of utilizing backward citations in the European context has been analyzed. Duguet and MacGarvie (2005) provide evidence that backward citations in EPO patents are a fairly good measure of firm level activities, such as M&As, R&D cooperation, etc. However, in line with the recent literature, we do not use individual backward citations as precise proxies but rather as count and ratio-measures for type of search, either scientific or technological, in the innovation process of a patented invention. There are two distinct types of backward citations: a) a non-patent literature citations (in the chemical and pharma industry, these are most often citations to scientific journals, which we use as a proxy for the underlying cognitive map guiding the search, namely the *science based cognitive map*, and b) backward

citations to prior patents, which we use to proxy the *technology based cognitive map guiding the search*.

In our estimations in Table 3, we use different types of backward citations as dependent variables: NPL_CIT is the number of backward citations to non-patent literature, PAT_CIT is the number of backward citations to prior patents.

The main independent variables in Table 3 are dummy variables that are coded 1 for each of the four patent types, and are described briefly here [in-depth descriptions available from the authors]:

- 1) *Platform Patents Category*: Methods for analyzing and selecting compounds and entities; methods for identifying molecules, etc.
- 2) *Compound Patents Category*: Compounds, molecules, proteins, peptides, enzymes, receptors, derivatives, analogues, and variants, etc.
- 3) *Utility (Use) Patents Category*: The usage of the compounds and the technologies developed; treatments and methods to alleviate the symptoms of various diseases; and the use of an entity to prepare or manufacture another useful product.
- 4) *Formulation Patents Category*: New dosage forms, pharmaceutical preparations, etc.

Instrument and process patents were removed from the sample, as they account for less than 50 patents. In Table 4 patent value is a dependent variable. We identify patent value by employing two distinct value correlates:

$$PATVAL = St(Familysize) + St(Forward citations)$$

According to Harhoff, Scherer, and Vopel (2003) and Gambardella, Harhoff et al. (2008), patent value indicators carry noise, this implies they should be applied with caution. The literature suggests a one-sided approach to valuing individual patents by counting forward citations. One way to improve this one-sided approach is to measure patent value using by several indicators (Lanjouw and Schankerman 2004). We therefore apply a measure that incorporates two distinct patent value correlates: family size and forward citations. In Lanjouw and Schankerman (2004) these two measures are the only variables presented as positive and significant for patents in the drug industry, when regressed as determining patent litigation and patent renewal. Family size and forward citations have been included in various empirical studies of value indicators, and are shown to be less noisy (Gambardella, Harhoff et al. 2008). Another reason for choosing these two dimensions is that they contribute to our understanding of patent value in different ways. Family size is the number of countries in which the patent has been applied for, and is a proxy for how core the patent is for the firm. Firms apply for patents in a range of countries depending on the importance to them of the patent: if the patent is non-core, the firm will apply for protection in a smaller number of countries; if it is core, the firm will apply to a higher number of countries. The correlate of forward citations is measured by the total number of forward citations the patent has received, a proxy for how important the patent has been for subsequent inventions within the area.

Inventions are cumulative in their protection of a given drug candidate. For example, a formulation patent is likely to build on a prior compound patent, whereas compound patents rarely cite their formulation counterparts. Thus inventions coming out of late stage R&D will tend to receive fewer citations. We therefore apply both value proxies and conduct tests to check their robustness. The two proxies for forward citations and family size have low correlation

(0.22). We standardize each proxy to ensure an equal balance of value. Two different independent variables are employed in Table 4, 5 and 6. The independent variable (NPL_RATIO) estimates to what degree the science based cognitive map has been replaced by the technology based cognitive map; the measure is created by taking the total number of non-patent literature citations and dividing them by the total number of backward citations, i.e. scoring 1 when search is in science only. The second measure for the linkage to science is a dummy variable that takes the value 1 if the invention has one or more non-patent literature citation(s) and 0 if there are no non-patent citations in the patent. This variable indicates whether any search in science has been undertaken.

3.5.1 Estimation Approach and Control Variables

To analyze the occurrence of citations to non-patent literature citations (NPL) and patent citations (PAT CITs) in patents protecting different types of inventions (Platform, Compound, Utility and Formulation) we estimate the following models (Hypotheses 1 and 2):

$$1) Y_{pft} = \alpha + \beta_1(Platform) + \beta_2(Compound) + \beta_3(Utility) + \beta_4(Formulation) + \delta_{pft}$$

The outcome variable Y is a count of either non-patent literature (NPL) or patent citations (PATCITs), the unit of analysis is the individual patent (p) applied by firm (f) at a given time (t). Since we are interested in non-patent literature and patent citations influenced by other possible patents, firms, and time variables, we control for the number of variables represented by δ_{pft} . As patent level controls we include the total number of backward citations, the technology scope of the patent measured by number of IPC codes, the log of patent family size, whether the patent has been granted, and whether the patent has been withdrawn. As firm-level controls, we use a firm size variable measuring the number of employees in the firm, the year of patent application, the number of the firm's patents applied for before the year of patent

application, firm type measured by whether the firm is focused on small or large molecules, and firm age (whether it is less than four years old) at the time of the patent application. For the time variable, we control for year of patent application. For the estimations, we considered a Poisson regression since the dependent variable is a count variable. However, the variance is higher than the mean, which indicates that the data are overdispersed. This suggests a negative binomial regression in preference to a Poisson regression (Wooldridge 2009). This choice is confirmed by our results, which show that α values are significantly different from zero. We employ robust estimators to avoid heteroskedasticity, and to test for multicollinearity we perform VIF tests.

To understand how differences in the composition of search between early and late R&D affects patent value (hyp 3 and hyp 4) NPL, we estimate:

$$2) PATENTVALUE_{pft} = \alpha + \beta_1(SCIENCE) + \delta_{pft}$$

The outcome variable is patent value and the unit of analysis is patent (p) applied for by firm (f) at a given time (t). The independent variable ‘SCIENCE’ is analyzed in two ways: considering the relative prevalence of scientific search (the NPL_RATIO), and applying the dummy NPL_DUM indicating whether a science based cognitive map has been utilized during innovation activities. We run separate models, for early inventions (Compound patents) and for late inventions (Formulation patents). Again, we are concerned with the influence of firm and time on patent value, and employ a number of variables to control for this, represented by δ_{pft} , and cluster for the effects of the single firm behind the invention. To estimate the model we initially use the Tobit technique since the dependent variable is lower limited (Wooldridge 2009); however, the empirical results for Compound and Formulation patents show very few observations at the lower limit (1 observation for Compound patents and 3 for Formulation

patents). We therefore present the results of an OLS regression in Table 3. The results do not differ much from the Tobit estimates but are easier to read. Since the OLS and Tobit regressions are mean centered, we may not capture the differences in the effects at different locations in the patent value distribution and also may not be able to explain the extreme observations in the tails. To explore the degree of ‘extreme tails’ we follow Koenker (Koenker and Bassett 1978; Koenker 2005) and use percentile regressions to investigate the effect at different locations in the patent value distribution (Table 4 and Figure 2).

3.6 Results

3.6.1 Descriptive results

Table 1 provides descriptive data for all variables.

Insert Table 1 here

Table 1 shows several interesting features. The patent type referring to compounds accounts for 52% of the total sample. This predominance is explained not just by the protection of the core technology of a drug candidate (Norman 2007). Compounds are invented early in the drug development process, and the high attrition rate in drug discovery means that development may be discontinued. Compound patents outnumber initial platform patents because a single platform is capable of multiple targets.

The correlation matrix in Table 2 shows only a few significant relationships. Multicollinearity (coefficient > 0.70) is found only where it would logically be expected, e.g. between the total number of backward citations and backward citations to patents or the non-

patent literature, and the number of non-patent literature citations and x citations to non-patent literature or citations to patents and x citations to patents.

Insert Table 2 here

3.6.2 Shifts in search patterns from early to late R&D processes

Hypotheses 1 and 2 address shifts in the R&D cycle related to its orientation to science vs. technology. Calculations (not presented here) show that for Platform patents 50% of all backward citations are to science, the share drops to 37-40% for Compound and Utility patents and declines further to 20% for Formulation patents in late R&D. So from a descriptive viewpoint shifts do occur in the role of science. These shifts occur in a setting where search throughout R&D predominantly has a technological orientation.

Hypothesis 1 proposes a decrease from early to late R&D in the role of science as a cognitive map. Model I in Table 3 takes as the dependent variable the number of backward citations to science (NPL) found in each patent. Differences across the R&D cycle are tested taking Platform patents as the benchmark, i.e. the patent type appearing at the front end of the drug R&D cycle. Negative significant estimates for the other patent types in Model I indicate their overall lower foundations in science. Differences between these other types are brought out by Wald tests. These tests show significant downward shifts in the estimates from Platform to Compound (see model I) and Compound to Formulation patents ($\chi^2=50.90^{***}$), confirming Hypothesis 1. The results for Utility patents do not follow the pattern suggested by a general R&D process although utility patents most often are filed just after compound patents, utility patents rely more heavily on NPLs than compound patents ($\chi^2=14.22^{***}$). The reason for

Utility patents citing non-patent literature significantly more than Compound patents is due to the underlying technological mechanisms expressed in utility patents. Use patents usually refer to basic biomedicine scientific literature for configurations of usage in humans. For inventions created during late R&D, Hypothesis 2 predicts a high number of citations to prior technologies. The number of these references forms the dependent variable in Model II. Comparisons among patent types use platform patents as the benchmark. Wald tests show a significant increase in citations to technology in the shift from Platform to Compound patents (see Model II) and from Compound to Formulation Patents ($\chi^2 = 43.91^{***}$), confirming Hypothesis 2. Models I and II control for the number of backward citations in each patent; Hypotheses 1 and 2 are confirmed for any level of search activity.

Hypotheses 3 and 4 concern the effects on patent value of different compositions of search. Models III and IV in Table 3 examine the case of early R&D as represented by Compound Patents. The composition of search is indicated by the ratio of citations to science over the total number of backward citations (NPL RATIO). The significant negative estimate for this ratio indicates decreasing value for an increasing share of citations to science, confirming Hypothesis 3. We also test the relationship (in Model IV) using a dummy that takes the value 1 for the presence of at least one NPL citation. A negative, significant estimate also is obtained for this more conservative indicator.

Further analysis of the ratio indicators offers insights into differences in the effect on patent value for different levels of science search predominance. To examine these differences we use percentile regressions and examine difference across the distribution by means of Wald tests. The results in Table 4 and Figure 2 show significant differences. When science search increases by 1 percentile, the coefficient estimates of the independent variable non-patent

literature ration (NPL RATIO) decrease for every percentile until 0.5. The effects are not significantly different from each other (-0.13 to -0.18) for lower levels of search in science (between values of the ratio from 0.1 to 0.5). However, after 0.5 the penalizing effect increases for every percentile, being four times more negative for very strong predominance of search in science (ratio value of 0.9) compared to moderate levels. Wald tests also show significant differences after 0.5 (q50 to q90: 6.73***, q 50 to q80:3.30**, q60 to q90:5.04** and q70 to q90: 3.07**). In short, patent value decreases to the same moderate extent up to the level where search in science defines roughly half of the cognitive maps guiding search; thereafter increases in the orientation towards science detract from patent value at an increasing rate.

Insert Table 4 & Figure 2 here

Turning to the effects on value of inventions made in late stage R&D, Models V and VI examine the case of Formulation patents. Two mechanisms are proposed as influencing the effect of science on the value of late stage inventions. Following the literature on cognitive variety would indicate that having a blend of both science and technology inputs would have a positive influence on outcome, while familiarity traps theory (Fleming 2001) would suggest that a positive effect on value would be conjectured from the presence of just an element of search in science. The descriptive data for late stage inventions (n=110), Formulation patents, on average show a total of six backward citations, of which only one 1.5 are to science and the rest are to prior technology (see Table 1). The estimate in Model V shows that the NPL ratio is not significant, thus not supporting the arguments about cognitive variety. However, the positive estimate of the dummy in Model VI indicates the positive effects on patent value conjectured in Hypothesis 4. This estimate is significant only at the 10% level, and is obtained without

controlling for the total number of backward citations. Supplementary models that include this control (not presented here) retain a positive sign, while significance drops to the 16% level. Overall, the results are mixed and suffer from the restrictions imposed by small sample size for this patent type. However, it seems that Hypothesis 4 is confirmed. Inventions from late stage R&D increase in value with the addition of elements of search in science.

Insert Tables 5, 6 and 7 here

3.7 Robustness checks

The results estimated in Models I to VI broadly support our hypotheses. Additional tests were performed to examine the robustness of our findings. Due to only a few censored observations, Models III-VI apply OLS rather than Tobit. Alternative estimates were performed applying Tobit (Wooldridge 2009) (see Table 6), using the tests indicated by Wiersema and Bowen (2009) and Bowen (2012). We also ran Model III-VI excluding the total number of backward citations to examine whether the effects rely on total scope of search. In all cases the results remain the same as in the main models.

To examine the robustness of our patent value measure (Model III-VI) we estimate the models splitting the dependent variable into its components of forward citations and family size (see Table 7). The results remain significant for Model III-IV for both robustness checks; however we find no support for hypothesis 4 in either of the single value estimations. This might indicate that when using patent value indicators as the dependent variable in empirical hypothesis testing with relatively low numbers, combining several well selected value indicators based on industry characteristics would enhance the accuracy of the indicator, and possibly remove noise from other indicators.

We also test Models I and II using only backward citations marked X by the patent examiners as referring to *“Particularly relevant documents when taken alone (a claimed invention cannot be considered novel or cannot be considered to involve an inventive step)”* (p.8 Webb, Dernis et al. 2005). Prior studies argue that restriction to X-marked citations reduces their noise as indicators of knowledge flow (Criscuolo and Verspagen 2008). Results are largely the same (see Table 5).

3.8 Discussion and Conclusions

In examining a science-based industry, this paper studied orientations in the cognitive maps applied across the R&D cycle. First, we investigated whether different steps in the R&D cycle have different emphasis on the two orientations of a science based cognitive map and a technology based cognitive map. Second, even if shifts occur across the R&D cycle in the composition of search, both orientations may be present in all the stages. We examined whether the two orientations exhibit orthogonal presence, balanced only in different proportions in different parts of the cycle, and whether shifts in these balances affect the value of the inventions associated with that particular part of the R&D cycle.

To address these issues we capitalized on the clearly structured steps characterizing R&D in biotech firms specialized in drug discovery. Given the tight and aggressive appropriability regime of this industry (Levin, Klevorick et al. 1987), firms tend to file patents on inventions coming out of specific steps in R&D leading to a single drug, for example, on the compound, its utility, or its formulation. On the basis of the fairly standardized sequence of these inventions, we made a clear distinction between early R&D (directed e.g. at compounds or at the platform developed for their discovery) and late R&D (directed e.g. at formulation).

The drug industry leaves detailed patent paper trails from each stage of the R&D. Particularly important for our purposes are the footprints left by each patent of the search associated with each invention. The backward citations in a patent to the non-patent literature indicate the extent to which the search behind the invention is guided by a science based cognitive map, or directed by a technology based cognitive map, indicated by backward citations to previous patents (Benner and Tushman 2002; Katila and Ahuja 2002; Laursen, Leone et al. 2010; Phelps 2010; Laursen 2011). As expected, science-based maps are more prevalent in the forward-looking explorative orientation of search in early R&D, while cognitive maps dominated by a technological orientation are more predominant in late R&D. However, in both cases we observed a blend of cognitive maps, rather than total replacement of one by the other. In essence, what differs is the balancing point between the two distinct different approaches. Although these relations seem intuitive, they are not established in the theoretical innovation literature and have previously not been made accessible for systematic large N-based statistical tests.

We next examined the effects on value associated with applying cognitive variety within each invention. Since orientations towards science and technology are balanced differently in the early and late stages of R&D, we designed separate tests. For early stage R&D, we found that increases in the prevalence of science in search detract from invention value. At the point when the increase in the science based cognitive map approaches total predominance, the decline in value accelerates markedly. Conversely, late stage R&D with its search pattern dominated by the technology based cognitive map, achieves increases in invention value if elements of science based cognitive search are added.

The main contribution of this paper is to the literature on sources of knowledge for innovation. Prior studies emphasize that both science and technology are potential useful sources for R&D (Rosenberg 1990; Brooks 1994; Tijssen 2002; Jensen, Johnson et al. 2007). Our results confirm this and extend the literature by empirically testing the variation in each source of knowledge at different stages of R&D, and the contribution of knowledge sources, relative to their position in R&D. We contribute to organizational theory by proposing how search during different stages affects performance in dynamic environments, and add to the research on the micro-foundations of superior performance in dynamic environments since the tests in this paper confirm the value of cognitive variety discussed in prior research (Brown and Eisenhardt 1997; Smith and Tushman 2005; Eisenhardt, Furr et al. 2010) supporting recent contributions in organizational science, that highlight how understanding the micro-foundations increases our understanding of organizational performance (Gavetti 2005; Teece 2007; Abell, Felin et al. 2008; Zahra and Wright 2011). We respond to recent calls for research on organizational learning processes and their interrelatedness (Argote and Miron-Spektor 2011). The methodological contributions of the paper include its use of citations as indicators of search direction and our input to the more general debate on the role of science. There is a small but growing literature on the contributions to value creation from science when it is an integral part of the problem solving in industrial R&D. So far these effects have been studied in the form of the direct impact of science citations/linkages on patent value (Harhoff, Scherer et al. 2003; Cassiman, Veugelers et al. 2008; Nemet and Johnson 2012). Previous studies provide inconclusive results from this approach. In contrast, we find fairly strong effects when applying a contingency design, conjecturing effects for early R&D as the reverse of those from late R&D. We find a negative, significant effect when the orientation towards science becomes predominant in the overall pattern of search. When this predominance is such that there is only

marginal attention to earlier technology, the negative effects on patent value accelerate when the share of citations to earlier technology drops to less than half of its average level. Conversely, the *positive* effects of including science in the search pattern emerge strongly in the context of late stage R&D. This result confirms the prior literature that claims that science is beneficial when coping with potential familiarity traps during later stages of R&D (Nelson 1982; Fleming 2001).

3.8.1 Limitations

As discussed in the method section, using backward citations as an indicator of search in either science and/or technology has some limitations. An alternative approach might be to reconstruct the cognitive maps applied in science-driven R&D using interviews or on site observation of inventors. This approach is not feasible for a large N dataset, and would introduce other biases into the econometric analysis, since individuals would be biased by familiarity with and perceptions of the social structures in the scientific community. Utilizing patent citations, and including patent examiners' citations, would reduce these biases. We tried to overcome the shortcomings of backward citations by relying on an industry where the link to science is strong, and where both patenting and scientific publishing is goals.

Our robustness checks do not control for self-citations, since this indicator is not available in our data. However, because we rely on EPO patents this should not have an effect on our findings. Criscuolo and Verspagen (2008) show that self-citation does not have any effect on qualitative results with regard to backward citations to EPO patents. However this would not apply to analysis based on U.S. patent data.

Finally, we do not control for “type” of backward citations. In the non-patent literature a deeper understanding of the type of science behind the individual citation would have had more

explanatory power, and would complement recent work aimed at understanding the nature of science and its interrelatedness with industry (Sauer mann and Stephan 2013).

The approach in the present paper could be extended in several ways. One important direction for further work would be to try to link individual types of inventions (platform, compound etc.) as contributions to the same drug. So far we have not identified a methodology allowing these linkages to be reliably established in a large N dataset.

3.9 Figures and tables

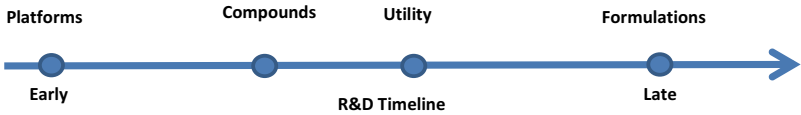


Figure 1: Patent types early vs. late in R&D

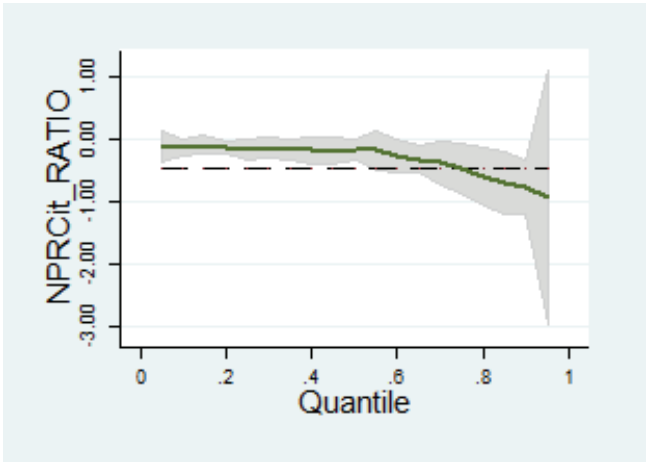


Figure 2: Percentile regression estimates for NPLCit_RATIO for compound patents

Table 1: Descriptive statistics

All patent types	Obs	Mean	Std. Dev.	Min	Max
Patent value	1058	-.143	1.40	-1.424	1.734
Compound patents	1058	.517	.49	0	1
Platform patents	1058	.224	.41	0	1
Utility patents	1058	.155	.36	0	1
Formulation patents	1058	.103	.30	0	1
Total number of backward citations	1058	7.28	5.15	0	35
Non-patent literature (NPL)	1058	3.03	3.53	0	22
Backward citations to patents (PAT_CIT)	1058	4.25	3.19	0	26
X-citations to non-patent literature (XNPL)	1058	1.61	2.91	0	22
X-citations to patents	1058	2.37	2.97	0	26
Technology scope	1058	9.70	11.28	1	86
Accumulated patents in the firm	1058	51.80	69.37	0	314
Firm size	1058	91.20	137.94	0	850
Type of firm	1058	.48	.50	0	1
Young firm	1058	.23	.42	0	1
Log of patent family size	1058	2.20	.83	0	4.882
Patent grant	1058	.33	.47	0	1
Patent withdrawn	1058	.23	.42	0	1
Year of patent application	1058			1997	2008
Compound patents					
Total number of backward citations	547	7.28	5.87	0	35
Non-patent literature citations (NPL)	547	2.70	3.66	0	22
Backward citations to patents	547	4.57	3.60	0	26
X-citations to non-patent literature (XNPL)	547	1.62	3.25	0	22
X-citations to patents	547	2.62	3.52	0	26
The total number of non-patent literature citations over total number of backward citations (NPL_RATIO)	547	.30	.28	0	1
Non-patent literature citations – dummy	547	.667	.471	0	1
Formulation patents					
Total number of backward citations	110	6.03	3.17	1	22
Non-patent literature citations (NPL)	110	1.53	2.26	0	13
Backward citations to patents	110	4.5	2.34	0	13
X-citations to non-patent literature (XNPL)	110	.59	1.46	0	7
X-citations to patents	110	2.36	2.18	0	10
The total number of non-patent literature citations over total number of backward citations (NPL_RATIO)	110	.210	.24	0	1
Non-patent literature citations – dummy	110	.563	.498	0	1

Table 2: Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1 Patent value	1.00														
2 Compound patents	0.06	1.00													
3 Platform patents	0.00	-0.56	1.00												
4 Utility patents	-0.06	-0.44	-0.23	1.00											
5 Formulation patents	-0.02	-0.35	-0.18	-0.15	1.00										
Total number of citations	0.09	-0.00	0.02	0.04	-0.08	1.00									
6 backward citations															
7 Non-patent literature	0.01	-0.09	0.17	0.06	-0.14	0.79	1.00								
8 Backward citations to patents	0.13	0.10	-0.15	0.01	0.02	0.74	0.17	1.00							
9 X-citations to non-patent literature	0.06	0.00	0.06	0.03	-0.12	0.72	0.83	0.25	1.00						
10 X-citations to patents	0.13	0.09	-0.15	0.05	-0.00	0.67	0.24	0.82	0.38	1.00					
11 Technology scope	0.37	0.18	-0.09	-0.02	-0.13	0.17	0.07	0.19	0.14	0.21	1.00				
12 Accumulated patents in the firm	-0.10	0.23	-0.22	0.09	-0.19	-0.05	-0.13	0.06	-0.00	0.06	-0.02	1.00			
13 Firm size	0.04	0.14	-0.08	0.02	-0.16	0.04	-0.02	0.09	0.05	0.10	0.11	0.53	1.00		
14 Type of firm	0.03	0.27	-0.22	0.09	-0.25	0.04	-0.05	0.13	0.07	0.13	0.14	0.53	0.41	1.00	
15 Young firm	0.14	-0.06	0.11	-0.03	-0.01	0.12	0.12	0.06	0.09	0.06	0.15	-0.23	0.15	-0.00	1.00

Table 3: Model I & II: Negative binomial regression models, dependent variable is non-patent literature citations and patent citations – benchmark is Platform patents (earliest invention type)
Model III-VI: OLS regressions the dependent variable is patent value.

	Model I NPL CIT	Model II PAT_CIT	Model III Compound patents	Model IV	Model V Formulation patents	Model VI
Compound patents	-0.462*** [0.097]	0.208*** [0.060]				
Utility patents	-0.260** [0.108]	0.186** [0.082]				
Formulation patents	-0.886*** [0.141]	0.484*** [0.073]				
NPL_RATIO (The total number of non- patent literature citations over total number of backward citations)			-0.482** [0.233]		0.310 [0.248]	
Citations to non- patent literature (dummy)				-0.315** [0.130]		0.254* [0.145]
Backward citations	0.132*** [0.008]	0.076*** [0.003]				
Technology scope	-0.001 [0.003]	0.002 [0.002]	0.021*** [0.004]	0.022*** [0.004]	0.102*** [0.036]	0.098*** [0.036]
Firmsize	0.000*** [0.000]	0.000 [0.000]	0.001*** [0.000]	0.001*** [0.000]	0.000 [0.003]	0.000 [0.003]
Accumulated patents in the firm	-0.003*** [0.000]	0.001** [0.000]	-0.002*** [0.001]	-0.002*** [0.001]	-0.003 [0.006]	-0.003 [0.006]
Type of firm	-0.175** [0.083]	0.032 [0.057]	0.109 [0.151]	0.104 [0.150]	-0.287 [0.244]	-0.260 [0.246]
Young firm	-0.072 [0.068]	-0.023 [0.064]	0.034 [0.180]	0.030 [0.178]	0.533 [0.364]	0.494 [0.363]
Log of patents family size	-0.074* [0.038]	0.039 [0.025]				
Patent grant	-0.100 [0.086]	0.030 [0.098]	0.284 [0.175]	0.300* [0.175]	0.266 [0.312]	0.248 [0.307]
Patent withdrawn	-0.062 [0.063]	0.081 [0.055]	-0.644*** [0.137]	-0.638*** [0.140]	-0.644* [0.332]	-0.615* [0.339]
Year of patent application	0.001 [0.010]	-0.009 [0.007]	-0.572*** [0.094]	-0.572*** [0.096]	-0.254 [0.159]	-0.260 [0.159]
Constant	-1.438 [21.036]	17.508 [13.973]				
lnalpha						
Constant	-1.555*** [0.189]	-3.397*** [0.253]	0.948*** [0.293]	1.000*** [0.293]	-0.347 [0.519]	-0.392 [0.494]
Pseudo LL	-1992775	-2185183				
No of Obs	1058	1058	547	547	110	110
Wald-Chi2	811.5829***	1263.675***				
R-squared			0.408	0.410	0.407	0.414
Adj.R-squared			.3979968	.3998012	.3536971	.3617736
F test			236.6396***	231.9679***	4.871587***	5.23622***

* p<0.1, ** p<0.05, *** p<0.01

Table 4: Coefficient estimates for percentile regression for compound patents

	.1	.2	.3	.4	.5	.6	.7	.8	.9
NPL RATIO	-0.147 [0.100]	-0.139** [0.059]	-0.158** [0.089]	-0.194* [0.102]	-0.181 [0.141]	-0.278*** [0.139]	-0.39*** [0.164]	-0.618*** [0.162]	-0.786*** [0.216]

Table 5: Negative binomial regression models , dependent variable is X-citations non patent related citations and X-citations to patent related citations – benchmark is Platform patents (earliest invention type)

	Model I X-NPR CIT	Model II X-NPR CIT	Model III X-PATCIT	Model IV X-PATCIT
Compound patents	-0.537*** [0.114]	-0.333** [0.153]	0.244** [0.100]	0.366** [0.151]
Utility patents	-0.391*** [0.088]	-0.229 [0.147]	0.391*** [0.113]	0.474*** [0.149]
Formulation patents	-1.109*** [0.195]	-1.226*** [0.290]	0.653*** [0.142]	0.478*** [0.158]
Backward citations	0.174*** [0.010]		0.118*** [0.008]	
Technology scope	0.008** [0.004]	0.022*** [0.006]	0.007** [0.003]	0.015*** [0.004]
Firm size	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]
Accumulated patents	-0.001** [0.001]	-0.002* [0.001]	0.001 [0.001]	-0.000 [0.001]
Type of firm	-0.032 [0.157]	0.274 [0.216]	0.026 [0.136]	0.209 [0.192]
Young firm	-0.272** [0.125]	0.209 [0.212]	-0.010 [0.114]	0.095 [0.155]
Log of patents family size	-0.136* [0.077]	-0.162 [0.110]	0.062 [0.050]	0.052 [0.068]
Patent grant	-0.187 [0.137]	-0.525*** [0.202]	-0.147 [0.134]	-0.358** [0.144]
Patent withdrawn	-0.047 [0.122]	-0.386*** [0.147]	-0.041 [0.091]	-0.164 [0.110]
Year of patent application	-0.015 [0.025]	-0.021 [0.036]	-0.009 [0.015]	-0.022 [0.027]
Constant	29.904 [50.419]	43.429 [72.288]	16.806 [30.309]	43.635 [53.659]
Lnalpha				
Constant	-0.276** [0.129]	0.808*** [0.106]	-0.880*** [0.125]	-0.020 [0.105]
Pseudo LL	-1.489.646	-1.715.555	-1.930.530	-2.127.699
No of Obs	1058	1058	1058	1058
Wald-Chi2	693.87***	132.9567***	817.5432***	174.7439***

* p<0.1, ** p<0.05, *** p<0.01

Table 6: TOBIT regressions, the dependent variable is patent value.

	Model V	Model VI	Model VII	Model VIII
	Compound patents		Formulation patents	
NPRcit RATIO (The total number of non patent literature citations over total number of backward citations)	-0.485** [0.231]		0.371 [0.243]	
Citations to non patent literature (dummy)		-0.316** [0.129]		0.275* [0.142]
Firm size	0.001*** [0.000]	0.001*** [0.000]	0.001 [0.003]	0.001 [0.003]
Accumulated patents in the firm	-0.002*** [0.001]	-0.002*** [0.001]	-0.002 [0.006]	-0.002 [0.006]
Type of firm	0.112 [0.150]	0.107 [0.148]	-0.359 [0.243]	-0.322 [0.241]
Young firm	0.036 [0.178]	0.031 [0.176]	0.561 [0.345]	0.517 [0.344]
Patent grant	0.279 [0.173]	0.295* [0.174]	0.263 [0.300]	0.244 [0.296]
Patent withdrawn	-0.654*** [0.136]	-0.648*** [0.139]	-0.709** [0.333]	-0.679** [0.341]
Year of patent application (three periods)	-0.578*** [0.094]	-0.578*** [0.096]	-0.300* [0.163]	-0.307* [0.162]
Technology scope	0.021*** [0.004]	0.022*** [0.004]	0.099** [0.034]	0.096*** [0.034]
Constant	0.960*** [0.291]	1.012*** [0.291]	-0.291 [0.512]	-0.333 [0.487]
sigma				
Constant	0.982*** [0.059]	0.980*** [0.059]	0.903** [0.121]	0.897*** [0.118]
No of Obs	547	547	110	110
Uncensored o~s	546	546	107	107
Log likelyhood	-7.653.264	-7.645.137	-1.433.748	-1.426.831
Pseudo R-squ~d	.1582612	.1591551	.1688589	.1728685
F test	227.8537***	225.8094***	5.401116**	5.818047***

* p<0.1, ** p<0.05, *** p<0.01

Table 7: Negative binomial regression models for compound and formulation patents, dependent variables patent value measured by forward citations and family size.

	Compound patents			Formulation patents				
	Model IX Forward citations	Model X Family size	Model XI Forward citations	Model XII Family size	Model XIII Forward citations	Model XIV Family size	Model XV Forward citations	Model XVI Family size
NPRC:it_RATIO (The total number of non patent literature citations over total number of backward citations)	-0.552** [0.267]	-0.242* [0.130]	-0.302** [0.128]	-0.137** [0.065]	0.127 [0.300]	0.260 [0.213]		
Citations to non patent literature (dummy)							0.178 [0.147]	0.149 [0.127]
Firm size	0.001* [0.000]	0.001*** [0.000]	0.001*** [0.000]	0.001*** [0.000]	0.010** [0.005]	-0.004 [0.004]	0.010** [0.005]	-0.004 [0.004]
Accumulated patents in the firm	-0.002*** [0.001]	-0.002*** [0.001]	-0.002*** [0.001]	-0.002*** [0.001]	-0.026* [0.013]	0.011** [0.005]	-0.025* [0.013]	0.011** [0.005]
Type of firm	0.229* [0.132]	0.045 [0.122]	0.227* [0.130]	0.042 [0.122]	-0.420 [0.463]	-0.039 [0.200]	-0.433 [0.447]	-0.006 [0.202]
Young firm	-0.039 [0.157]	0.009 [0.105]	-0.046 [0.158]	0.008 [0.105]	0.725*** [0.270]	-0.045 [0.196]	0.690** [0.276]	-0.068 [0.196]
Patent grant	-0.099 [0.124]	0.484*** [0.073]	-0.082 [0.124]	0.495*** [0.073]	-0.034 [0.251]	0.653*** [0.169]	-0.066 [0.230]	0.637*** [0.162]
Patent withdrawn	-0.572*** [0.176]	-0.379*** [0.115]	-0.575*** [0.174]	-0.375*** [0.116]	-0.699** [0.293]	-0.237 [0.247]	-0.681** [0.298]	-0.216 [0.246]
Year of patent application (three periods)	-0.777*** [0.114]	-0.253*** [0.070]	-0.779*** [0.114]	-0.252*** [0.070]	-0.208 [0.216]	-0.359*** [0.130]	-0.227 [0.210]	-0.360*** [0.126]
Technology scope	0.012*** [0.004]	0.008*** [0.002]	0.013*** [0.004]	0.009*** [0.002]	0.082*** [0.021]	0.020 [0.013]	0.079*** [0.020]	0.018 [0.013]
Constant	2.469*** [0.328]	2.888*** [0.176]	2.495*** [0.326]	2.895*** [0.186]	0.845* [0.479]	2.594*** [0.443]	0.832* [0.494]	2.577*** [0.413]
Inalpha	-0.109 [0.098]	-1.464*** [0.121]	-0.106 [0.103]	-1.464*** [0.122]	-0.402 [0.270]	-1.310*** [0.151]	-0.414 [0.273]	-1.319*** [0.143]
Pseudo LL	-1.122.805	-1.759.003	-1.123.403	-1.759.312	-220.107	-337.322	-219.819	-337.091
No of Obs	547	547	547	547	110	110	110	110
Wald-Chi2	868.302***	691.1537***	988.8566***	690.7214***	97.05693***	140.2927***	103.9132***	141.7833***

* p<0.1, ** p<0.05, *** p<0.01

3.1 References

- Abell, P., T. Felin, et al. (2008). Building micro-foundations for the routines, capabilities, and performance links. *Managerial and Decision Economics* 29(6): 489-502.
- Achilladelis, B. and N. Antonakis (2001). The dynamics of technological innovation: the case of the pharmaceutical industry. *Research Policy* 30(4): 535-588.
- Ahuja, G. and C. M. Lampert (2001). Entrepreneurship In The Large Corporation: A Longitudinal Study Of How Established Firms Create Breakthrough Inventions. *Strategic Management Journal* 22(6/7): 521-543.
- Alcacer, J. and M. Gittelman (2006). Patent citations as a measure of knowledge flows: The influence of examiner citations. *Review of Economics and Statistics* 88(4): 774-779.
- Alcacer, J., M. Gittelman, et al. (2009). Applicant and examiner citations in US patents: An overview and analysis. *Research Policy* 38(2): 415-427.
- Argote, L. and E. Miron-Spektor (2011). Organizational Learning: From Experience to Knowledge. *Organization Science* 22(5): 1123-1137.
- Benner, M. J. and M. L. Tushman (2002). Process management and technological innovation: A longitudinal study of the paint and photography industries. *Administrative Science Quarterly* 47: 676-698.
- Benner, M. J. and M. L. Tushman (2003). Exploitation, exploration, and process management: The productivity dilemma revisited. *Academy of Management Review* 28(2): 238-256.
- Bowen, S. (2012). Testing Moderating Hypotheses in Limited Dependent Variable and Other Nonlinear Models: Secondary Versus Total Interactions. *Journal of Management* 38(3): 860-889.
- Brooks, H. (1994). THE RELATIONSHIP BETWEEN SCIENCE AND TECHNOLOGY. *Research Policy* 23(5): 477-486.
- Brown, J. S. and P. Duguid (2001). Knowledge and organization: A social-practice perspective. *Organization Science* 12(2): 198-213.
- Brown, S. L. and K. M. Eisenhardt (1997). The art of continuous change: Linking complexity theory and time-paced evolution in relentlessly shifting organizations. *Administrative Science Quarterly* 42(1): 1-34.
- Bruno Cassiman, R. V. and P. Zuniga (2007). In Search of Performance Effects of (in)direct Industry Science Links.

- Carroll, J. B. (1993). *Human Cognitive Abilities: A Survey of Factor-Analytic Studies.* , Cambridge University Press, New York.
- Cassiman, B., Di Guardo, M.C., Valentini, G. (2010). Organizing links with science: Cooperate or contract?: A project-level analysis. *Research Policy* 39(7): 882-892.
- Cassiman, B., R. Veugelers, et al. (2008). In search of performance effects of (in)direct industry science links. *Industrial and Corporate Change* 17(4): 611-646.
- Chandy, R., B. Hopstaken, et al. (2006). From invention to innovation: Conversion ability in product development. *Journal of Marketing Research* 43(3): 494-508.
- Cohen, M., R. Nelson, et al. (2000). Protecting their intellectual assets: Appropriability conditions and why US manufacturing firms patent (or not). . *National Bureau of Economic Research*.
- Criscuolo, P. and B. Verspagen (2008). Does it matter where patent citations come from? Inventor vs. examiner citations in European patents. *Research Policy* 37(10): 1892-1908.
- DiMasi, J. A. (2001). New drug development in the United States from 1963 to 1999. *Clinical Pharmacology & Therapeutics* 69(5): 286-296.
- Dimberger, D. (2011). A guide to efficient keyword, sequence and classification search strategies for biopharmaceutical drug-centric patent landscape searches - A human recombinant insulin patent landscape case study. *World Patent Information* 33(2): 128-143.
- Duguet, E., MacGarvie, M., (2005). How well do patent citations measure flows of technology? Evidence from French innovation surveys. *Economics of Innovation and New Technologies* 14, 375-394.
- Eisenhardt, K. M., N. R. Furr, et al. (2010). Microfoundations of Performance: Balancing Efficiency and Flexibility in Dynamic Environments. *Organization Science* 21(6): 1263-1273.
- EPO, USPTO, et al. (1998). Trilateral Project 24.1 Biotechnology Comparative Study on Biotechnology Patent Practices Comparative Study.
- Fleming, L. (2001). Recombinant uncertainty in technological search. *Management Science* 47(1): 117-132.
- Fleming, L. and O. Sorenson (2004). Science as a map in technological search. *Strategic Management Journal* 25(8-9): 909-928.
- Gambardella, A., D. Harhoff, et al. (2008). The value of European patents *European Management Review* 5(2): 69-84.

- Gavetti, G. (2005). Cognition and hierarchy: Rethinking the microfoundations of capabilities' development. *Organization Science* 16(6): 599-617.
- Gavetti, G. and D. Levinthal (2000). Looking forward and looking backward: Cognitive and experiential search. *Administrative Science Quarterly* 45(1): 113-137.
- Gibbons, M. and R. Johnston (1974). ROLES OF SCIENCE IN TECHNOLOGICAL INNOVATION. *Research Policy* 3(3): 220-242.
- Gittelman, M. and B. Kogut (2003). Does good science lead to valuable knowledge? Biotechnology firms and the evolutionary logic of citation patterns. *Management Science* 49(4): 366-382.
- Griliches, Z. (1984). *R&D, Patents and Productivity*, University of Chicago Press: Chicago.
- Griliches, Z. (1986). PRODUCTIVITY, RESEARCH-AND-DEVELOPMENT, AND BASIC RESEARCH AT THE FIRM LEVEL IN THE 1970S. *American Economic Review* 76(1): 141-154.
- Gupta, A. K., K. G. Smith, et al. (2006). The interplay between exploration and exploitation. *Academy of Management Journal* 49(4): 693-706.
- Gupta, P. and A. K. Bansal (2002). Patent Opportunities in Matrix-Based Oral Controlled Release Drug Delivery Systems, Part I. *Pharmaceutical Technology Europe*, 14(9): 49.
- Harhoff, D., F. Scherer, et al. (2003). Citations, family size, opposition and the value of patent rights. *Research Policy* 32(8): 1343-1363.
- Hopkins, M. M., P. A. Martin, et al. (2007). The myth of the biotech revolution: An assessment of technological, clinical and organisational change. *Research Policy* 36(4): 566-589.
- Iansiti, M. and J. West (1999). From Physics to Function: An Empirical Study of Research and Development Performance in the Semiconductor Industry. *Journal of Product Innovation Management* 16(4): 385-399.
- Jaffe, A. B., M. Trajtenberg, et al. (2000). Knowledge spillovers and patent citations: Evidence from a survey of inventors. *American Economic Review* 90(2): 215-218.
- Jensen, M. B., B. Johnson, et al. (2007). Forms of knowledge and modes of innovation. *Research Policy* 36(5): 680-693.
- Katila, R. and G. Ahuja (2002). Something old, something new: A longitudinal study of search behavior and new product introduction. *Academy of Management Journal* 45(6): 1183-1194.
- Kaushal, A. M. and S. Garg (2003). An Update on Osmotic Drug Delivery Patents. *Pharmaceutical Technology* 27(8): 38.

- Kline, S. J. and N. Rosenberg (1986). An Overview of Innovation" in Landau, R. and Rosenberg, N.: *The Positive Sum Strategy. Washington D. C. 1986, excerpt pp. 285 - 298.*
- Koenker, R. (2005). *Quantile Regression*, Cambridge University Press.
- Koenker, R. and G. Bassett (1978). REGRESSION QUANTILES. *Econometrica* 46(1): 33-50.
- Langlois, R. N. (1999). Scale, Scope and the Reuse of Knowledge. *Economic Organization and Economic Knowledge*. . S. C. a. E. Dow, Peter E. , Cheltenham, Edward Elgar. : 239-254.
- Lanjouw, J. and M. Schankerman (1997). Stylized facts of patent litigation: value, scope, ownership, . *NBER Working Paper No. 6297. National Bureau of Economic Research, Cambridge, MA.*
- Lanjouw, J. O. and M. Schankerman (2004). Patent quality and research productivity: Measuring innovation with multiple indicators. *Economic Journal*.
- Laursen, K. (2011). Keep searching and you'll find: What we know about variety creation through firms' search activities for innovation? *Forthcoming Industrial and Corporate Change*.
- Laursen, K., M. I. Leone, et al. (2010). Technological exploration through licensing: new insights from the licensee's point of view. *Industrial and Corporate Change* 19(3): 871-897.
- Leonard-Barton, D. (1992). Core capabilities and core rigidities: A paradox in managing new product development. *Strategic Management Journal* 13(S1): 111-125.
- Levin, R. C., A. K. Klevorick, et al. (1987). Appropriating the Returns from Industrial Research and Development. *Brookings Papers on Economic Activity* 1987(3): 783-831.
- Mansfield, E. (1972). CONTRIBUTION OF R AND D TO ECONOMIC GROWTH IN UNITED-STATES. *Science* 175(4021): 477-&.
- Mansfield, E. (1991). ACADEMIC RESEARCH AND INDUSTRIAL-INNOVATION. *Research Policy* 20(1): 1-12.
- Mansfield, E. (1998). Academic research and industrial innovation: An update of empirical findings. *Research Policy* 26(7-8): 773-776.
- March, J. G. (1991). Exploration and Exploitation in Organizational Learning. . *Organization Science*, : 2(1): 71-87.
- Neisser, U. (1976). *Cognition and Reality: Principles and Implications of Cognitive Psychology*, W. H. Freeman, San Francisco.
- Nelson, R. R. (1982). The Role of Knowledge in R&D Efficiency. *The Quarterly Journal of Economics* 97(3): 453-470.

- Nemet, G. F. and E. Johnson (2012). Do important inventions benefit from knowledge originating in other technological domains? *Research Policy* 41(1): 190-200.
- Nightingale, P. (2000). Economies of scale in experimentation: knowledge and technology in pharmaceutical R&D. *Journal of Industrial and Corporate Change* 9: 315–359.
- Norman, P. (2007). Patent Protection Strategies - Maximising Product Revenues. B. Insights.
- OECD (2005). A FRAMEWORK FOR BIOTECHNOLOGY STATISTICS.
- Phelps, C. C. (2010). A LONGITUDINAL STUDY OF THE INFLUENCE OF ALLIANCE NETWORK STRUCTURE AND COMPOSITION ON FIRM EXPLORATORY INNOVATION. *Academy of Management Journal* 53(4): 890-913.
- Piaget, J. (1985). *The Equilibration of Cognitive Structures: The Central Problem of Intellectual Development.*, University of Chicago Press, Chicago.
- Pisano, G. (1996). *Development Factory: Unlocking the Potential of Process Innovation.*
- Roach, M. and W. Cohen (2012). “Lens or Prism? An Assessment of Patent Citations as a Measure of Knowledge Flows from Public Research.”. *forthcoming Management Science*.
- Rosenberg, N. (1974). SCIENCE, INVENTION AND ECONOMIC GROWTH. *Economic Journal* 84(333): 90-108.
- Rosenberg, N. (1990). Why do firms do basic research (with their own money)? *Research Policy* 19(2): 165-174.
- Rosenberg, N. and R. R. Nelson (1994). AMERICAN UNIVERSITIES AND TECHNICAL ADVANCE IN INDUSTRY. *Research Policy* 23(3): 323-348.
- Sauermann, H. and P. Stephan (2013). Conflicting Logics? A Multidimensional View of Industrial and Academic Science. *Organization Science* 24(3): 889-909.
- Schumpeter, J. A. (1939). *Business Cycles*.
- Smith, W. K. and M. L. Tushman (2005). Managing strategic contradictions: A top management model for managing innovation streams. *Organization Science* 16(5): 522-536.
- Stankiewicz (2000). The concept of 'design space'. *Technological Innovation as an Evolutionary Process* J. Ziman, Cambridge University Press, Cambridge: 234-247.
- Sternitzke, C. (2010). Knowledge sources, patent protection, and commercialization of pharmaceutical innovations. *Research Policy* 39(6): 810-821.

Sternitzke, C. (2013). An exploratory analysis of patent fencing in pharmaceuticals: The case of PDE5 inhibitors. *Research Policy* 42(2): 542-551.

Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal* 28(13): 1319-1350.

Tijssen, R. J. W. (2002). Science dependence of technologies: evidence from inventions and their inventors. *Research Policy* 31(4): 509-526.

Tuahene-Gima, K. (2005). Resolving the Capability-GCöRigidity Paradox in New Product Innovation. *Journal of Marketing* 69(4): 61-83.

Tushman, M. L. and C. A. Oreilly (1996). Ambidextrous organizations: Managing evolutionary and revolutionary change. *California Management Review* 38(4): 8-&.

Webb, C., H. Dernis, et al. (2005). ANALYSING EUROPEAN AND INTERNATIONAL PATENT CITATIONS: A SET OF EPO PATENT DATABASE BUILDING BLOCKS *STI WORKING PAPER 2005/9*

Wiersema, M. F. and H. P. Bowen (2009). THE USE OF LIMITED DEPENDENT VARIABLE TECHNIQUES IN STRATEGY RESEARCH: ISSUES AND METHODS. *Strategic Management Journal* 30(6): 679-692.

Wooldridge (2009). *Introductory Econometrics - A Modern Approach*, South Western Cengage Learning.

Wooldridge, J. (2009). *Introductionary Econometrics - A modern approach*, South-Western Cengage Learning.

Yayavaram, S. and G. Ahuja (2008). Decomposability in knowledge structures and its impact on the usefulness of inventions and knowledge-base malleability. *Administrative Science Quarterly* 53(2): 333-362.

Yoo, H., C. Ramanathan, et al. (2005). Intellectual property management of biosequence information from a patent searching perspective. *World Patent Information* 27(3): 203-211.

Zahra, S. A. and M. Wright (2011). Entrepreneurship's Next Act. *Academy of Management Perspectives* 25(4): 67-83.

Acknowledgements: The authors would like to thank Thomas Rønde, Toke Reichstein, Hans Christian Kongsted, Stefano Brusoni, Ulrich Kaiser and Keld Laursen, and participants in the CBS-seminar, EPIP 2011, SEI-conference 2012, DRUID 2012 and EURAM 2013, for useful feedback. We are particularly grateful for the support received from patent experts at H.

Lundbeck A/S and to Susanne Høiberg for helping to verify the algorithm. Karin Beukel thanks H. Lundbeck A/S, Copenhagen University Faculty of Health and Science, Molecular Disease Biology and Copenhagen Business School for sponsoring this research.

CHAPTER 4

4 TYPES OF LEARNING IN COMPLEX TECHNOLOGICAL INNOVATIONS

By Lars Alkærsig, Karin Beukel, Giancarlo Lauto and Finn Valentin

ABSTRACT

The literature on organizational learning suggests that the degree of integration among bodies of technological knowledge affects the outcomes of the innovation process. However, the literature is in its infancy in terms of the relationship between the structure of the knowledge base and the degree of technological complexity of innovations. The present study investigates this relationship to provide a better understanding of it. Our empirical case is hydrocracking, a rather mature technology widely applied in the oil industry. Innovations in hydrocracking are based on the combination of elementary technologies in three technology areas: feeds and products, catalyst preparation, and refinery processing. Using detailed patent information we find that related learning matters for low-complexity innovations, whereas, a knowledge base characterized by combinations within one technology domain has both indirect and direct negative effects on the creation of complex innovations. More specifically our findings highlight the importance of complex learning, since the level of complexity of knowledge bases is a determinant of the likelihood that both high and low complexity innovations will be created.

Keywords: organizational learning, knowledge bases, complex innovations, related, unrelated, and specialized learning

4.1 Introduction

That innovations are created on the basis of recombining resources, including knowledge of technologies, has deep roots in the literature (Schumpeter 1939; Nelson and Winter 1982). Early studies focused on variation in technological knowledge bases and its effect on generating incremental, radical, and architectural innovations (Nelson and Winter 1982; Tushman and Anderson 1986; Henderson and Clark 1990). More recently scholars have tried to identify how a knowledge base composed of only a few technological elements can give rise to a large number of innovations because different patterns of combinations of technical elements can generate many alternative potential innovations (Fleming 2001; Yayavaram and Ahuja 2008). Specifically, this literature shows how variations observed in technological knowledge bases create novel innovations (Fleming 2001; Katila and Ahuja 2002), radical innovations (Majchrzak, Cooper et al. 2004), particularly useful innovations (Yayavaram and Ahuja 2008), and high impact innovations (Argyres and Silverman 2004). However, this overlooks an important characteristic of the innovations generated: their level of complexity. The literature on external search processes argues that use of scientific knowledge characterizes highly complex innovations (Fleming and Sorenson 2004); however, these contributions do not model the firm's *internal* knowledge bases in terms of what is favorable for generating inventions characterized by different levels of technological complexity. This is the research gap we address in this paper.

We do so by drawing on influential work in psychology on *horizontal* and *vertical* problem solving (Kendler and Kendler 1962) as well as more recent contributions concerning complexity in horizontal and vertical learning (Schilhab 2013). The focus on types of learning (vertical or horizontal) as determinants of more complex innovations is underpinned also by

findings in innovations studies. For instance, Majchrzak, Cooper et.al (2004) identify types of knowledge bases as determinants of the generation of radical innovations. In their study, they highlight the importance of meta-knowledge (vertical learning) for radical innovation, and how meta-knowledge is assessed differently at different levels in the process of reusing the organizational knowledge (Majchrzak, Cooper et al. 2004). We embrace the concepts of vertical and horizontal learning, and hypothesize how each of these types of learning facilitates complex innovation. By *horizontal learning* we refer to the identification of analogies and differences among technological problems with similar levels of complexity. This concept embraces known concepts such as specialized, related and unrelated learning (e.g.Argote 1993; Argote 1999; Schilling, Vidal et al. 2003; Boh, Slaughter et al. 2007; Eggers 2012). By *vertical learning* we refer to our understanding of the interrelationships between the levels at which a problem is structured –meta-learning (Majchrzak, Cooper et al. 2004). This type of learning takes account of the variation in the recombination of technologies for innovation in terms of their levels of complexity, and that each level of complexity reflects a level of meta-learning, expressed here as degree of ‘complex learning’.

By combining these elements we advance the organizational learning literature, building a theory predicting a positive effect from horizontal learning on generating medium complex technological innovations through related and unrelated learning. We predict that more complex technological inventions can be generated based only on prior experience with vertical learning at the same level of complexity. We predict also that having a (horizontal) related knowledge base and generating a medium complex technological invention is negatively moderated by possession of a less complex knowledge base. This penalizing effect is due to *lack* of vertical

learning: lower complexity learning does not enhance the organization's capabilities to combine across technological domains.

We take the empirical case of hydrocracking to explore these issues. Hydrocracking is a mature technology widely used as part of the oil refinery process to transform crude oil into high value petroleum products. Innovations in hydrocracking technology are developed by vertically integrated oil companies, refinery operators, and chemicals firms, and are anchored in three main technological areas: feeds and products, catalyst preparation, and refinery processing, and any combinations thereof. Thus, this technology provides an ideal setting to compare the learning processes developed to generate innovations based on a single technology area (e.g. a catalyst), lower complex inventions, a combination of two technology areas resulting in a medium complex technological invention (e.g. a new technology combining both the technological domain of catalysts and the refinery processing), or inventions including three knowledge domains, namely higher technological complexity inventions. As a result, each of these three levels expresses different degrees of integration. Our empirical results broadly support our theory, degree of complexity in learning is a significant determinant of the level of complexity of the innovations generated, organizations encompassing a knowledge base characterized by learning processes grounded in two technological areas are able to generate innovations characterized by medium technological complexity innovations (innovations characterized by combining two technology areas). However, this does not enable generation of highly complex technological innovations (those combining all three areas); highly technologically complex innovations require firms to develop a knowledge base characterized by learning processes grounded in all three technology areas, and to have prior experience in combining all three technology domains. We also explain the negative effects, both direct and

indirect, of having a less complex knowledge base and learning (combining knowledge from within a single technology domain), on the generation of medium technological complexity innovations and higher technological complex innovations. With respect to horizontal learning, we confirm prior studies and show the positive effects of related learning.

The remainder of this paper is organized as follows: in the first section, we illustrate the concept of vertical learning, namely the degree of complexity of the knowledge base, and then discuss the role of horizontal learning exemplified by two types of learning – specialized and related. Our empirical analysis follows, and we conclude with a discussion of some implications, limitations, and potential extensions to this research.

4.2 How firms search for multi-technological innovations

Generating a highly complex technological innovation can be seen as the challenge of recombining different knowledge bases by utilizing vertical and horizontal learning types. Even a knowledge base composed of only a few elements can give rise to a large number of innovations because different patterns of combinations of those elements may generate many alternative potential innovations (Fleming 2001; Yayavaram and Ahuja 2008). Search strategies, both internal and external to the firm, in the combinatorial space, have traditionally been conceived in terms of ‘search scope’, but more recently the dimension of ‘search depth’ has been integrated in this framework (Katila and Ahuja 2002; Laursen and Salter 2006). Search scope captures the distance of firms’ search behavior, from a cognitive or organizational point of view. Firms search locally when they build their innovations on technologies that are related to the domains in which they are specialized (Stuart and Podolny 1996) and when they rely on their internal knowledge base. Broad search scope generally refers to investigations in domains in which firms lack prior experience or competences (Schilling and Green 2011) and want to

develop new capabilities (Danneels 2002). Local search permits firms to strengthen capabilities in a given technological area, but also promotes technological path dependence by locking the firm into a technological trajectory (Dosi 1988; Arthur 1989). Search depth captures the extent to which firms repeatedly use their existing knowledge while searching for new solutions. The application of a stable set of knowledge elements permits firms to develop search routines and to improve their application of those elements. This opens up to the possibility of identifying non-obvious linkages among concepts and disclosing opportunities for recombination. However, excessive reliance on the existing knowledge base binds the firm to a specific technological trajectory (Katila and Ahuja 2002).

4.2.1 Vertical learning and complex innovations

In the case of a decomposable knowledge base (Yayavaram and Ahuja 2008), innovations can be generated at the architectural level (Henderson and Clark 1990) by establishing novel relationships among constituent technologies or modifying existing relationships. The number of technological domains that potentially can be coupled, and the number of interdependencies among their elements increase the space for possible inventions quite dramatically (Simon 1969; Fleming 2001), and also increase the complexity of the innovation process. Figure 1 provides an example of the hierarchy of combinatorial innovation in an industry characterized by three core technologies. We argue that the degree of complexity entailed in a combinatorial innovation increases with the number of basis technology areas involved, since the firm is required to learn about and define the linkages among a greater number of elements and interfaces.

Insert Figure 1 here

The literature on organizational learning (Argote 1993) suggests that a firm's knowledge base is based on the accumulation of capabilities formed through experience and learning-by-doing. In this sense, capabilities are the repositories of firm learning. Yayavaram and Ahuja (2008) introduce the concept of 'malleability' to characterize the capacity of a knowledge base to change. Firms reconfigure their knowledge bases by elaborating new conjectures about the relationships existing between their elements. In this process, firms replace existing linkages between components of the knowledge base, with new ones. Yayavaram and Ahuja (2008) suggest that a nearly-decomposable knowledge base offers search economies that allow firms to develop more useful technological innovations. We suggest that it is possible to interpret malleability of a knowledge base as the result of a learning process. Firms' decisions about which technology areas to couple are driven by routines in technological search. Learning about a technology provides guidance to firms about establishing new linkages and dissolving old ones that restrict the space for possible recombinations.

An important aspect of learning concerns how firms learn to deal with complex problems. Inspired by Schilhab (2013), we divide this process into two types of learning: horizontal learning and vertical learning. Horizontal learning is defined as the identification of analogies and differences between technological problems of the same level of complexity. Vertical learning refers to understanding the interrelationships between the levels at which a problem is structured. To exemplify the translation of knowledge developed by combining technologies from technology areas A and B to technology areas B and C can be regarded as an example of horizontal learning, since the combinatorial activity requires an analogous effort. The effort to extend the learning developed in combinatorial inventions in areas A and B to areas A, B and C is higher because it requires development of knowledge relative to the

interrelationship among all three areas. We define three levels of vertical learning: learning when combining within one technological domain (lower complex learning), learning when combining within two technological domains (medium complex learning), and learning when combining within three technological domains (higher complex learning). It is important to note that the levels of learning are characterized by a different degree of tacitness of the knowledge involved. Schilhab (2013 p.71), in line with the idea of tacit knowledge proposed in Polanyi (1962), explains that '*Obviously complex learning might take place without subjects being consciously aware. The learning is simply stored as a difference in response to certain stimuli and not as a conscious rule or strategy subjects control or are capable of volunteering verbally on request.*' Therefore, innovations building on the combination of many technology areas are characterized by higher levels of tacit knowledge because the specific patterns of combination of the constituting elements are the result of learning processes specific to each firm. Therefore, in line with the literature on organizational learning suggesting that subsequent attempts at complex technological innovations have a higher chance of success with increasing returns, we expect the following concerning *vertical learning*:

HYP 1a *The probability of generating a lower technological complexity innovation is positively associated with having experience with lower complex learning.*

HYP 1b *The probability of generating a medium technological complexity innovation is positively associated with having experience with medium complex learning.*

HYP 1c *The probability of generating a higher technological complexity innovation is positively associated with having experience with higher complex learning.*

These three hypotheses suggest strong state dependence on vertical learning, exemplified by each level of the integrating technologies, from low, medium to high complexity, which capture the degree of complexity of vertical learning at each level which, in turn, will be of benefit to succeeding inventions at the same level of complexity. However, this dependence on level of complexity also makes it difficult to change the level of complexity, something we discuss in the next section.

4.2.2 The negative effects of lower complex learning for generating medium and high complexity innovations

Another possible use of combinative capabilities refers to the situation where firms combine different technologies in the absence of multi-technological capabilities. In this case, the firm is familiar with each technology, but lacks knowledge about their mutual relationships. We suggest that combinatorial capabilities allow firms to overcome this gap. However, strong technological specialization in a narrow set of domains can cause core rigidities (Leonardbarton 1992) and competency traps (Levitt and March 1988; Levinthal and March 1993), preventing firms from further exploring novel technological domains. For this reason, we expect the following with respect to *vertical learning* across levels of complexity:

HYP 2a The probability of generating a medium technological complexity innovation is negatively associated with having experience with lower complex learning.

HYP 2b The probability of generating a higher technological complexity innovation is negatively associated with having experience with lower complex learning.

4.2.3 Horizontal learning and complex innovations

At the same time, horizontal learning can be ongoing at each of the three levels, through specialized, related, and unrelated learning (Schilling, Vidal et al. 2003). We define specialized learning as accumulated experience in innovating in one *specific* technological domain, and conceive related capabilities as accumulated experience in innovating by *combining* related but different technological fields.

The use of existing capabilities (in our case, exploiting a specialized knowledge base in a given domain) to build a new capability – such as development of knowledge based on the integration of multiple elements – has been defined as ‘competence leveraging’ (Danneels 2002; Miller 2003; Danneels 2007). Learning how to recombine specialized technological capabilities, firms develop second-order ‘combinative capability’. This concept was introduced by Kogut and Zander (1992 p.391) who refer to ‘*the intersection of the capability of the firm to exploit its knowledge and the unexplored potential of the technology*’. By using their combinative capabilities, firms can exploit their knowledge bases to pursue technological opportunities that are distant from their current knowledge. The pursuit of new opportunities can help firms to develop new competencies, decreasing the likelihood of ‘core rigidities’ setting in (Leonardbarton 1992), and the firm becoming overly reliant on a specific set of competences and excluding potentially better solutions. This idea is further elaborated through the concept of absorptive capacity, explained by (Cohen and Levinthal 1990 p.128) as,

‘the ability to evaluate and utilize outside knowledge is largely a function of the level of prior-related knowledge. At the most elemental level, this prior knowledge includes basic skills or even a shared language but may also include knowledge of the most recent scientific or technological developments in a given field. Thus, prior knowledge confers an ability to recognize the value of new information, assimilate it, and apply it to commercial ends.’

Similar the concept of combinative capability introduced by Kogut and Zander (1992), the argument is that the transfer of prior-related knowledge can provide learning about how to combine technologies, and a broader understanding of the interfaces of the technologies involved or simply may provide learning about how to communicate with engineers and researchers working predominantly in other areas. Therefore, we note that in the case of multi-technology innovations, firms may rely on combinative capabilities in the following circumstance: If the firm develops a multi-technology capability relative to the coupling of two specific technological domains – e.g. it knows how to deal with the interdependencies and complementarities of two given technologies – and applies it to generate recombinant innovations involving other domains. In this case, the firm is experienced in generating combinatorial innovations but lacks specific knowledge within the technological domains that are coupled. The theory on ‘competence leveraging’ suggests that cumulated experience in technological coupling in a given domain can be fruitfully applied in another domain. Therefore, we expect, in regards to horizontal learning:

HYP 3 The probability of generating a medium technological complexity innovation is positively associated with having experience with related medium complex learning.

4.2.4 Lower complex learning, related learning and complex innovations

Lower complex learning, defined as specialized learning within one core technological domain, and related knowledge bases enable firms to pursue different innovation strategies. The former permits the firm to deepen its understanding of the properties of a specific technological area even though this might lead to the development of core rigidities (Rothaermel and Alexandre 2009) that lock firms into a particular learning trajectory. The latter allows the possibility to escape such a trajectory by entailing knowledge of alternative technologies and the interfaces

that link them (Quintana-Garcia and Benavides-Velasco 2008). Thus, these two types of knowledge base have opposite effects in the innovation process. Empirically, firms may develop either type of knowledge base, or both. When the firm develops both specialized and related knowledge bases their effects interact to drive the generation of combinatorial innovation: the conducive effect of combinatorial capabilities associated with a related knowledge base is hindered by the core rigidities linked to specialization in a single technology and lack of complex learning. For this reason we expect:

HYP 4 The relationship between having a related knowledge base (horizontal learning) and generating a medium complexity technological innovation is negatively moderated by having experience in lower complex learning (vertical learning).

Figure 2 summarizes the proposed relationships in our model. In sum the suggested theory outlines which knowledge bases will be absorbed, processed, and retained, and how, during successive innovation efforts in firms, depending on the complexity of the innovation, and based on vertical and horizontal learning in technological innovation.

Insert Figure 2 here

4.3 Data & Variables

To examine our hypotheses, this study draws on a unique dataset consisting of the collective patent applications related to *hydrocracking*. We conduct our analysis at the level of the individual patent in line with prior research (e.g. Fleming 2001; Yayavaram and Ahuja 2008; Gruber, Harhoff et al. 2013), using each as a proxy for a technological invention consisting of

one or more technology areas. Aggregation of patent data has proven useful for generating firm level controls, such as technological scope of the firm (Brouwer and Kleinknecht 1999; Brusoni, Lissoni et al. 2003), and we base our approach on this knowledge. These patent data are classified into distinct technology areas within the industry at the level of each innovation, and the uses and combinations of these classifications, to indicate whether innovations combine different technology areas, and which areas are combined. In this study we offer an alternative to counting IPC classes to determine the breadth of the technology area(s) of a patent¹. With the aid of a technical expert in the hydrocracking field², we identified three distinct technology areas within the industry and to each we attributed the relevant nine-digit IPC classes. These three technology areas are used to classify all patents within our sample as covering either a single technology area or a combination of multiple technology areas. In the literature, two nine-digit IPC subclasses are considered similar if they share the first seven digits. However we found that this apparent similarity cannot be taken for granted. It is not uncommon for two IPC subclasses to share the first seven digits to describe conflicting processes or the use of different technologies within a process. Thus, two IPC subclasses that may seem very similar due to being grouped within the same seven-digit class but may be mutually exclusive and essentially describe conflicting or competing technologies. Therefore, the full informative potential of the IPC classification can only be extracted by means of expert advice, and even in large scale

¹ Previous studies looking into technology combinations in patent data rely predominantly on the *International Patent Classification* (IPC) system to determine the technological scope of the patent (Lerner 1994, Harhoff, Scherer et al. 2003). Each patent is assigned by the patent examiner to a number of nine-digit IPC classes. While examiners within the same patent office apply these codes coherently, key differences exist among regions, e.g. between the US and the EU. The primary classification of more than 50% of US patents is changed after examination by the German patent office. This lack of clarity in patent classification is more apparent when examining the use of multiple IPC classes for a single patent. In a study examining the use of co-classification of IPC codes at the 3- and 4-digit levels in a sample of 138,681 patents, Leydesdorff (2008) found a weak relation among classifications. Previous studies show that SIC and IPC codes are weakly correlated, indicating that a technology area cannot easily be defined in IPC codes, and that a technology area might cover multiple IPC codes from different parts of the classification (Cohen, Nelson et al. 2002).

² Initially we interviewed both technical experts and a patent expert working in the hydrocracking sector. After identifying the three technology classes A, B and C (and combinations hereof) we presented the technological domains and developments for each firm in the industry over time to a group of experts to test whether they could verify that the firm level results we obtained utilizing this approach were consistent with their knowledge of the industry. The experts confirmed that the findings matched their real world experience in the industry.

econometric studies the use of IPC codes should be done conducted with care and should take account of the IPC codes which, in reality, relate to competing technologies despite belonging to the same seven digit IPC classification.

Hydrocracking is a technology that is part of the later stages in the process of refining crude oil to obtain high value petroleum products. The forerunner of this technology was developed in 1927 to hydrogenate distillates from coal, and the current version, hydrocracking, is a catalytic cracking process that converts heavy hydrocarbons into higher added value, lower molecular weight compounds under hydrogen pressure (Billon and Bigeard 2001). This is a technology aimed at increasing the yield of high value products from crude oil, and converts the lower value lubricating oils and heavy gas oils that invariably result from refining crude oil into higher value products such as low-sulfur diesel fuel and jet fuel. While hydrocracking is a mature technology, the continued application of the technology in modern refineries ensures that the technology is continuously developed.

With expert help³, we identified three distinct technology areas within hydrocracking. Process technologies (A) are primarily associated with how the process of hydrocracking is integrated into the overall refinery process, and therefore includes technologies concerned with the flow of petroleum based liquids, including valves, pipes, and the associated controllers. Catalyst preparation (B) is concerned with the manufacturing process of the catalyst necessary for hydrocracking to take place. This includes both manufacture of the carrier of the catalyst (the base to which the active component in the catalyst is applied), and application of the active component onto the carrier in the manufacturing process. The area of feeds and products (C) is concerned with the chemical nature of the refinery raw materials (feeds), and the chemical

³ Refer to fin. 2 for further information.

reactions that change specific feeds into specific products. These three technology areas find application both alone and in combination with each other⁴, where, for example, patents combining the development of the active component (C) with the manufacturing technology (B) are a common combination (BC). Table 1 shows how IPC classes refer to technology areas within hydrocracking.

Insert Table 1 here

However, while the subclasses are generally related, as seen above, exceptions exist where a few specific IPC classes are mutually exclusive from the rest of the subclass. For instance, in Table 1 we exclude the IPC subclasses C10G-47/24-30 from category C (feeds and products) as these constitute a competing technology to hydrocracking, which utilizes an entirely different technology and cannot be compared to the hydrocracking process.

Our dataset is merged utilizing data from Derwent Innovation Index, EPO/OECD citations data and ORBIS. Our patent sample within hydrocracking consists of 3,902 patents applied for in the period 1977 to 2007 collected from the Derwent Innovation Index. We identified 26 firms with five or more patents in this period from the patent assignees, and collected firm level data from the Orbis database. This yielded a data set of 2,416 patents associated with these firms, with the remaining patents assigned to individuals, universities, or firms with fewer than five hydrocracking patents. In order to obtain a measure of patent value, we linked our patent data to the OECD 2010 citations database, which contains citation data for all WIPO and EPO patents. However, these data are not complete, as not all patents is applied

⁴ A combination of different technology areas is based on the nature of the innovation and the technologies utilized, not on the patent claim itself.

for to the WIPO or EPO. It is not uncommon for applications to be made on to the respective national patent office, rather than one of the international patent offices. Patents not submitted to the WIPO and EPO are usually of little or no commercial value or not sufficiently important for the firm to apply for worldwide protection. Firms in the US, Japan, and China can apply only to their respective national patent offices. Therefore, if each patent family is counted only once, if only patents that are applied for by applicants with more than five patents in total are included, and when patent families are linked to the OECD citations dataset we obtain a total of 936 patent families. The findings presented in this paper therefore may be biased towards firms with significant investments in the technology (since they have more than 5 granted patents from WIPO/EPO). Table 2 lists the patent holders in the hydrocracking industry.

Insert Table 2 here

4.3.1 Measures

The base unit of analysis in this paper is the individual patent, which is associated with patent citation data, firm level data, and the IPC classes and patent family data associated with each patent.

Dependent variables

In the first model we generate a categorical variable measuring the level of complexity of the resulting invention. The variable takes the value 0 if it is a lower complex invention, 1 if it is a medium complex invention, and 2 if it is a higher complex invention (we call this variable INVENTION_COMPLEXITY).

Next, to test hypotheses 3 and 4 about horizontal learning, we generated an outcome variable to investigate medium complex innovations indicating whether a patent is a combination of exactly two technology areas is indicated by the dummy variable `MEDIUM_COMPLEX_INVENTION`, which assumes the value 1 if a patent combines, e.g., technology areas A and B ('AB') but not technology area C.

Independent variables

Vertical learning

In the first model, we measure the effect of experience with lower complex learning, medium complex learning, and higher complex learning on the likelihood of a given patent being a lower, medium or higher technological complexity invention. Three variables are generated: `HIGH_COMPLEX_LEARNING` is a dummy variable taking the value 1 if the firm applied for patents combining all three technology areas within the previous two years.

`MEDIUM_COMPLEX_LEARNING` is a dummy variable showing whether the firm had experience in the two years prior to patent application of combining two technological areas (AB, AC or BC). To isolate the effects of having a specialized knowledge base, we use a dummy variable that takes the value 1 if the firm applied for a lower complex learning patent (A, B or C) two years prior to the patent application and 0 otherwise (`LOW_COMPLEX_LEARNING`).

Horizontal learning

In the first model, which measures the effect of prior experience and combining technology areas on the likelihood of a given patent being a combination (e.g. AB), we construct two variables. `SAME_MEDIUM_LEARNING` is a count of the number of previous patents with the same combination as the given patent (e.g. AB), and indicates the degree to which the firm is

experienced at combining exactly these two technologies; `RELATED_MEDIUM_LEARNING` is a count of the number of previous patents with other combinations of two technologies, different from those in the focal patent (e.g. AC or BC). To isolate the effects of having in-depth knowledge about the individual constituent technology areas in a combination (e.g. A and B), `LOW_COMPLEX_LEARNING` is a count of the number of previous patents covering one of the two technology areas (e.g. As and Bs). This measure includes both patents that utilize a single technology area and patents that utilize combinations of technology areas, and is a proxy for the firm's overall experience in the individual technology areas.

Control variables

We include firm level country dummies to control for regional differences, merging data from ORBIS, Derwent Innovation Index and OECD/EPO citations data (Webb, Dernis et al. 2005).

We use one dummy for EU countries as a benchmark and two dummies for the non-EU countries included in the analyses. The country dummies included are:

`DEVELOPING_COUNTRY` (for firms from China, Brazil, and South Africa, and

`OTHER_WESTERN` countries, for firms from the United States (US) and Japan. The individual firm is associated with the country where it is stock exchange listed.

At firm level, control variables are included for firm size as the log of number of employees (`LN_FIRMSIZE`), and level of firm internationalization as log of the number of branch locations (`LN_FIRMINTER`). These are included because our data include both large fully-integrated oil firms and smaller firms with a narrower focus. The size of a firm's patent portfolio is included (`FIRM_HCPATYEAR`) as a proxy for the firm's overall activity and potential expenditure on R&D in a given year, within hydrocracking. At patent level, we include a number of control variables: `AGE_PAT` is a count variable indicating number of years since

patent application. To control for patents receiving input from external scientific sources such as universities, the control NPL_CITS is included, which is a dummy variable measuring whether the focal patent cites non-patent literature. We control also for the number of inventors (INVENTORCOUNT) as well as the number of assignees (ASSIGNEECOUNT).

The degree of firm specialization (SPECFIRM) is defined as the degree to which a firm has more patents within a single technology area or a combination of technology areas, than the majority of the firm population in a given year. The majority of the population is defined as 90% of the firms, meaning that, to be identified as a specialized firm, a firm needs to have a higher share of patents within a specific technology or technology combination than 90% of the population. As the type of patent identifies the threshold it reflects the relative prevalence of the type. This variable changes over time, with some firms starting out as highly specialized but losing this label as they accumulate patents in different technology areas. The reverse occurs if the firm starts out with a broad patent portfolio but switches to developing primarily a single technology or technology combination.

4.4 Methods

Our empirical analysis is conducted in two steps. First, we explore the type of previous knowledge base that supports the generation of a patent based on either low, medium, or high complexity level. Since the variable invention complexity is an ordered categorical variable we employ a generalized ordered logit model. The purpose of our study is to understand how a knowledge base can affect the potential for creating new inventions that are either of lower, medium or higher complexity so our analyses are performed at the level of the individual invention. The model for examining the vertical learning can be written as follows:

$$Pr(\text{Invention complexity}=0,1,2|lcl, mcl, hcl, c, \beta)$$

where the probability of generating an invention with different levels of complexity depends on the firm's vertical knowledge base, lower complex learning, labeled *lcl*, experience with medium complex learning, *mcl*, and experience in higher complex learning, *hcl*, and a vector of the control variables, *c*. We cluster by firm, and since the dependent variable is ordered categorically this dictates an ordered logit. Since the parallel regression assumption was violated, we utilized a generalized ordered logit because only a few variables actually violated the parallel regression assumption. We further present the results of a generalized ordered logit, where the parallel lines constraint is relaxed only for those variables where it is not justified (using the `autofit` function in STATA).

The model examining horizontal learning can be written as:

$$Pr(\text{generate a medium technological complex invention}=1|rck, mcl, lcl, rcl*lcl, c, \beta)$$

where the probability of generating a medium complex invention depends on the firm's knowledge base, having horizontal learning experience namely *related* complex knowledge, *rcl*, meaning experience combining technologies within a related technological domain in the form at a medium complex learning level, as well as vertical learning experience namely with same medium complex learning, *mcl*, as well as lower complex learning, *lcl*, and an interaction between related learning and lower complex learning, *rcl*lcl*, and a vector of the control variables, *c*. Since medium complex invention is dichotomous, we employ logit models in the second part of our analysis. (A probit model was also tested, but did not produce different results.)

4.5 Results

Table 3 presents the descriptive results for the sample of 936 patents included in the analysis. Several interesting features emerge concerning the generation of innovations in hydrocracking technology. First, 11% of the innovations disclosed combine refinery processing, catalyst preparation and feeds and product technologies which are highly complex inventions, indicating that these complex combinations are infrequent despite the maturity of the industry and the high firm age⁵. Second, 54% of patents are combinations of two technological areas, medium complex inventions, which highlight the reliance of this industry on combining different technology areas for innovation. The remaining 34% of the sample are innovations that rely on knowledge from a single technology area, namely low complexity inventions.

The variables describing the firm's knowledge bases are the learning variables, 37% have a high complex knowledge base, 75% a medium complex knowledge base, and 82% a low complex knowledge base. The variable low complex learning, a proxy for the overall experience of the firm within a distinct technology area (A or B or C), is highly skewed, which is as expected due to the number of firms in our sample and the differences in their total patent portfolios. Some firms have many years of experience in working with a specific technology, others are relatively smaller and have significantly less experience in developing innovations within a certain technological area. The two variables that indicate the degree to which the firm has experience in combining two technology areas are a) experience in combining same technologies, same medium complex learning, and b) experience in combining related technologies, related medium complex learning, which are both skewed toward zero. Some of

⁵ The majority of the firms in the sample are more than 20 years old, and many are major oil companies that have been in the industry for more than 50 years.

these zeros are inevitable as some technology combinations are bound to be novel for the individual firm.

Insert Table 3 here

Table 4 presents a correlation matrix of the dependent and independent variables. Some of our independent variables are highly correlated which is as expected. For example, prior experience within a certain technological field, same low complex learning, is highly correlated (0.86) with having prior experience with combinatorial innovations (same medium complex learning). This is because medium complex learning essentially provides two different learning effects; the firm gains experience in the same medium complexity invention following a traditional learning curve, and also increases its combinative capability, essentially using prior-related knowledge to develop different medium complexity inventions.

Insert Table 4 here

Similarly, R&D activity within hydrocracking technology in Year t (FIRM_HCPATYEAR) also correlates with the probability of having previous technological learning within a technological field (low complex learning), or combinatorial experience within the field (medium complex learning) or a related area (related medium learning). No independent variables approach a 0.7 correlation with any of the dependent variables. However, we were conscious of the high correlation between some of the variables when interpreting our results, and performed the necessary tests (including VIF and robustness checks) to ensure the reliability of our results.

Our first estimation are done using a generalized ordered logit, presented in Table 5, Model 1 and a generalized ordered logit and with the autofit function described above in Model 2. Since it is an ordered logit model the upper part of the estimations show category 0 (low complex invention) which contrasts with categories 1 and 2 (medium and high complex inventions) and the lower part compares categories 0 and 1 (low and medium) with category 2 (high). First we analyze the control variables, whether they change across models. One variable (SPECFIRM) the degree to which the firm has more patents within a single technology area or a combination of technology areas than the majority of the firm population in a given year, is significant and negative when contrasting low and medium categories with high, telling us that a specialized firm is less likely to generate a high complex invention. However, this result is not confirmed in Model 2. The variable SPECFIRM does not violate the parallel-lines assumption (0.893 and 0.533), whereas in model 2 it is constrained, and the negative significance (* $p < 0.1$) of being a specialized firm becomes insignificant.

Table 5 refers to our analysis of vertical learning, first in relation to hypothesis 1a which proposes that having a knowledge base consisting of prior lower complex learning should be associated with generating lower complexity innovations. We find support for hypothesis 1a since lower complex learning is negative and significant in three out of four estimations, meaning that possession of a lower complex knowledge base will increase the likelihood of generating low complexity inventions (upper part of the model) or low and medium complexity inventions (lower part of the model). Our hypothesis 1b states that vertical learning at the medium level will also be present, such that the probability of generating a medium complexity invention will be associated with prior experience with medium-complex learning. We would expect therefore that the estimations for medium complex learning when contrasting category 0 (low) with 1 (medium) and 2 (high) would be positive and significant, this is not the case in

Model 1; but in Model 2, to increase our understanding of generating medium complex inventions, we estimate a logit model for the probability of generating a medium complex invention. The estimations, presented in Table 6, Models 4, 7 and 8, show positive and significant coefficients for medium learning (inserted in this model as the count of previous experience in the same medium combination); these models suggest a positive and significant relationship, which supports hypothesis 1b. However, since the estimates are related to a limited dependent variable, we compute, at each observation, the value of the marginal effect, its standard error, and Z-statistic, in order to test the significance of each value to see whether the results in Table 6 hold (Wiersema and Bowen 2009). To estimate the direct effect of our explanatory variable we investigate the marginal effects; because it is a limited dependent variable we examine the effects following Wiersema and Bowen (2009). We use the following equation to estimate it:

Marginal Effect of X =

$$= \frac{\partial \Pr(\text{INVENTION} = 1 | V, \beta)}{\partial X}$$

$$= \frac{\partial \pi(V\beta')}{\partial X} = \pi(V\beta')\beta_x$$

This indicates that the marginal effect of X is proportional to its model coefficient, β_x . Here we can see that the value and significance of X is not given by the estimates of the model coefficients. We therefore compute, at each observation, the value of the marginal effect, its standard error and Z-statistic in order to test the significance of each value, and we investigate the marginal effects using the graphical plots in figure 3. The blue dots represent marginal effects values (recorded on the left axis), and the red dots represent Z-values (recorded on the

right axis). As shown in the graphical representation the marginal effects of having the same medium complex knowledge base for generating a medium complexity invention range from 0 to 10.855. The Z-values associated with most marginal effects exceed 1.28 (0.10) in absolute value, except at very high and very low probabilities of generating a medium complexity invention. Since the slope of the logistic distribution approaches zero at the extremes, the lack of significance at the extremes is expected (Wiersema and Bowen 2009). Analysis of the graphical representation together with the logistic regression in table 6, and the results of the generalized ordered logit model in table 5 provide support for hypothesis 1b of a positive significant relationship between having experience in the same medium complex learning and generating a medium complexity invention.

Insert Table 5 & 6 and Figure 3 here

The third hypothesis concerning vertical learning (hyp 1c), suggests that we will also find a positive association between prior experience in high complex learning and generating highly complex inventions. The results in the ordered logit, models 1 and 2, confirm this relationship; in the robustness section we examine this hypothesis in a logit model, estimating the probability of also generating a highly complex invention.

For hypothesis 2, we investigate the proposed negative effect of having experience in lower complex learning (a specialized knowledge base) for generating both medium technological complex inventions (H2a) and higher technological complex inventions (H2b). The results from the generalized ordered logit model support the proposed relationship but we also investigate the relationship in separate logit model. With regard to H2a, which concerns the role of specialization in a single technological knowledge base, Model 6 in table 6 shows a

positive effect of prior experience in the domains that constitute combinatorial technology. Such an effect should be considered spurious, as the relationship turns negative and significant in Models 7 and 8, where we introduce the variables related to medium technological knowledge bases, the multi-technological knowledge bases, and the interaction effect. This means that for any level of multi-technological knowledge bases, increasing the focus on specialization in a single technological knowledge base reduces the firm's ability to innovate across technological domains. This is consistent with the concept of 'core rigidities'. The graphical plot in Figure 4 presents the marginal effects and the associated Z-values for low complex learning. The blue dots represent the values of the marginal effects (recorded on the left axis) and the red dots represent the Z-values (recorded on the right axis). The marginal effects of low complex learning range from 0 to -0.494. As shown in the graphical representation, the Z-values associated with most marginal effects exceed 1.28 (0.10) in absolute value except at very high and very low probabilities of generating a medium complexity invention, confirming hypothesis 2a. In H2b we hypothesized that the probability of generating a highly complex innovation, would be negatively associated with previous experience in patenting in the individual constituent technological domains. We found support for this hypothesis since having a low complex knowledge base is negatively associated with generating both medium and high complexity inventions (see table 5). This suggests that specialization, through lower complex learning, penalizes organizational meta-learning and the firm has a negative probability of generating a highly complex innovation.

 Insert Figure 4 here

The prediction of H3, that the probability of a firm generating a medium technological complexity invention is positively associated with previous experience in patenting across the related two technology domains, can be tested only with regard to inventions combining two technology domains. In Table 6 Models 5, 6 and 7, and the graphical analysis in Figure 5 provide support for hypothesis 3. In other words, we find that combinatorial innovations in a given domain benefit from the firm's experience in a related domain, signaling the existence of combinatorial knowledge bases, also when controlling for the effect of the same knowledge base. To investigate the relationship between the same and related medium knowledge bases we conducted a Wald test. The results from the Wald test are significant and positive (56.60***) indicating that the same knowledge (vertical learning) is significantly more important for generating new medium complex inventions than related knowledge (horizontal learning).

 Insert Figure 5 here

To test hypothesis 4 that the relationship between having a related knowledge base and generating a medium complex invention is negatively moderated by having a specialized knowledge base, we follow the method presented by Ai and Norton (2003) on true interaction effects. We find that the interaction effect is statistically significant in Model 8 (-0.005***), which examines the marginal effect of having same low complex learning (moderating variable) on the relationship between related medium learning and generating a medium complexity invention. As with the marginal effects examined in the main effects, we apply the graphical plot presented in figure 6 to investigate each observation. As shown, the value, sign, and significance of the true interaction effect differ greatly over the range of predicted values for medium complex inventions. The values of the true interaction range from -.0296 to .0294; the

Z-values range from -2.680 to 2.793. Model 8 shows that the interaction effect is negative and significant; however, figure 6 shows a more complex relationship. As shown in figure 6, the interaction effect is mainly positively significant at lower values of a medium complex invention, when the probability of generating a medium invention is below 0.4; however, there are also significant observations after 0.65. Although the effect is strongly negative, there are a few dots that are also significantly positive. The results provide support for the hypothesis that having a high number of specialized knowledge bases has a negatively moderating effect on the likelihood of the firm generating medium complexity inventions on the basis of related medium complex knowledge.

Insert Figure 6 here

4.6 Robustness

The results presented in Tables 5 and 6 broadly support the hypotheses proposed in this paper, however, additional robustness checks were conducted. We investigated whether experience in high complex learning generates highly complex inventions, using a logit model. The results of Models 12 and 13 in Table 7 indicate that hypothesis H1b is confirmed. In the graphical plot in Figure 7, we depict how having a prior knowledge base for generating higher complexity inventions has a marginal effect on the probability of generating a highly complex invention. Figure 7 shows that for lower values of the dependent variable, there are more insignificant observations, but significant at the mean, which means the shift could be due to the effect of the vector. Therefore, the positive impact of high complex learning on new higher technological complexity inventions is not strong, except when the value of the dependent variable is above approximately 0.2. In this case, the results are constantly significant but very

few observations fall within this value distribution. This means that having knowledge based on experience in high complex learning has a positive and significant effect on the firm's generating another invention of the same kind, and this applies to both levels of complexity (lower and higher). However, the effect is much stronger for medium technological complex inventions than for higher technological complex inventions, since higher technological complex inventions are only constantly significant when the value of the dependent variable is above 0.2. Despite the importance of the insignificant results for higher complex learning the tests confirm H1b and H1c.

It has been argued that time compression (Dierickx and Cool 1989) and related absorptive capacity (Cohen and Levinthal 1990) have an impact on the process in which learning takes place in organizations. To test whether controlling for this effect influences our results, we added a variable 'TIME COMPRESSION' to our model to measure time (in years) from the firm's last invention of the same technological type (A, B, C, AB, etc.). Using such a control variable limits the number of observations to 832, as observations where the firm has no prior experience within the field are generated as missing variables. We run all models (Model 1 to 13) controlling for time compression. We present results including time compression variable for both medium complex inventions (see Table 8) and high complex inventions (see Table 9). The variable for time compression is positive and significant for generating highly complex inventions, indicating that the longer the time since the creation of the last highly complex invention, the higher the probability of generating another. Time compression is also significant for medium complexity inventions, however, this is not consistent across all models. Adding the time compression variable as a control does not change our findings with regard to our explanatory variables. We tested also for the effects of time compression with respect to high

complexity inventions to investigate the effects of changing the lag time to one year instead of two. Our main results are confirmed: high complex learning proves again to be significantly positive while low complex learning is significant and negative. This result suggests that very accurate timing is an issue in learning based on specialized knowledge and indicates that reaping the rewards of specialized knowledge is more dependent on timing than in the case of knowledge combining technological areas and related knowledge bases.

In respect to generating high complexity inventions we investigated the findings using count variables for our three explanatory variables of low complex learning, medium complex learning and high complex learning, measuring whether the firm has that type of knowledge base and the extent of the type of learning. The results are confirmed and are similar to the results in Model 13; however, the model has some multicollinearity issues, suggesting a bad fit (table not included here but available from authors).

4.7 Discussion and conclusion

The findings reported above provide support for our contention that innovations characterized by highly complex configurations rest on the firm's prior experience in developing innovations that combine different technological knowledge (i.e. multi-technological innovations) rather than *combining* specialized bodies of technological knowledge. This puts firms with specialized knowledge bases at a disadvantage in complex technological domains, since combinative capabilities are of no advantage for recombining specialized knowledge for complex innovation. Below, we explore the implications of our findings for the innovation literature and also its value for studies of organizational learning.

In line with the resource based view and organizational learning theories, the initial part of our analysis provides support for the contention that the firm undergoes a process of organizational learning (Argote 1993), in which the firm accumulates different types of knowledge to create a knowledge base that underpins the ability to develop new innovations (Penrose 1959; Nelson and Winter 1982; Wernerfelt 1984). The knowledge bases we explore are technical capabilities and combinative capabilities (Kogut and Zander 1992). The analyses in this paper suggest that technical capabilities are less important than combinative capabilities for generating innovations based on combinations of technology areas. This study confirms prior studies in the organizational learning literature indicating that not all learning is equally difficult and therefore equally valued (Eggers 2012). This study also reaffirms some of the main conclusions in the learning and organizational literature by emphasizing that the ability to develop more difficult innovations is dependent on the prior learning in the organization, that acquiring combinative capabilities can be done in related areas, and that this increases the probability of creating more complex innovations (Schilling, Vidal et al. 2003; Clark and Huckman 2009). We contribute to the discussion on related combinative capabilities by providing evidence that the effects of related combinative capabilities disappear when firm acquire the specific combinative capability in question. Related combinative capabilities can be an important step in learning, but have demarcated effects. However, as the technological complexity of a combination increases, the effect of related combinative capabilities diminishes. When firms attempt to innovate using all three technology domains – the most complex type of patent – only prior experience in combining all three technology domains has a positive effect. Furthermore, experience within the individual constituent technology domains has a negative effect on the ability of the firm to generate patents encompassing all three technology domains.

This highlights the steep learning curve associated with complex technological domains, where only prior experience or serendipity are helpful.

The current study is limited by the empirical context. Our study is limited in explaining how firms can reach high complex learning, developing technologies consisting of all three technology areas in the industry. Our setup does not allow us to test whether horizontal learning is beneficial at the highest level of complexity, nor did we find firm level indicators, that could be used to predict this. Also, the use of patent data does not come without some level of unobserved heterogeneity. While firms active in the hydrocracking industry would appear to be highly active in patenting, some inventions might not lend themselves to patenting. The knowledge may be kept secret within the firm, or disseminated publicly through scientific publications. While the exact level of non-patented inventions and the utility these inventions is unknown, this bias is likely similar across all firms within the industry, which means our findings would be unaffected.

4.8 Figures and tables

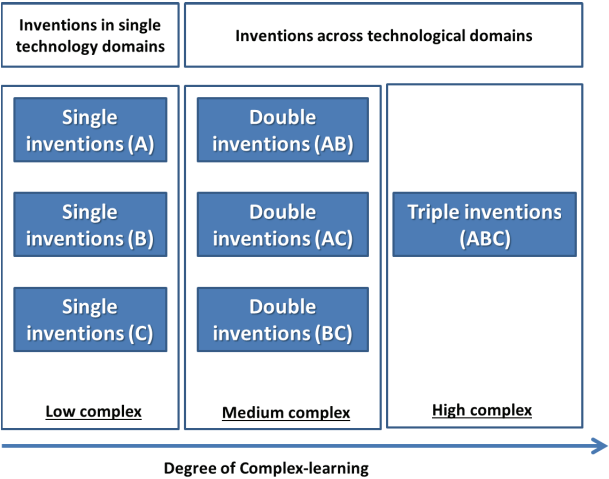


Figure 1: Vertical learning, low, medium or high degree of complex learning

Learning approach	Vertical ('complex learning')	Experience with low complex learning	+ (hyp 1a)		
		Experience with medium complex learning		+ (hyp 1b)	
		Experience with higher complex learning			+ (hyp 1c)
	Horizontal learning	Experience with lower complex learning		÷ (hyp 2a)	÷ (hyp 2b)
		Related prior experience		+ (hyp 3)	
		Experience with lower complex learning moderates related prior experience		÷ (hyp 4)	
			Low complex inventions	Medium complex inventions	High complex inventions
			Degree of Complexity		

Figure 2: Hypothesized relationship between learning approach and technological complexity of innovations.

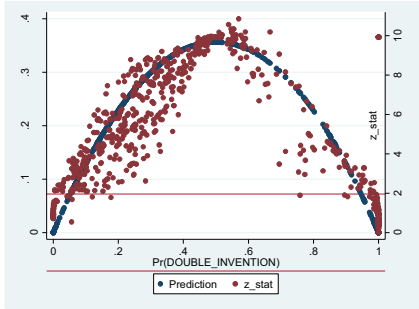


Figure 3 Analysis of the marginal effect of vertical learning at medium level on the probability of generating a medium complex invention

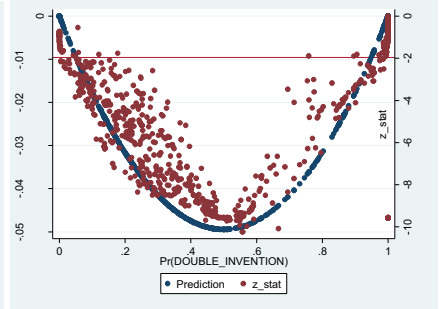


Figure 4: Analysis of the marginal effect of vertical learning: having the low complex learning on the probability of generating a medium complex invention

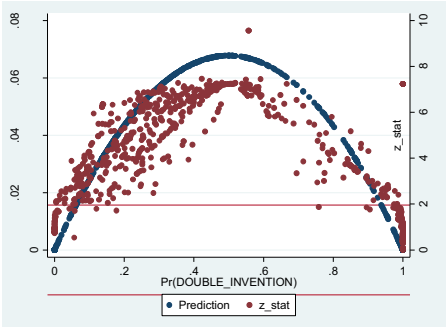


Figure 5 Analysis of the marginal effect of horizontal learning: related learning on the probability of generating a medium complex invention

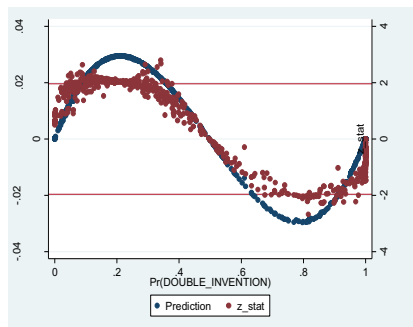


Figure 6: Analysis of the interaction effect of lower complex learning (specialized knowledge) on a related knowledge base and the probability of generating a medium complex invention

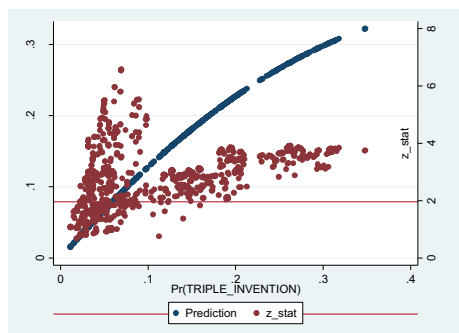


Figure 7: Analysis of the marginal effect of having vertical learning at high level on the probability of generating a high complex invention

Table 1 – Hydrocracking technology areas and IPC classes⁶

Step 1: Identifying all patents in hydrocracking, IPC codes and words phrases

IPC classes: IPC=C10G47/* OR ((C10G63/04 OR C10G63/08 OR C10G65/10 OR C10G65/18 C10G49/* OR C10G45*) AND (hydrocrack* OR (hydrog* crack*)))

Step 2: Identifying the technological domains within hydrocracking

Technology area	Associated IPC classes	Excluded IPC classes
Process technologies (A)	C10G-065/00 B01J-008/00	
Catalyst preparation (B)	B01J-021/00 to B01J-049/00	B01J-023/76 B01J-029/00
Feeds and products (C)	C10G-045/00 C10G-047/00 C10G-049/00	C10G-045/44 C10G-045/54 C10G-045/58 C10G-047/24-30

⁶ IPC classes ending in /00 signify that all nine-digit subclasses within the seven-digit class are included, unless otherwise noted.

Table 2 – Distribution of patents and firm-year observations

Firm name	Total patents	Total years
ExxonMobil	265	30
Shell	190	29
IFP Energies Nouvelles	104	24
Chevron	90	26
UOP	73	23
Dow Chemical	32	8
Albemarle	20	9
Japan Energy	20	12
British Petroleum	19	12
Conoco	17	10
Sinopec	16	10
Total	15	10
Akzo	14	10
BASF	14	10
Mitsubishi	14	6
Ashland	13	4
Grace	13	9
Eurecat	12	9
Eni	11	6
Veba	11	9
IdemitsuKosan	9	7
Haldor Topsoe	7	6
NipponKetjen	7	5
Kellogg Co.	6	5
Petrobras	5	4
Sasol	5	4
Total number of patents	936	

Table 3 Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
INVENTION_COMPLEXITY	.769	.637	0	2
HIGH_COMPL_INVENTION	.114	.318	0	1
MEDIUM_COMLEX_INVENTION	.540	.498	0	1
LOW_COMPLEX_INVENTION	.345	.475	0	1
HIGH_COMPLEX_LEARNING	.376	.484	0	1
MEDIUM_COMPLEX_LEARNING	.756	.429	0	1
LOW_COMPL_LEARNING	.829	.376	0	1
RELATED_MEDIUM_LEARNING	13.408	21.559	0	118
SAME_MEDIUM_LEARNING	9.752	15.009	0	77
SAME_LOW_LEARNING	51.059	69.608	0	282
MEDIUM_AB	.036	.187	0	1
MEDIUM_AC	.131	.338	0	1
MEDIUM_BC	.372	.483	0	1
LOW_A	.051	.220	0	1
LOW_B	.210	.407	0	1
LOW_C	.083	.276	0	1
ASSIGNEECOUNT	1.839	.954	1	10
AGE_PAT	13.823	7.775	0	29
SPEC_FIRM	.199	.400	0	1
NPL_CITS	.085	.279	0	1
LN_FIRMINTERNATIONAL	1.433	1.813	0	6.302
LN_FIRMSIZE	8.007	3.687	0	1.171
INVENTORCOUNT	4.585	4.321	1	74
FIRM_HCPATYEAR	8.202	7.236	1	25

Table 4 Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	16	17	18	19	20	21	22	23	24
1 INVENTION_COMPLEXITY																							
2 HIGH_COMPL_INVENTION	0.69																						
3 MEDIUM_COMPLEX_INVENTION	0.39	-0.38																					
4 LOW_COMPLEX_LEARNING	-0.87	-0.26	-0.78																				
5 HIGH_COMPLEX_LEARNING	0.20	0.22	-0.02	-0.12																			
6 MEDIUM_COMPLEX_LEARNING	0.14	0.10	0.05	-0.12	0.44																		
7 LOW_COMPL_LEARNING	0.06	0.04	0.02	-0.05	0.35	0.78																	
8 RELATED_MEDIUM_LEARNING	0.43	0.19	0.30	-0.45	0.43	0.30	0.24																
9 SAME_MEDIUM_LEARNING	0.35	0.01	0.44	-0.47	0.34	0.30	0.24	0.69															
10 SAME_LOW_LEARNING	0.58	0.38	0.26	-0.53	0.45	0.34	0.27	0.84	0.86														
11 MEDIUM_AB	0.07	-0.06	0.17	-0.14	-0.05	-0.03	-0.04	0.11	-0.06	-0.00													
12 MEDIUM_AC	0.14	-0.13	0.35	-0.28	0.12	0.04	0.02	0.47	0.09	0.13	-0.07												
13 MEDIUM_BC	0.27	-0.27	0.71	-0.55	-0.09	0.03	0.02	-0.06	0.41	0.17	-0.14	-0.29											
14 LOW_A	-0.28	-0.08	-0.25	0.32	0.00	-0.02	-0.02	-0.14	-0.15	-0.17	-0.04	-0.09	-0.17										
15 LOW_B	-0.62	-0.18	-0.56	0.71	-0.15	-0.12	-0.03	-0.32	-0.33	-0.37	-0.10	-0.20	-0.39	-0.12									
16 LOW_C	-0.36	-0.10	-0.32	0.41	0.00	-0.00	-0.02	-0.18	-0.19	-0.22	-0.05	-0.11	-0.23	-0.07	-0.15								
17 ASSIGNEECOUNT	0.03	0.01	0.02	-0.03	-0.01	-0.01	-0.07	0.03	0.02	0.03	-0.00	0.03	0.00	-0.06	-0.00	0.00							
18 AGE_PAT	-0.16	-0.13	-0.04	0.13	-0.19	-0.17	-0.06	-0.35	-0.27	-0.28	-0.00	-0.21	0.10	-0.02	0.19	-0.04	-0.33						
19 SPEC_FIRM	-0.02	-0.05	0.03	-0.00	-0.12	-0.14	-0.11	-0.14	-0.13	-0.19	0.00	0.02	0.01	0.04	0.03	-0.08	0.02	-0.07					
20 NPL_CITS	-0.04	-0.04	0.00	0.02	-0.06	-0.04	-0.05	-0.03	0.02	-0.01	-0.05	-0.07	0.08	-0.07	0.03	0.04	0.13	-0.05	-0.06				
21 LN_FIRMINTERNATIONAL	-0.07	-0.06	-0.01	0.05	-0.27	-0.14	-0.13	-0.19	-0.18	-0.24	0.05	-0.04	-0.00	-0.02	0.09	-0.02	-0.04	0.04	0.16	0.04			
22 LN_FIRMSIZE	-0.03	0.02	-0.06	0.05	0.01	-0.08	-0.10	0.01	0.03	0.06	0.01	-0.01	-0.06	-0.00	0.01	0.07	0.17	0.03	-0.24	0.06	0.27		
23 INVENTORCOUNT	0.04	0.03	0.01	-0.04	0.04	0.06	0.03	0.15	0.12	0.13	-0.00	0.03	-0.00	-0.04	-0.06	0.05	0.30	-0.30	0.00	0.09	-0.08	0.00	
24 FIRM_HCAPYEAR	0.09	0.09	0.00	-0.06	0.57	0.45	0.39	0.28	0.21	0.29	-0.02	0.03	-0.01	-0.01	-0.05	-0.02	-0.07	0.04	-0.20	-0.12	-0.25	-0.03	-0.00

Table 5 Generalized ordered logit, dependent variable is categorical variable Invention complexity (low, medium and high)

	Model 1 Generalized ordered logit		Model 2 Generalized ordered logit with autotfit	
0				
HIGH_COMPL_LEARNING	0.357**	[0.159]	0.365*	[0.189]
MEDIUM_COMPL_LEARNING	0.610	[0.436]	0.642**	[0.263]
LOW_COMPL_LEARNING	-0.438	[0.455]	-0.545*	[0.283]
ASSIGNEECOUNT	0.030	[0.057]	0.009	[0.077]
AGE_PAT	-0.026***	[0.008]	-0.031***	[0.010]
NPL_CITS	-0.191	[0.229]	-0.276	[0.235]
LN_FIRMINTER~T	-0.007	[0.042]	-0.017	[0.040]
LN_FIRMSIZE	-0.031	[0.019]	-0.017	[0.020]
INVENTORCOUNT	0.001	[0.014]	-0.001	[0.016]
FIRM_HCPATYEAR	-0.001	[0.017]	-0.005	[0.012]
SPEC_FIRM	0.027	[0.201]	-0.084	[0.176]
Constant	1.015***	[0.323]	1.159***	[0.338]
1				
HIGH_COMPL_LEARNING	1.461***	[0.244]	1.297***	[0.247]
MEDIUM_COMPL_LEARNING	1.820***	[0.564]	0.642**	[0.263]
LOW_COMPL_LEARNING	-2.210***	[0.797]	-0.545*	[0.283]
ASSIGNEECOUNT	-0.086	[0.081]	0.009	[0.077]
AGE_PAT	-0.048***	[0.011]	-0.031***	[0.010]
NPL_CITS	-0.702	[0.563]	-0.276	[0.235]
LN_FIRMINTER~T	-0.046	[0.050]	-0.017	[0.040]
LN_FIRMSIZE	0.006	[0.020]	-0.017	[0.020]
INVENTORCOUNT	-0.003	[0.029]	-0.001	[0.016]
FIRM_HCPATYEAR	-0.023	[0.015]	-0.005	[0.012]
SPEC_FIRM	-0.540*	[0.307]	-0.084	[0.176]
Constant	-1.286**		-2.139***	
Pseudo LL	-842100	[0.529]	-848629	[0.364]
No of Obs	936		936	
Wald-Chi2	2211.516***		76.64253***	

*p<0.1, ** p<0.5, *** p<0.001

Table 6 Logit regression, the dependent variable is medium complex innovation

	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
SAME_MEDIUM_LEARNING		0.160*** [0.059]			1.445*** [0.246]	1.368*** [0.217]
RELATED_MEDIUM_LEARNING			0.051*** [0.018]		0.266*** [0.083]	0.264*** [0.073]
SAME_LOW_LEARNING				0.012*** [0.004]	-0.199*** [0.036]	-0.128*** [0.037]
SAME_LOW_LEARNING * RELATED_MEDIUM_LEARNING						-0.005*** [0.001]
ASSIGNEECOUNT	0.068 [0.059]	0.245*** [0.073]	0.197** [0.077]	0.157*** [0.059]	0.311** [0.159]	0.338* [0.188]
AGE_PAT	-0.008 [0.011]	0.050** [0.023]	0.040** [0.019]	0.023 [0.016]	0.090*** [0.034]	0.088*** [0.033]
NPL_CITS	0.049 [0.212]	0.078 [0.355]	0.139 [0.278]	0.086 [0.256]	-0.085 [0.531]	0.125 [0.513]
LN_FIRMINTER	0.013 [0.044]	0.098 [0.085]	0.066 [0.061]	0.087 [0.056]	-0.020 [0.151]	-0.042 [0.177]
LN_FIRMSIZE	-0.040** [0.021]	-0.075** [0.031]	-0.062*** [0.024]	-0.070*** [0.026]	0.012 [0.070]	0.015 [0.075]
INVENTORCOUNT	-0.001 [0.009]	-0.017 [0.027]	-0.011 [0.024]	-0.008 [0.018]	-0.019 [0.027]	0.004 [0.019]
FIRM_HCPATYEAR	0.003 [0.008]	-0.049* [0.027]	-0.030* [0.016]	-0.024 [0.019]	-0.077*** [0.015]	-0.105*** [0.027]
SPEC_FIRM	0.085 [0.209]	0.368 [0.340]	0.282 [0.307]	0.279 [0.279]	0.053 [0.455]	0.130 [0.498]
Constant	0.415* [0.248]	-1.201** [0.491]	-0.709 [0.450]	-0.397 [0.375]	-2.582*** [0.815]	-2.872*** [0.922]
Pseudo LL	-641.979	-481.653	-576.695	-596.163	-308.275	-267.969
No of Obs	936	936	936	936	936	936
Wald-Chi2	16.9584**	66.68478***	35.54628***	40.67581***	81.37533***	143.7592***

* p<0.1, ** p<0.05, *** p<0.01

Table 7 Logit regression, dependent variable is high complex invention

	Model 9	Model 10	Model 11	Model 12	Model 13
LOW_COMPLEX_LEARNING		0.251 [0.465]			-0.762 [0.882]
MEDIUM_COMPLEX_LEARNING			0.598 [0.399]		0.567 [0.737]
HIGH_COMPLEX_LEARNING				1.362*** [0.251]	1.350*** [0.293]
ASSIGNEECOUNT	-0.149* [0.082]	-0.142* [0.083]	-0.141* [0.081]	-0.040 [0.096]	-0.051 [0.096]
AGE_PAT	-0.066*** [0.013]	-0.065*** [0.013]	-0.062*** [0.014]	-0.039*** [0.012]	-0.039*** [0.013]
NPL_CITS	-0.697 [0.486]	-0.699 [0.488]	-0.700 [0.490]	-0.708 [0.470]	-0.705 [0.470]
LN_FIRMINTER	-0.104 [0.070]	-0.103 [0.067]	-0.107* [0.062]	-0.068* [0.040]	-0.070* [0.040]
LN_FIRMSIZE	0.034 [0.022]	0.034 [0.022]	0.037* [0.021]	0.057*** [0.017]	0.058*** [0.018]
INVENTORCOUNT	0.001 [0.024]	0.000 [0.023]	0.000 [0.023]	0.000 [0.019]	0.001 [0.019]
FIRM_HCPATYEAR	0.031** [0.015]	0.028* [0.015]	0.022 [0.015]	-0.012 [0.016]	-0.012 [0.015]
SPEC_FIRM	-0.286 [0.467]	-0.279 [0.465]	-0.239 [0.460]	-0.215 [0.382]	-0.199 [0.388]
Constant	-1.267*** [0.451]	-1.499** [0.600]	-1.796*** [0.561]	-2.469*** [0.420]	-2.256*** [0.613]
Pseudo LL	-315.413	-315.235	-314.097	-303.790	-303.306
No of Obs	936	936	936	936	936
Wald-Chi2	64.05743***	68.08584***	67.25106***	122.2113***	134.3674***

* p<0.1, ** p<0.05, *** p<0.01

Table 8: Logit regression, Dependent variable is medium complex invention

	Model 14	Model 15	Model 16	Model 17
SAME_MEDIUM_COMPLEX_LEARNING	0.168*** [0.059]			2.279*** [0.643]
RELATED_MEDIUM_COMPLEX_LEARNING		0.053*** [0.018]		0.465*** [0.139]
SAME_LOW_LEARNING			0.012*** [0.004]	-0.328*** [0.091]
TIME_COMPRESSION	0.127** [0.057]	0.061* [0.034]	0.069** [0.033]	0.101 [0.111]
----- SAME CONTROLS AS TABLE 6-----				
Constant	-1.574*** [0.588]	-0.841* [0.501]	-0.519 [0.410]	-4.473*** [1.181]
Pseudo LL	-401.611	-502.715	-522.066	-192.315
No of Obs	830	830	830	830
Wald-Chi2	81.59084***	48.41278***	48.85246***	41.70356***

* p<0.1, ** p<0.05, *** p<0.01

Table 9: Logit regression, Dependent variable is high complex invention

	Model 18	Model 19	Model 20	Model 21
LOW_COMPLEX_LEARNING	1.053 [0.802]			-15.318*** [3.139]
MEDIUM_COMPLEX_LEARNING		2.020* [1.203]		16.281*** [4.886]
HIGH_COMPLEX_LEARNING			2.374*** [0.471]	2.269*** [0.436]
TIME_COMPRESSION	0.123** [0.061]	0.191 [0.155]	0.250*** [0.067]	0.374 [0.317]
----- SAME CONTROLS AS TABLE 7-----				
Constant	-2.540*** [0.927]	-3.557*** [1.379]	-3.909*** [0.623]	-4.982** [2.400]
Pseudo LL	-273.026	-269.708	-253.051	-249.569
No of Obs	830	830	830	830
Wald-Chi2	122.3347***	105.683***	689.6895***	.

* p<0.1, ** p<0.05, *** p<0.01

4.9 References

- Ai, C. R. and E. C. Norton (2003). "Interaction terms in logit and probit models." Economics Letters **80**(1): 123-129.
- Argote, L. (1993). "GROUP AND ORGANIZATIONAL LEARNING-CURVES - INDIVIDUAL, SYSTEM AND ENVIRONMENTAL COMPONENTS." British Journal of Social Psychology **32**: 31-51.
- Argote, L. (1999). Organizational Learning: Creating, Retaining and Transferring Knowledge., Kluwer Academic Publishers, Boston.
- Argyres, N. S. and B. S. Silverman (2004). "R&D, organization structure, and the development of corporate technological knowledge." Strategic Management Journal **25**(8-9): 929-958.
- Arthur, W. B. (1989). "COMPETING TECHNOLOGIES, INCREASING RETURNS, AND LOCK-IN BY HISTORICAL EVENTS." Economic Journal **99**(394): 116-131.
- Barney, J. (1991). "FIRM RESOURCES AND SUSTAINED COMPETITIVE ADVANTAGE." Journal of Management **17**(1): 99-120.
- Billon, A. and P.-H. Bigeard (2001). Petroleum Refining, Technip, Paris.
- Boh, W. F., S. A. Slaughter, et al. (2007). "Learning from experience in software development: A multilevel analysis." Management Science **53**(8): 1315-1331.
- Brouwer, E. and A. Kleinknecht (1999). "Innovative output, and a firm's propensity to patent. An exploration of CIS micro data." Research Policy **28**(6): 615-624.
- Brunsoni, S., F. Lissoni, et al. (2003). "Knowledge-relatedness in firm technological diversification." Research Policy **32**: 69-87.
- Clark, J. and R. Huckman (2009). Broadening focus: Spillovers and benefits of specialization in the hospital industry.
- Cohen, W. and P. Levinthal (1990). "Absorptive capacity: A new perspective on learning and innovation." Administrative Science Quarterly **35**(1).
- Cohen, W. M. and D. A. Levinthal (1990). "ABSORPTIVE-CAPACITY - A NEW PERSPECTIVE ON LEARNING AND INNOVATION." Administrative Science Quarterly **35**(1): 128-152.
- Danneels, E. (2002). "The dynamics of product innovation and firm competences." Strategic Management Journal **23**(12): 1095-1121.
- Danneels, E. (2007). "The process of technological competence leveraging." Strategic Management Journal **28**(5): 511-533.
- Dierickx, I. and K. Cool (1989). "ASSET STOCK ACCUMULATION AND SUSTAINABILITY OF COMPETITIVE ADVANTAGE." Management Science **35**(12): 1504-1511.
- Dosi, G. (1988). "SOURCES, PROCEDURES, AND MICROECONOMIC EFFECTS OF INNOVATION." Journal of Economic Literature **26**(3): 1120-1171.
- Eggers, J. P. (2012). "All experience is not created equal: learning, adapting, and focusing in product portfolio management." Strategic Management Journal **33**(3): 315-335.
- Fleming, L. (2001). "Recombinant uncertainty in technological search." Management Science **47**(1): 117-132.
- Fleming, L. (2001). "Recombinant uncertainty in technological search." Management Science **47**(1).
- Fleming, L. and O. Sorenson (2004). "Science as a map in technological search." Strategic Management Journal **25**(8-9): 909-928.

- Henderson, R. M. and K. B. Clark (1990). "ARCHITECTURAL INNOVATION - THE RECONFIGURATION OF EXISTING PRODUCT TECHNOLOGIES AND THE FAILURE OF ESTABLISHED FIRMS." Administrative Science Quarterly **35**(1): 9-30.
- Henderson, R. M. and K. B. Clark (1990). "Architectural Innovation: The Reconfiguration of Existing Product Technologies and the Failure of Established Firms." Administrative Science Quarterly **35**(1): 9-30.
- Katila, R. and G. Ahuja (2002). "Something old, something new: A longitudinal study of search behavior and new product introduction." Academy of Management Journal **45**(6): 1183-1194.
- Kendler, H. H. and T. S. Kendler (1962). "VERTICAL AND HORIZONTAL PROCESSES IN PROBLEM-SOLVING." Psychological Review **69**(1): 1-16.
- Kogut, B. and U. Zander (1992). "Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology." Organization Science **3**(3): 383-397.
- Laursen, K. and A. Salter (2006). Open for innovation: the role of openness in explaining innovation performance among U.K. manufacturing firms. Strategic Management Journal, John Wiley & Sons, Inc. / Business. **27**: 131-150.
- Leonardbarton, D. (1992). "CORE CAPABILITIES AND CORE RIGIDITIES - A PARADOX IN MANAGING NEW PRODUCT DEVELOPMENT." Strategic Management Journal **13**: 111-125.
- Levinthal, D. A. and J. G. March (1993). "THE MYOPIA OF LEARNING." Strategic Management Journal **14**: 95-112.
- Levitt, B. and J. G. March (1988). "ORGANIZATIONAL LEARNING." Annual Review of Sociology **14**: 319-340.
- Majchrzak, A., L. P. Cooper, et al. (2004). "Knowledge reuse for innovation." Management Science **50**(2): 174-188.
- Marc Gruber, Dietmar Harhoff, et al. (2013). "Knowledge Recombination Across Technological Boundaries: Scientists vs. Engineers " Management Science **59**(4).
- Miller, D. (2003). "An asymmetry-based view of advantage: Towards an attainable sustainability." Strategic Management Journal **24**(10): 961-976.
- Nelson, R. and S. Winter (1982). An Evolutionary Theory of Economic Change, Cambridge, Harvard University Press.
- Penrose, E. (1959). "Theory of the Growth of the Firm."
- Polanyi, M. (1962). Personal knowledge: Toward a post critical philosophy, New York, Harper and Row.
- Quintana-Garcia, C. and C. A. Benavides-Velasco (2008). "Innovative competence, exploration and exploitation: The influence of technological diversification." Research Policy **37**(3): 492-507.
- Rothaermel, F. T. and M. T. Alexandre (2009). "Ambidexterity in Technology Sourcing: The Moderating Role of Absorptive Capacity." Organization Science **20**(4): 759-780.
- Schilhab, T. (2013). "Vertical and Horizontal Learning. Some Characteristics of Implicit and Explicit Learning." Evolution und Cognition 170-177.
- Schilling, M. A. and E. Green (2011). "Recombinant search and breakthrough idea generation: An analysis of high impact papers in the social sciences." Research Policy **40**(10): 1321-1331.
- Schilling, M. A., P. Vidal, et al. (2003). "Learning by doing something else: Variation, relatedness, and the learning curve." Management Science **49**(1): 39-56.
- Schumpeter, J. A. (1939). Business Cycles.

- Simon, H. A. (1969). The Sciences of the Artificial. In Frenken, K. (2006). A fitness landscape approach to technological complexity, modularity, and vertical disintegration. Structural Change and Economic Dynamics 17(3): 288-305., MIT Press, Cambridge, MA & London.
- Stuart, T. E. and J. M. Podolny (1996). "Local search and the evolution of technological capabilities." Strategic Management Journal 17: 21-38.
- Tushman, M. L. and P. Anderson (1986). "TECHNOLOGICAL DISCONTINUITIES AND ORGANIZATIONAL ENVIRONMENTS." Administrative Science Quarterly 31(3): 439-465.
- Webb, C., H. Dermis, et al. (2005). " ANALYSING EUROPEAN AND INTERNATIONAL PATENT CITATIONS: A SET OF EPO PATENT DATABASE BUILDING BLOCKS " STI WORKING PAPER 2005/9
- Wernerfelt, B. (1984). "A RESOURCE-BASED VIEW OF THE FIRM." Strategic Management Journal 5(2): 171-180.
- Wiersema, M. F. and H. P. Bowen (2009). "The use of limited dependent variable techniques in strategy research: Issues and methods." Strategic Management Journal.
- Yayavaram, S. and G. Ahuja (2008). "Decomposability in knowledge structures and its impact on the usefulness of inventions and knowledge-base malleability." Administrative Science Quarterly 53(2): 333-362.

Acknowledgements: The authors would like to thank Maikel Pellens, Hans Christian Kongsted, Ulrich Kaiser, Keld Laursen, and participants at DRUID 2012 and AOM 2013 for useful feedback. We are particularly grateful for the support received from anonymous patent experts and scientists in the Hydrocracking industry. Karin Beukel would like to thank H. Lundbeck A/S, Copenhagen University Faculty of Health and Science, Molecular Disease Biology and Copenhagen Business School for sponsoring her part of this research.

CHAPTER 5

5 THE EFFECT OF RARITY AND UNCERTAINTY ON INNOVATION VALUE

By Lars Alkærsig, Karin Beukel and Giancarlo Lauto

ABSTRACT

This paper addresses the Resource Based View notion that rare assets enhance performance. We examine the limits of rarity as a driver of innovation. We find that uncertainty affects the innovation process, directly and by moderating the effects of rarity. Using patent data from 1977 to 2007 for firms belonging to the hydrocracking industry, we find that rarity has a U-shaped effect on innovation value, as both rare and less rare inventions are valuable to the innovation process. In addition, we find that uncertainty has an inverted U-shaped effect on innovation value. In particular, under conditions of low uncertainty, incremental innovation tends to prevail, while high uncertainty fosters imitation of successful practices. Low but not high uncertainty moderates the relationship between rarity and innovation value.

Keywords: rarity, uncertainty, knowledge spillovers, innovation, resource based view, patent value

5.1 Introduction

A vibrant scholarly debate has emphasized the challenges of using the Resource Based View (Wernerfelt 1984; Barney 1991) as a theoretical approach to strategic management research (Priem and Butler 2001a; Priem and Butler 2001b; Hoopes, Madsen et al. 2003; Lockett, Thompson et al. 2009; Kraaijenbrink, Spender et al. 2010; Wernerfelt 2013), a debate that has been particularly focused on the shortcomings of the concept of competitive advantage (Powell 2001), the indeterminateness of the notion of value and resources (Priem and Butler 2001a; Priem and Butler 2001b) and the fact the applicability of the theory is too limited (Miller 2003; Gibbert 2006; Levitas and Ndofo 2006). Recently, one of the core concepts of the Resource Based View – the notion that the rarity of a resource or of a capability contributes to a firm’s performance – has been questioned and, for the first time, empirically tested. It has been observed that firms benefit from rare *combinations* – rather than rare individual resources and capabilities (Kor and Leblebici 2005; Teece 2007; Newbert 2008) – and that it is the rarity of dynamic but not ordinary capabilities that matters for firm performance (Drnevich and Kriauciunas 2011). These contributions emphasize the need for an improved framework as well as for systematic empirical evidence of the theorized propositions of the Resource Based View.

We contribute to this debate by investigating the conditions under which *rare* and *less rare* capabilities contribute to firm performance. Following Drnevich and Kriauciunas (2011), we qualify a capability as “rare” when it is developed and used only by one or a few firms in an industry. Furthermore, we analyze the role of uncertainty as a key moderating factor with respect to the value captured by either rare or less rare capabilities. Uncertainty has been highlighted as an important theoretical concept in the Resource Based framework (Foss and Knudsen 2003), but our knowledge of its impact remains limited (eg. Schmidt and Keil 2013).

In this paper, we seek to deepen our understanding of the concept of resource value by examining a crucial function of sustainable competitive advantage: innovation management. We explore the relationship between the value of an invention, the rarity of the technological capabilities upon which it is based and uncertainty surrounding the technology associated with it. It is well known that not all inventions are patented, and a single invention may give rise to several patents pertaining to each of its components (Arundel and Kabla 1998; Jaffe 2000; Zeebroeck 2011). In any case, patents are important assets of firms and play a central role in technology management. Scholars and practitioners are increasingly interested in measuring their value (Ernst 2003; Gambardella 2013).

A patent is both an asset of a firm and an expression of its technological capabilities (Trajtenberg 1990). Within the theoretical framework of the Resource Based View (eg. Wernerfelt 1984; Barney 1991), it has been proposed that firms not only acquire but also develop resources internally (Dierickx and Cool 1989). It is then possible to argue that firms that develop unique technological capabilities and protect them by means of patents –legal tools that protect firms from imitators – may achieve a competitive advantage. This theoretical approach suggests an association between the rarity of a technological capability and the contribution to performance of the patented invention that exploits that capability. However, we argue that not only are rare technological capabilities used in innovations valuable and a source of competitive advantage but that innovations that are closely related to complementary innovations are likely to build on less rare technological capabilities, which helps to explain why less rare capabilities are also valuable.

Our study moves one step further, suggesting that the value of technological capabilities is not fully explained by their rarity (or less rare) but that their value is also contingent on uncertainty in the technological environment. The *uncertainty* that characterizes a technology or set of interrelated

technologies depends on the dynamics of demand (Fontana and Guerzoni 2008), the stage of development of the technology and the existence of competing technologies (Ragatz, Handfield et al. 2002). Uncertainty tends to increase the value of less rare technologies, in particular because uncertainty tends to increase with technological complexity (Tushman and Rosenkopf 1992). Indeed, uncertainty increases transaction costs, which ultimately increase operational costs (Artz and Brush 2000).

We suggest that companies achieve a competitive advantage when they develop technological capabilities that are consistent with the degree of technological uncertainty of the environment in which they compete. We use the empirical case of hydrocracking to explore these issues. Hydrocracking is a mature technology widely used in the oil refining process in transforming crude oil into high-value petroleum products. Innovations in hydrocracking are based on both rare and less rare combinations of technological capabilities, making it an ideal setting in which to explore the effects of technological rarity. Furthermore, the degree of uncertainty surrounding this technology has fluctuated, particularly after 1970.

The findings of our study show, consistent with expectations, that both rare and less rare technological capabilities result in above-normal returns in terms of patent value and that the relationship between uncertainty and value is inverted U-shaped. The benefits from increasing uncertainty are subject to negative returns, indicating that there is a point at which higher levels of uncertainty become unfavorable. Finally, we find that low uncertainty has a negative moderating influence on the relationship between rarity and patent value.

This paper contributes to the ongoing debate regarding the academic standing of the Resource Based View, providing an empirical test of its core propositions and more clearly specifying to what extent rare resources and capabilities contribute to competitive advantage. In addition, it addresses a central issue in Management of Innovation, namely, the generation of inventions, and provides insight into the internal and external conditions that support the invention process. Such insights, by helping to characterize the features of an environment conducive to innovation, provide managers with information relevant to the organization of Research & Development (R&D) activities.

The remainder of this paper is structured as follows. First, we introduce key theoretical concepts and develop our hypotheses. This is followed by an overview of the data and the methodology used, the presentation of our empirical findings and, finally, a discussion of our results.

5.2 Effects of rarity and uncertainty on individual innovation value

5.2.1 Rarity of competencies and value of innovations

The Resource-Based View (Penrose 1959; Wernerfelt 1984; Barney 1991; Teece, Pisano et al. 1997; Hamel and Prahalad 1993; Teece, Rumelt et al. 1994) is one of the leading theoretical frameworks in Strategic Management (Rouse and Daellenbach 2002; Newbert 2008), providing a powerful tool to examine the relationship between the accumulation of technological capabilities and the value of technological innovations. This theoretical approach argues that a sustainable competitive advantage is achieved through bundles of valuable, rare, inimitable, and/or non-substitutable resources and capabilities. If a resource or competence enables a firm to reduce costs and/or respond to environmental opportunities and threats, it is valuable to the extent that a firm can effectively deploy such resources or capabilities, it will attain a competitive advantage (Barney 1991). According to this perspective, patents are a competitive advantage-enabling asset, as they protect inventions from imitation. The resource-

based perspective thus helps us to understand how the internal environment of the firm affects the process of innovation and how the values of resources and competencies are associated with their 'rarity'.

The idea that invention results from a process of recombination of knowledge regarding the components of a product or the reconfiguration of a product's architecture is well established in the management of technology literature (Henderson and Clark 1990; Fleming and Sorenson 2004). Deepening knowledge of specific technological components adds to the technological capability of a firm, which is distinct from the architectural capability of a firm and consists of combining different technology areas. Increased knowledge of technological components and original recombinations of them are sources of technological innovation (Makri, Hitt et al. 2010).

It has been argued that the rarity of a combination of capabilities related to a specific functional area is a driver of competitive advantage (Newbert 2008), and studies of technological capability have shown that the rarity of such combinations is associated with the ability to produce innovations that are rare in the market (Danneels 2002; Miller 2003; Danneels 2007). However, less rare capabilities also contribute to competitive advantage. This is the case with capabilities that all firms in an industry should possess to compete effectively (Winter 2003) or that represent effective ways to address common technical problems and are thus adopted homogeneously by firms in an industry (Eisenhardt and Martin 2000). Broad diffusion of a capability generates a shared knowledge base that firms in an industry can exploit through imitation and incremental development, as existence of such a pool of knowledge reduces the costs associated with imitation and incremental development of a capability (Aghion and Howitt 1998). Under such conditions, the cost of using a common resource

is less than that of developing a unique resource or capability internally (Greve 2009; Drnevich and Kriauciunas 2011).

With regard to the management of innovation, less rare capabilities provide two additional sources of value. First, a rare capability represents discontinuity with the existing technological base of an industry. This may be a source of competitive advantage, but at the same time, reliance on rare technological capabilities limits the possibilities for a firm to exploit the advantages of complementary technologies, thus limiting the strategic options of an innovating firm. On the other hand, a less rare capability may better fit with the existing capability base of an innovating firm, thus carrying more value than a rare capability (Butler 1988; Makri, Hitt et al. 2010; Wu, Wan et al. 2013). Second, the learning literature emphasizes that deepening knowledge of less rare technologies activates learning processes. Such knowledge thus becomes a strategic resource (Argote 1993; Levinthal and Wu 2010).

For these reasons, a firm's ability to generate valuable innovations may arise either from developing technological competencies that are widespread in the industry and have a broader scope of application or from creating rare technological competencies that may sustain the generation of discontinuous innovations. We also consider an "intermediate" strategy that consists in developing capabilities that are neither rare nor less rare. Innovations with an intermediate level of rarity could have the disadvantages of both rare and less rare innovations, without being attributed with the value associated broad diffusion or rare resources. Thereby innovations with an intermediate level of rarity would experience relatively lower value compared to rare and less rare innovations.

For this reason, we expect:

Hypothesis 1: The relationship between the value of an innovation and rarity is curvilinear and takes a U-shape.

5.2.2 Uncertainty and innovations value

Environmental dynamics affect a firm's competence base, as they determine the possibility that a competence will be deployed to generate an innovation. In particular, substantial changes in the technological environment may make a competence obsolete, eroding its value (Danneels 2002). While rare technological capabilities can generate discontinuous innovations and thus are valuable assets of firms, they tend to be associated with a higher degree of uncertainty than are less rare technological capabilities (Fleming 2001). The process of innovation is influenced by uncertainty and serendipity, so that firms cannot predict whether their R&D efforts will succeed in generating an innovation or that such efforts constitute the most efficient strategy for addressing a research puzzle (Ahuja, Lampert et al. 2008) or that the firm's investment in complementary resources necessary to commercialize an invention will be suitable (Reitzig 2006). Furthermore, it is well known that the degree of uncertainty surrounding a given technology varies across the various stages of its development (Anderson and Tushman 1990). In addition, uncertainty pertains to the pattern of development of technology, the resources required for its elaboration (Makadok and Barney 2001), and the combined effects of market and technological forces (Souder, Sherman et al. 1998).

When a firm can easily predict the development of technologies and markets, decision-making, and the organization of R&D are relatively simple, as interpretations of consumer preferences and competitors' moves require relatively minimal computational effort. A clear picture of the environmental dynamics permits a firm to focus its R&D efforts on the development of the technological capabilities that are likely to drive a competitive advantage.

However, in conditions of low uncertainty, there is less room for differentiation, as all firms then have shared expectations of technological dynamics. Furthermore, low uncertainty can be characterized by incremental technical change, allowing little opportunity for radical innovation (Tushman and Rosenkopf 1992).

In conditions of high uncertainty, firms establish more sophisticated R&D organizations with strong inter-functional integration (Artz and Brush 2000). This allows firms to experiment with novel approaches to R&D, either increasing or reducing their investment and commitment to specific technology trajectories. In conditions in which it is difficult to assess the relative values of different technology combinations (Ragatz, Handfield et al. 2002), firms tend not to follow optimization criteria in formulating their R&D strategies but rather base their decision-making on heuristics (Bingham, Eisenhardt et al. 2007; Bingham and Halebian 2012). During uncertainty, firms tend to imitate the innovative decisions and decision-making processes of successful firms, so that innovation models diffuse quickly across an industry (Dimaggio and Powell 1983; Davis 1991; Westphal, Seidel et al. 2001; Ahuja, Lampert et al. 2008). These two opposing forces suggest that an optimal environment for innovation is one that lies between high and low uncertainty.

We thus expect:

Hypothesis 2: The relationship between the value of an innovation and uncertainty is curvilinear and takes an inverted U-shape.

This paper aims to shed new light on the effect of uncertainty on the relationship between the rarity of technological capabilities on which an innovation is built and the value of the innovation. We expect that the potential for a firm to fashion a valuable innovation out of either a rare or less rare combination of technological capabilities is contingent on the uncertainty that characterizes the pattern of evolution of the technology.

In conditions of high uncertainty, irreversible investments in the development of technological capabilities have high opportunity costs. Indeed, investments in capabilities that are suitable to a given technological trajectory may lose value if the industry shifts to an alternative technological trajectory. Firms must thus evaluate their commitment to specific technological patterns, comparing alternative options; this may lead firms to delay investment decisions as well as invest in capabilities that can be exploited in different technological domains (McGrath 1997; Leiblein 2003). In these environmental conditions, firms developing less rare technological capabilities appear to have an advantage in adapting to alternative future scenarios, provided such capabilities entail a high degree of generality. However, these environmental conditions also strengthen the value of rarer capabilities; indeed, future development of technologies can make intensive use of specific combinations of technological competencies, the value of which is thus increased vis-à-vis alternative combinations of competencies. The actual value of competencies under high uncertainty is difficult to predict; however, one can argue that rare competencies benefit from increased uncertainty.

By contrast, under conditions of low uncertainty the value of rare and less rare capabilities changes. A clear competitive and technological map of demand reduces risks associated with the development of unique capabilities (Sorenson 2000) as well investment in less rare capabilities. In these conditions, a broader range of technological capabilities becomes useful in generating

innovations – not only those at the extremes of the distribution, i.e., those that are either extremely unique or widespread in the industry. For this reason, we expect:

Hypothesis 3a: The relationship between the value of an innovation and rarity is moderated by high uncertainty, thus sharpening the U-shaped relationship.

Hypothesis 3b: The relationship between the value of an innovation and rarity is moderated by low uncertainty, thus flattening the U-shaped relationship.

5.3 Data and variables

To explore the hypotheses presented above, this study draws upon a unique dataset consisting of all the patent applications that pertain to *Hydrocracking* technology. We classify patent applications in our dataset into distinct technology areas characteristic of hydrocracking at the level of each innovation, using these as representations of the applied research outcomes within the industry (Meyer 2000). Combinations of these classifications are used to indicate whether an innovation builds upon a combination of more than one technology area. Thus, we can identify how rare a given technological combination underlying an innovation is at a given time within the industry.

The use of patent data to explore technology combinations has predominantly relied on international patent classification (IPC) codes to identify the technological scope of a patent, although prior studies have found some discrepancies in this measure (Lerner 1994; Harhoff, Scherer et al. 2003). The latter are caused in part by the IPC, as patents are assigned codes by individual patent examiners; while individual patent offices follow coherent classification schemes, regional differences have a significant effect on how a patent is classified (Harhoff, Scherer et al. 2003). This observation is supported by a prior study finding only a weak correlation between Standard Industrial Classification

(SIC) and IPC codes. The latter study, in addition, found that some technology areas are covered by different sections of the IPC (Cohen, Nelson et al. 2002). These issues are still more apparent when we consider that a single patent can be classified by multiple IPC codes, where a weak relationship is found between IPC codes at the three- and four-digit levels (Leydesdorff 2008). Therefore, to address these issues, we offer an alternative to the use of IPC classes to determine the technological scope of a patent. This is achieved through a novel approach in which IPC codes are grouped according to their technological applications through a qualitative process with the aid of a technical expert within the field. Through this process, we identify three distinct technology areas, each associated with a group of IPC codes relevant to a distinct technology area. Each patent application in our sample is classified according to one or more of these technology areas. This process highlights the deficiency of using IPC codes as an indicator of technological proximity, a deficiency that arises from the fact that IPC codes that are similar to one another in the classification scheme may cover alternative applications or competing technologies. Such issues are difficult to identify through quantitative methods, as very different IPC codes often share the first seven of nine digits in the IPC coding scheme, making it difficult to positively identify technological proximity without expert advice.

Hydrocracking is a technology applied at the later stages of the oil refining process, utilizing a process of catalytic cracking to convert heavy hydrocarbons into higher value-added, lower molecular weight compounds under hydrogen pressure (Billon and Bigeard 2001). This technology thus increases the value of refinery output through a conversion of lower-value petroleum products, such as lubrication oils, into higher-value products, such as jet fuel. While this is a mature technology originally developed in 1927 to hydrogenate coal distillates, the continued application of this technology in modern refineries ensures that the technology is continuously developed.

Hydrocracking technology has evolved over time in terms of innovation output. In Figure 1, we present patents applied for per year and the accumulated number of patents applied for in the industry. In the graph showing the number of patents applied for annually, it is clear that the industry has had its ups and downs, peaking in 1983 and 1998 and experiencing its lowest numbers of patent applications in 1979, 1992 and 2006. These fluctuations make the industry suitable for an examination of uncertainty.

Insert Figure 1 here

With the aid of an expert, we identified three distinct technology areas within hydrocracking. Process technologies (which we term ‘A’) are primarily associated with how the process of hydrocracking is integrated into the overall refining process. It therefore includes technologies involved in the flow of petroleum based liquids, for example, valves, pipes, and associated controllers. Catalyst preparation (which we term ‘B’) concerns the manufacturing process of the catalyst needed for hydrocracking to occur. This includes both the manufacture of the carrier of the catalyst (the base to which the active component in the catalyst is applied) and the application of the active component to the carrier in the manufacturing process. The area of feeds and products (which we term ‘C’) is concerned with the chemical nature of the raw materials of the refineries (feeds) and the chemical reactions that convert specific feeds into specific products. These three technology areas have applications both individually and in combination with one another⁷. For example, patents combining

⁷ A combination of different technology areas is based on the nature of the innovation and the technologies utilized, not on the patent claim itself.

the development of the active component (C) with the manufacturing technology (B) are common (BC). The table below shows how IPC classes refer to technology areas within hydrocracking.

Insert Table 1 here

However, while the subclasses are generally related, as observed above, exceptions exist. In particular, several IPC classes are incompatible with the remainder of the subclass. For instance, in the above table, we exclude the IPC subclasses C10G-47/24-30 from C, as these constitute a technology that competes with hydrocracking, one that is entirely different from and cannot be compared with the hydrocracking process.

Our patent sample within hydrocracking consists of 3,902 patents from 1977 to 2007, collected from the Derwent Innovation Index. We identified 26 firms with five or more patents in this period from the assignees of these patents and for which we have collected firm level data. This yields a data set of 2,416 patents associated with these firms, with the remaining patents assigned to individuals, universities or firms with fewer than five hydrocracking patents. To obtain a measure of patent value, we linked our patent data to the OECD 2010 citations database (Webb, Dernis et al. 2005), which contains citation data for all WO and EPO patents. However, these data are not complete, as many patents are not submitted to the WO or EPO. It is not uncommon for patents to be submitted only to a national patent office and not to the international patent offices. Patents not submitted to the WO and EPO are commonly patents of little or no commercial value or patents that are not important enough for the firm to require worldwide coverage. In particular, firms from the US, Japan, and China submit numerous patents to their national patent offices only. Therefore, when each patent family is

counted only once, when only patents that are applied for by applicants with more than five patents in total are used, when patent families are linked to the OECD citations dataset, and when the data are linked to the necessary variables, the result is a total of 934 patent families. The findings presented in this paper may therefore be biased in favor of firms with significant investments in hydrocracking technology, in that such firms have five or more patents published by the WO/EPO. But on the other hand securing a sample in which firms that tend not to focus on innovation, or have limited success in the patent application process are left out. As this in either case, the value of the resulting patents is liable to be noisy.

5.3.1 Dependent variable

PAT_VAL

Our empirical study adopts a multidimensional conceptualization of patent value, one inspired by Lanjouw and Schankerman (1999), that captures both technological importance and market value. Indeed, most of the measures available in the literature rely predominantly on forward citations (Gambardella, Harhoff et al. 2008; van Zeebroeck and van Pottelsberghe de la Potterie 2011). Our dependent variable (*Pat_Val*) combines two measures: standardized technological importance (expressed by forward citations) and standardized geographical scope (expressed by family size). Patent value is therefore defined as:

$$PAT_VAL = st(forward\ citations) + st(family\ size)$$

5.3.2 Explanatory variables

1-RARITY OF INVENTION

We develop a measure as a proxy for the rarity of a patent in the industry, one that considers both the technology area it refers to and the extent to which it results from a recombination of technological capabilities. With the help of an expert, we identified three broad technology areas that characterize the hydrocracking technology: “process technology” (category A), “catalyst preparation” (category B), and “feeds and products” (category C). Table 1 shows the IPC codes defining each category. The IPC codes that describe a given patent may be associated with one, two or all three technology categories. This allows us to propose a seven-fold classification of the technology areas of hydrocracking patents. We measure the rarity of a given patent as the ratio of the number of patents described by a given category, that is, the number of patents in the focal category up through the given year to the total number of registered patents. Rarity is defined as one minus this ratio.

$$1 - RARITY\ OF\ INVENTION = 1 - \frac{\sum Patent\ type, t_n}{\sum Patents\ types\ in\ industry, t_n}$$

As we assume a curvilinear relationship between rarity and patent value, we also include in our regression models a squared term for this variable.

UNCERTAINTY

We capture the uncertainty of the technological environment, using the measure suggested by Luque (2002) and applied in various studies, for example, Park, Park and Lee (2012). This measure considers the annual variation rate in patents generated in a given industry or relative to a given technology. Because patents denote dynamic change, negative values of the measure are related to less frequent change and hence low levels of uncertainty. In the formula:

$$\Delta P_{it-(t-1)} = \frac{NP_{it} - NP_{i(t-1)}}{NP_{it} + NP_{i(t-1)}/2}$$

the term $\Delta P_{it-(t-1)}$ represents the percentage change in the number of patents generated in industry i at time t , and NP_{it} is the number of patents assigned to industry i at time t .

As we assume a curvilinear relationship between uncertainty and patent value, we also include in our regression models a squared term for this variable. Since the unit of observation is each patent assigned to the firm, this means that the focal patent is added both to the denominator and the numerator, an option could have been to exclude the observation patent from the uncertainty measure, however, as it only affects the constant term in the regression, we decided not to, and prefer to keep the measure as applied in earlier studies.

LOW and HIGH UNCERTAINTY

The variables Low_Uncertainty and High_Uncertainty are generated as dummy variables, taking values of 1 when Uncertainty is one standard deviation below and above the mean, respectively.

5.3.3 Control variables

We apply both firm specific and patent specific controls. At the firm level, control variables are included for the firm size, operationalized as the number of employees, and for the degree of firm internationalization, operationalized as the number of branch locations. We gathered these data from ORBIS. We include these controls because our data cover both large fully integrated oil firms and smaller firms with a narrower focus. We control for industry experience, as a measure of the size of firms' R&D departments by including the total number of hydrocracking patents applied for. The degree of *firm specialization* is defined as the extent to which a firm has more patents within a single technology area or combination of technology areas than the majority of firms in the population in a given year. The majority of the population is defined as 90% of firms. Therefore, to be identified as a

specialized firm, a firm must have a higher share of patents within a specific technology area or combination of technology areas than 90% of the population. As the threshold is identified for types of patents, it reflects the relative prevalence of specific patent types. This variable changes over time, with some firms starting out as highly specialized but losing this label as they accumulate patents in different technology areas. The reverse also occurs, when a firm starts out with a broad patent portfolio but switches to developing primarily a single technology or technology combination. We also control for prior specific experience accumulated in specific patent types. This is the number of patents of a specific type in $t-1$ as a share of the total accumulated hydrocracking patents in the firm in $t-1$.

At the patent level, several control variables are included. The age variable is a count variable indicating the number of years since the patent was applied for. To control for patents receiving inputs from external scientific sources, such as universities, a dummy variable measuring whether the focal patent cites non-patent related literature is included. We also control for the number of inventors as well as the number of assignees to ensure that both the number of persons and firms behind the invention are controlled for. Other measures identified as indicators of patent value at the patent level include whether the patent is granted. We include a dummy variable that takes a value of 1 if the patent is granted. We also employ a dummy variable that takes a value of 1 if the patent has been opposed.

5.4 Statistical method and results

5.4.1 Method

To improve our understanding of the conditions under which capabilities are a source of competitive advantage and superior performance, we conducted a study aimed at assessing how the rarity of

capabilities and the level of uncertainty affect the value of a technological invention. The unit of analysis in our study is thus the individual invention, operationalized as a patent.

The empirical analysis is conducted in three stages: first, we explore the relationship between patent value and technological rarity; we then consider the effect of uncertainty; and finally, we explore the moderating effects of low or high uncertainty on the relationship between technological rarity and patent value. The dependent variable in these models (Pat_Val) is censored, as it is the product of standardized forward citations and standardized family size, with values ranging between -1.989 and 15.115. Although a Tobit model is appropriate for censored data (Wooldridge 2009), given the presence of only four observations at the lowest value and the variable has no upper bound, we rely on OLS estimations. The model can be written as follows:

$$Pr(PAT_VAL) = r, r^2, u, u^2, r * u_{low/high}, r^2 * u_{low/high}, u_{low/high}, c$$

where the probability of generating high value patents (PAT_VAL) depends on the ratio of rarity (r) and of rarity squared (r^2) and the ratio of uncertainty (u) and of uncertainty squared (u^2), a dummy for low uncertainty (u_{low}), a dummy for high uncertainty (u_{high}), and control variables denoted as (c).

Descriptive statistics are presented in Table 2, and correlations are presented in Table 3. In Table 2, it can be observed that the explanatory variable, Rarity of inventions, ranges between 0.029 and 1, with a mean of 0.465 and a standard deviation of 0.254, indicating that the data points are spread out over the range of possible outcomes. The variance in hydrocracking patents over time, showing peaks in 1984 and 1999, is presented in Figure 1. We thus observe that the technological environment

changed significantly over time. The uncertainty variable, which ranges from -1.259 to 2, with a mean of 0.149 and a standard deviation of 0.541 (indicating high variance), also reflects this.

We present pairwise correlations in Table 3. It is interesting to note the very low correlation (0.04) between the two patent value indicators, Forward citations and Family size. This indicates that the two measures might, as expected, express different dimensions of value. We will perform a robustness analysis, taking each of these indicators individually into account, to verify the results of the measure we propose for patent value.

Insert Tables 2 and 3 here

5.4.2 Regression results

Table 4 shows our regression results. Model 1 is the baseline model, which includes only the controls; in Models 2 and 3, we separately examine the effects of Rarity and Uncertainty, while Model 4 presents the fully specified model; finally, Models 5 and 6 consider the interaction between Rarity and low and high Uncertainty, respectively.

We begin our analysis by addressing *Hypothesis 1* that the relationship between the value of an innovation and rarity is curvilinear, taking a U-shape. Model 4 shows that both the linear and the squared terms for Rarity are significant, the former taking a negative sign and the latter a positive sign. This indicates a U-shaped relationship between rarity and patent value, as graphically depicted in Figure 2. This result is consistent with Model 2, which considers the effect of Rarity alone. These results support Hypothesis 1, indicating that highly valuable inventions build on either rare or less rare technological capabilities. Model 4 also provides support for *Hypothesis 2*, indicating that the

relationship between the value of an innovation and uncertainty is curvilinear and takes an inverted U-shape, as the graphical representation in Figure 3 shows. Both the linear and the squared terms for Uncertainty are significant, taking positive and negative signs, respectively. We find partial support for this result in Model 3, in which the quadratic term is slightly above the 10% significance threshold. This indicates that only a moderate level of technological dynamism is beneficial for the value of inventions.

From these models, we learn that the optimal environmental conditions for development of valuable inventions are conditions of moderate uncertainty. Models 5 and 6 aid our understanding of the drivers of value when uncertainty takes values outside the optimal zone of moderate uncertainty. While conditions of high uncertainty (Model 6) do not affect the relationship between rarity and patent value, we find statistically significant moderating effects of low uncertainty (Model 5). Figure 4 graphically shows the change in the relationship as a flattening of the curve, providing support for *Hypothesis 3b*, while *Hypothesis 3a* is not supported.

 Insert Table 4, Figure 2, 3 and 4 here

With respect to the controls, the models consistently show that patents that rely on scientific knowledge, have multiple inventors and have been granted and opposed are associated with high values.

5.5 Robustness checks

To validate the reliability of our findings, the models presented in Table 4 included both robust and clustering subcommand. We also tested the models using the `vce(robust)` subcommand to test for heteroskedacity. The results (not included, however available from authors) resembles that of Table 4,

however, Uncertainty of environment squared is becomes significant negative in the estimates resembling those presented in Model 3, instead of insignificant as in the main model. We also test for joint significance with a F-test of the quadratic terms of rarity and the quadratic term of uncertainty. The test show that they are jointly significant, proving their explanatory power to the model. To further validate the reliability of our findings, we apply a Tobit regression to the models tested using OLS. The use of a Tobit is indicated, as our dependent variable is censored; however, it presents only four observations at the lower limit. The results (which do not consider the interaction between high uncertainty and rarity) are presented in Table 5. We applied to these results the tests proposed by Wiersema and Bowen (2009) and Bowen (2012) (results not presented here), finding that they are consistent with the results of our principal model.

Insert Table 5 here

To further address issues associated with the use of a compound dependent variable, we run all models with both Forward citations and Family size as the dependent variables individually. In Table 6, we present the results of negative binomial regression models (Models 12-16), where the dependent variable is the number of forward citations, finding that the key explanatory variables maintain their signs and significance levels.

Insert Table 6 here

In Table 7 (Models 17 to 21), we also run all specifications, utilizing only the count of Family_Size as the dependent variable. Interestingly, the results are significantly different when we analyze the moderating effects in Model 21. While all the results for controls are consistent with the main results, the result for the interaction becomes insignificant, and the signs of the coefficients are the opposite of those in our main results and in the results that only take Forward citations into account. This could indicate that, during periods of low uncertainty, the family size measure as the dependent variable is less reliable, as this indicator is firm-driven.

Insert Table 7 here

In addition, tests of different specifications of specialized firms were conducted. In our main models, we use a measure of whether the firm behind an invention is specialized in terms of its patent portfolio relative to the majority of the population of firms, where the majority of the firm population is defined as 90% of firms. In robustness checks, we use two other specifications of specialization: one where the majority is defined as 75% of the firm population and one where the majority is defined as the mean plus one standard deviation. Employing these specifications, the results remain unaffected (results not presented here, available from authors).

5.6 Concluding remarks

In this study, we theorized and examined a central research question: under what conditions do rare and less rare capabilities contribute to superior innovation value? We thus investigated the relationship between the rarity of a capability and competitive advantage. The notion that unique resources provide a competitive advantage is one of the core concepts of the Resource Based View, which has recently

been subjected to critical assessments in a number of studies (Kor and Leblebici 2005; Teece 2007; Newbert 2008; Drnevich and Kriauciunas 2011). We contribute to this emerging stream of research by investigating the limits of rarity as a source of value for firms.

In our analysis of the effects of the rarity of the capabilities from which an invention derives its value, we found evidence, beyond a certain point, of positive returns from less rare innovations. Thus, we identify positive returns from less rare innovations. This indicates that capabilities that are idiosyncratic to a firm as well as capabilities that are widely diffused in an industry lead to superior performance. These results provide empirical support for the core theoretical proposition of the Resource Based View that rarity of resources and capabilities permits firms to develop competitive advantages – in this case, an innovation-based strategy – that ultimately drive superior performance, a result that is consistent with the findings of Newbert (2008). Furthermore, our results improve our understanding of the *limits of rarity*. Similar to Drnevich and Kriauciunas (2011) finding that the development of current activities may provide more value than the development of rare capabilities, we find that less rare capabilities can also drive competitive advantage.

This paper has also shown that that an optimum level of uncertainty permits firms to build competitive advantages based on innovation strategy, in accordance with the insights of (Ragatz, Handfield et al. 2002; Bingham, Eisenhardt et al. 2007; Bingham and Halebian 2012). Our data show that conditions of both low and high uncertainty dampen the value of inventions, as they do not provide adequate incentives to innovate. We argue that a moderate level of uncertainty leaves room for experimentation and the introduction of inventions that could fit – or even trigger – the evolution of the technological trajectory. By contrast, we argue that in conditions of low uncertainty, a tendency to develop incremental improvements of existing technology reduces the value of inventions, as does a

tendency to imitate competitors' strategies under conditions of high uncertainty. We believe that these results contribute to a better understanding of the effect of uncertainty within the framework of the Resource Based View. These results are also relevant to the specialized stream of literature that investigates patent value (eg. Harhoff, Scherer et al. 2003; Gambardella, Harhoff et al. 2008), as they underscore the importance of including environmental factors in the analysis.

We suggest that these findings are important to the management of innovation literature, as they help disentangle the factors underlying the generation of valuable inventions. The findings reported in this paper shed further light on how innovation value is affected by both the degree of rarity of the competencies of a firm and the level of uncertainty of technology. Importantly, we show that even with mature technology, innovation can be the outcome of different strategic patterns characterized, in this case, by the development of either rare or less rare capabilities.

As with all research, this study has limitations. First, our data permit us to observe only inventions that are patented. We are thus unable to observe competencies deployed in projects that generated unpatented inventions, for example, those protected by trade secrets or that proved to be unsuccessful and thus were not patented. Relatedly, we could not observe to what extent competencies developed in failed projects have subsequently underpinned successful inventions. Future studies could pursue a closer investigation of how environmental uncertainty and existing competence endowments of firms impact the trial-and-error process of invention and how capabilities are transferred to related inventions. Second, our study focuses on single inventions rather than on clusters of inventions that typically give rise to innovation. In other words, we examine the values of single patents without considering complementarities with existing or future inventions. Future research could examine the nature of capabilities needed to exploit these complementarities. Such studies could analyze a firm's

product portfolio in combination with its patent portfolio. In this study, however, we addressed this effect by including, for each firm, the total number of patents pertaining to hydrocracking and by measuring firms' degrees of specialization at each point in time. With regard to our empirical measures, it should be noted that our classification of technological capabilities relies on IPC codes. These codes are attributed to patents by examiners of patent offices and thus are prone to some degree of subjectivity. Although use of such codes is standard in patent studies, we validated and improved the measure by discussing their use both with technical and patent experts with years of experience in this industry.

We restrict our analysis to a single technology employed in a single industry, raising the question of the generalizability of our findings. Other industry settings covering a novel technology or product area, such as cellular phones or genetically modified foods, might exhibit different returns to the relative rarity of innovation. In addition, the level of competition in an industry could also affect both patenting behavior and the returns to patent protection. The empirical setting used in this study resembles a fairly broad level of competition between heterogeneous actors, and in the case of oligopolistic or monopolistic competition, the results could be different. Thus, further research could address other technologies applied in different industries.

Despite these limitations, we believe that this paper provides a worthwhile contribution to the academic debate regarding the Resource Based View and management of innovation and that it offers important insights for firm management. Managers may be interested in our finding that less rare capabilities – which arguably require less investment and time to be deployed compared with firm-specific capabilities – may contribute to the value of an invention as much as rare capabilities. Managers should also consider the external forces that affect the development of a technological

trajectory, in particular, environmental uncertainty. We find that the predictability of the environment lowers the expected value of innovation, requiring managers to more carefully assess investments in the development of rare capabilities.

5.7 Tables and figures

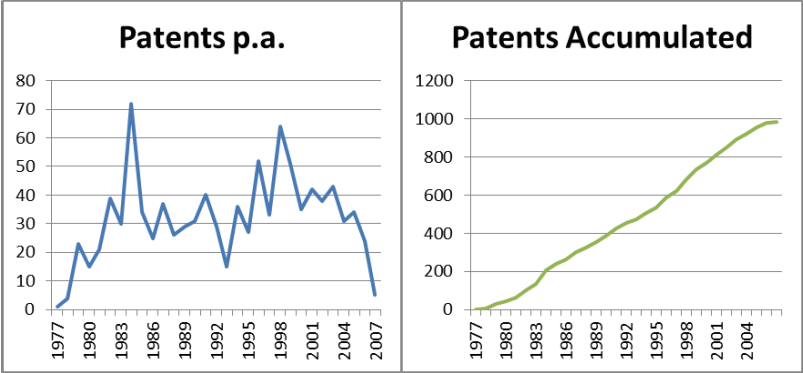


Figure 1 –Annual hydrocracking patent applications and accumulated hydrocracking patents

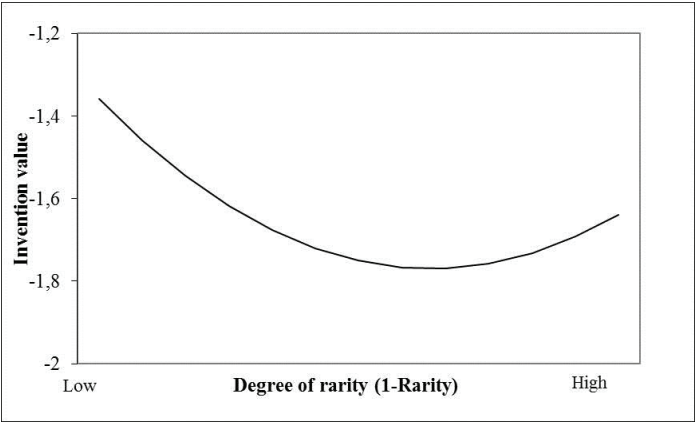


Figure 2: Graphical plot of a U-shaped relationship between 1-rarity and patent value

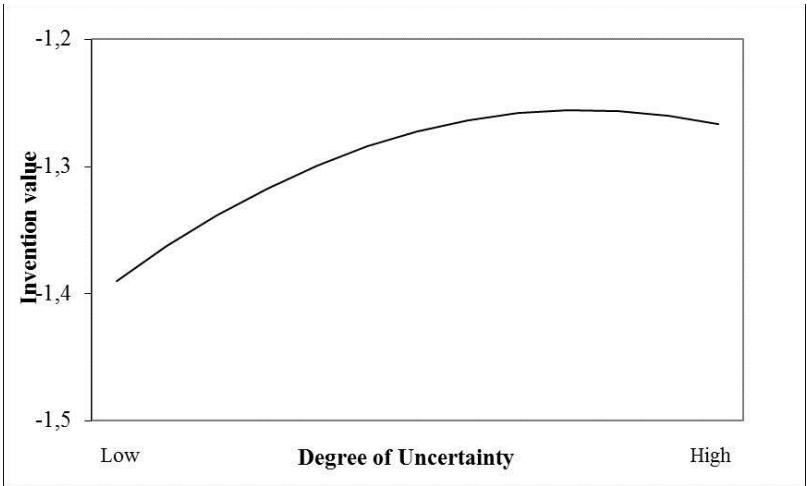


Figure 3: Graphical plot of an Inverted U-shaped relationship between uncertainty and patent value

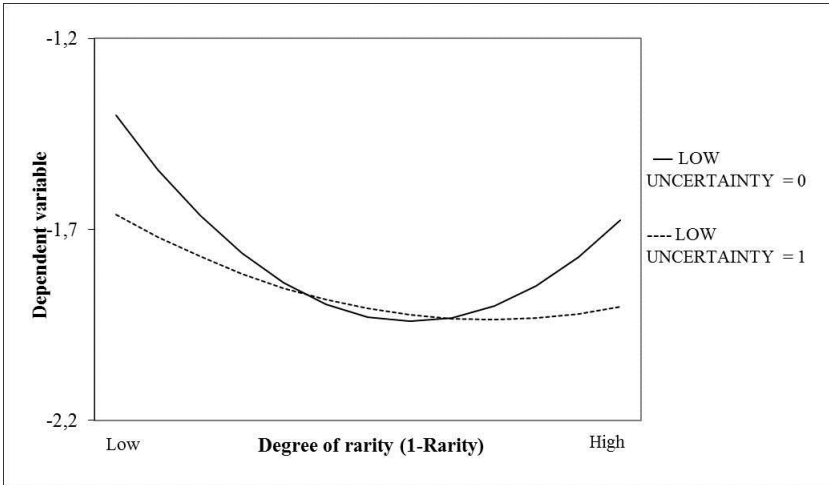


Figure 4: Graphical plot of an inverted U-shaped relationship between uncertainty and patent value, moderated by low uncertainty

<i>Table 1 Hydrocracking technology areas and IPC classes⁸</i>			
Technology area	Associated IPC classes	Excluded IPC classes	Percentage of observations
Process technologies (A)	C10G-065/00 B01J-008/00		5%
Catalyst preparation (B)	B01J-021/00 to B01J-049/00	B01J-023/76 B01J-029/00	21%
Feeds and products (C)	C10G-045/00 C10G-047/00 C10G-049/00	C10G-045/44 C10G-045/54 C10G-045/58 C10G-047/24-30	8%
AB			4%
AC	Combinations of above classes		13%
BC			37%
ABC			11%

⁸ IPC classes ending in /00 signify that all nine-digit subclasses within the seven-digit class are included, unless otherwise noted.

Table 2: Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
Patent value	.001	1.446	-1.85	15.12
Forward citations	3.124	6.155	0	95
Family size of patent	10.73	7.253	0	111
1-Rarity of invention	.465	.254	.029	1
1-Rarity of invention (sq)	.281	.238	.0008	1
Uncertainty of environment	.149	.541	-1.259	2
Uncertainty of environment (sq)	.315	.418	.0015	4
Low uncertainty (dummy)	.111	.314	0	1
Non patent related citations (dummy)	.085	.280	0	1
Specialized firm	.200	.400	0	1
Experience	.546	.838	-16	1
Internationalization	1.435	1.814	0	6.302
Firm size	8.004	3.689	0	11.71
Patents age	13.80	7.774	0	29
Experience within the industry	66.20	65.11	1	246
Patent grant	.602	.489	0	1
Patent opposition	.009	.097	0	1
Number of inventors on patent	4.585	4.326	1	74
Number of assignees on patent	1.841	.954	1	10

Table 3: Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1 Patent value	1.00																		
2 Forward citations	0.72	1.00																	
3 Family size of patent	0.72	0.04	1.00																
4 1-Rarity of invention	-0.02	0.09	-0.11	1.00															
5 1-Rarity of invention (sq)	-0.00	0.11	-0.11	0.97	1.00														
6 Uncertainty of environment	0.08	0.12	-0.01	0.08	0.10	1.00													
7 Uncertainty of environment (sq)	0.01	0.13	-0.11	0.15	0.18	0.56	1.00												
8 Low uncertainty (dummy)	-0.03	-0.01	-0.04	0.01	0.02	-0.51	0.10	1.00											
9 Non patent related citations (dummy)	0.09	0.04	0.10	0.11	0.09	-0.12	-0.04	0.03	1.00										
10 Specialized firm	0.01	0.02	-0.01	0.00	-0.00	-0.03	-0.03	-0.05	-0.07	1.00									
11 Experience	-0.03	-0.10	0.05	-0.37	-0.40	-0.09	-0.32	-0.02	-0.07	-0.01	1.00								
12 Internationalization	0.02	0.04	-0.01	0.08	0.09	-0.04	-0.06	-0.03	0.04	0.16	-0.05	1.00							
13 Firm size	0.06	0.00	0.08	0.01	0.02	-0.01	-0.01	-0.05	0.07	-0.25	-0.10	0.28	1.00						
14 Patents age	0.12	0.31	-0.14	0.25	0.29	0.33	0.48	0.08	-0.05	-0.08	-0.21	0.05	0.04	1.00					
15 Experience within the industry	-0.08	-0.17	0.05	-0.22	-0.22	-0.09	-0.18	-0.02	-0.03	-0.24	0.17	-0.36	0.01	-0.47	1.00				
16 Patent grant	0.32	0.18	0.28	0.03	0.03	0.18	0.17	0.03	0.03	0.03	-0.05	-0.04	-0.10	0.42	-	1.00			
17 Patent opposition	0.10	0.01	0.13	-0.01	-0.02	-0.01	-0.03	-0.03	0.01	0.03	0.00	0.02	-0.04	-0.04	0.03	0.08	1.00		
18 Number of inventors on patent	0.33	-0.01	0.48	-0.04	-0.06	-0.10	-0.16	-0.03	0.09	0.01	0.05	-0.08	0.00	-0.31	0.21	-	0.04	1.00	
19 Number of assignees on patent	0.15	-0.06	0.27	-0.02	-0.04	-0.10	-0.19	-0.05	0.14	0.02	0.06	-0.05	0.17	-0.34	0.07	-	0.04	0.05	1.00

Table 4 OLS regression, the dependent variable is patent value

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
1-Rarity of invention		-1.983*** [0.291]		-2.026*** [0.293]	-2.353*** [0.321]	-2.128*** [0.711]
1-Rarity of invention (sq)		1.778*** [0.379]		1.799*** [0.380]	2.175*** [0.390]	1.901** [0.760]
Uncertainty of environment			0.186** [0.071]	0.194** [0.075]		
Uncertainty of environment (sq)			-0.231 [0.144]	-0.261* [0.132]		
1-Rarity of invention* Low uncertainty (dummy)					2.868** [1.114]	
1-Rarity of invention (sq)* Low uncertainty (dummy)					-3.035*** [0.980]	
Low uncertainty (dummy)					-0.641** [0.245]	
1-Rarity of invention* High uncertainty (dummy)						0.640 [2.189]
1-Rarity of invention (sq)* High uncertainty (dummy)						-0.587 [1.921]
High uncertainty (dummy)						0.051 [0.551]
Non patent related citations (dummy)	0.229 [0.160]	0.284* [0.164]	0.257 [0.164]	0.315* [0.168]	0.302* [0.168]	0.294* [0.168]
Specialized firm	0.063 [0.104]	0.056 [0.105]	0.066 [0.102]	0.059 [0.104]	0.050 [0.105]	0.043 [0.111]
Experience	-0.003 [0.083]	-0.022 [0.082]	-0.027 [0.081]	-0.052 [0.079]	-0.021 [0.082]	-0.028 [0.085]
Internationalization	0.028 [0.043]	0.028 [0.043]	0.025 [0.041]	0.025 [0.041]	0.027 [0.043]	0.031 [0.042]
Firm Size	0.022 [0.014]	0.020 [0.014]	0.022 [0.014]	0.019 [0.015]	0.018 [0.015]	0.019 [0.015]
Patent age	0.026*** [0.009]	0.026*** [0.009]	0.027** [0.010]	0.027** [0.010]	0.026*** [0.009]	0.020** [0.008]
Experience within the industry	-0.000 [0.001]	-0.001 [0.001]	-0.000 [0.001]	-0.001 [0.001]	-0.000 [0.001]	-0.001 [0.001]
Patent grant	0.794*** [0.066]	0.782*** [0.065]	0.778*** [0.069]	0.763*** [0.068]	0.789*** [0.064]	0.784*** [0.061]
Patent opposition	0.895 [0.530]	0.939* [0.528]	0.895* [0.527]	0.939* [0.524]	0.926* [0.537]	0.941* [0.530]
Number of inventors on patent	0.117*** [0.028]	0.118*** [0.029]	0.117*** [0.028]	0.118*** [0.029]	0.118*** [0.029]	0.118*** [0.030]
Number of assignees on patent	0.128** [0.061]	0.135** [0.061]	0.122** [0.059]	0.130** [0.059]	0.135** [0.059]	0.132** [0.061]
Constant	-1.840*** [0.211]	-1.381*** [0.223]	-1.772*** [0.218]	-1.293*** [0.230]	-1.305*** [0.226]	-1.292*** [0.219]
R-squared	0.244	0.253	0.248	0.257	0.256	0.255
Adj.R-squared	.2347247	.2422059	.2368784	.2449886	.2427993	.2418396
No of obs	934	934	934	934	934	934
F test	67.77946***	156.9885***	61.59315***	153.5754***	137.2706***	169.3541***

* p<0.1, ** p<0.05, *** p<0.01

Table 5 Tobit regression, the dependent variable is patent value

	Model 7	Model 8	Model 9	Model 10	Model 11
1-Rarity of invention		-1.996*** [0.270]		-2.053*** [0.264]	-2.350*** [0.310]
1-Rarity of invention (sq)		1.795*** [0.314]		1.825*** [0.316]	2.166*** [0.347]
Uncertainty of environment			0.213*** [0.075]	0.223*** [0.078]	
Uncertainty of environment (sq)			-0.282* [0.146]	-0.314** [0.130]	
1-Rarity of invention*Low uncertainty (dummy)					2.721** [1.061]
1-Rarity of invention (sq)*Low uncertainty (dummy)					-2.822*** [0.969]
Low uncertainty (dummy)					-0.654*** [0.252]
Non patent related citations (dummy)	0.229 [0.163]	0.285* [0.164]	0.262 [0.164]	0.321* [0.165]	0.303* [0.167]
Specialized firm	0.063 [0.093]	0.055 [0.098]	0.067 [0.092]	0.060 [0.099]	0.050 [0.099]
Experience	-0.004 [0.061]	-0.022 [0.062]	-0.033 [0.054]	-0.058 [0.054]	-0.022 [0.062]
Internationalization	0.029 [0.026]	0.029 [0.026]	0.025 [0.026]	0.025 [0.025]	0.028 [0.026]
Firm size	0.021 [0.014]	0.019 [0.014]	0.021 [0.014]	0.018 [0.014]	0.017 [0.014]
Patents age	0.026*** [0.007]	0.026*** [0.007]	0.028*** [0.008]	0.029*** [0.008]	0.027*** [0.007]
Experience within the industry	-0.000 [0.001]	-0.001 [0.001]	-0.000 [0.001]	-0.001 [0.001]	-0.000 [0.001]
Patent grant	0.794*** [0.063]	0.782*** [0.061]	0.775*** [0.065]	0.760*** [0.062]	0.788*** [0.059]
Patent opposition	0.894 [0.543]	0.939* [0.539]	0.895* [0.539]	0.939* [0.534]	0.923* [0.546]
Number of inventors on patent	0.117*** [0.023]	0.118*** [0.024]	0.117*** [0.023]	0.118*** [0.023]	0.118*** [0.024]
Number of assignees on patent	0.132** [0.063]	0.139** [0.062]	0.126** [0.061]	0.133** [0.060]	0.139** [0.061]
Constant	-1.852*** [0.139]	-1.391*** [0.148]	-1.774*** [0.153]	-1.289*** [0.161]	-1.314*** [0.154]
Sigma	1.262***	1.255***	1.258***	1.251***	1.252***
Constant	[0.011]	[0.011]	[0.010]	[0.010]	[0.011]
No of obs	934	934	934	934	934
Uncensored o~s	930	930	930	930	930
Log likelihood	-1.543.876	-1538.26	-1.540.763	-1.534.642	-1536.28
Pseudo R-squ~d	.0782187	.0815721	.0800777	.0837321	.0827542
F test	439.7257***	399.1957***	362.471***	279.8561***	460.9796***

* p<0.1, ** p<0.05, *** p<0.01

Table 6 Negative Binomial regression, the dependent variable is Forward Citations

	Model 12	Model 13	Model 14	Model 15	Model 16
1-Rarity of invention		-2.058*** [0.334]		-2.017*** [0.331]	-2.744*** [0.357]
1-Rarity of invention (sq)		2.029*** [0.408]		1.913*** [0.414]	2.825*** [0.430]
Uncertainty of environment			0.198** [0.101]	0.201** [0.099]	
Uncertainty of environment (sq)			-0.408*** [0.131]	-0.418*** [0.126]	
1-Rarity of invention*Low uncertainty (dummy)					5.603*** [1.967]
1-Rarity of invention (sq)*Low uncertainty (dummy)					-6.596*** [1.979]
Low uncertainty (dummy)					-0.835** [0.416]
----- Same controls as Table 4-----					
Constant	-0.582* [0.315]	-0.124 [0.334]	-0.531* [0.309]	-0.061 [0.326]	-0.036 [0.322]
Lalpha					
Constant	0.132** [0.067]	0.111 [0.070]	0.120* [0.070]	0.098 [0.074]	0.092 [0.070]
Pseudo LL	-1.962.886	-1.957.758	-1.958.934	-1.953.643	-1.952.594
No of obs	934	934	934	934	934
Wald-Chi2	642.6914***	1336.384***	793.2447***	1913.349***	2094.292***

* p<0.1, ** p<0.05, *** p<0.01

Table 7 Negative Binomial regression, the dependent variable is Family Size

	Model 17	Model 18	Model 19	Model 20	Model 21
1-Rarity of invention		-0.551*** [0.168]		-0.574*** [0.168]	-0.501*** [0.181]
1-Rarity of invention (sq)		0.308* [0.162]		0.322* [0.166]	0.224 [0.172]
Uncertainty of environment			0.083** [0.035]	0.089*** [0.031]	
Uncertainty of environment (sq)			-0.106* [0.059]	-0.124** [0.058]	
1-Rarity of invention*Low uncertainty (dummy)					-0.425 [0.464]
1-Rarity of invention (sq)*Low uncertainty (dummy)					0.688 [0.471]
Low uncertainty (dummy)					-0.033 [0.471]
----- Same controls as Table 4-----					
Constant	1.798*** [0.087]	1.972*** [0.092]	1.826*** [0.084]	2.011*** [0.087]	1.971*** [0.089]
Lalpha					
Constant	-2.334*** [0.353]	-2.371*** [0.361]	-2.348*** [0.353]	-2.387*** [0.361]	-2.376*** [0.361]
Pseudo LL	-2.672.592	-2.662.187	-2.669.193	-2.657.988	-2.660.929
No of obs	934	934	934	934	934
Wald-Chi2	2122.063***	3003.254***	2369.501***	2908.646***	3645.035***

* p<0.1, ** p<0.05, *** p<0.01

5.8 References

- Aghion, P. and P. Howitt (1998). On the Macroeconomic Effects of Major Technological Change. General purpose technologies and economic growth., E. Helpman, The MIT Press: Cambridge (MA).
- Ahuja, G., C. M. Lampert, et al. (2008). "Moving Beyond Schumpeter: Management Research on the Determinants of Technological Innovation." Academy of Management Annals 2: 1-98.
- Anderson, P. and M. L. Tushman (1990). "TECHNOLOGICAL DISCONTINUITIES AND DOMINANT DESIGNS - A CYCLICAL MODEL OF TECHNOLOGICAL-CHANGE." Administrative Science Quarterly 35(4): 604-633.
- Argote, L. (1993). "GROUP AND ORGANIZATIONAL LEARNING-CURVES - INDIVIDUAL, SYSTEM AND ENVIRONMENTAL COMPONENTS." British Journal of Social Psychology 32: 31-51.
- Artz, K. W. and T. H. Brush (2000). "Asset specificity, uncertainty and relational norms: an examination of coordination costs in collaborative strategic alliances." Journal of Economic Behavior & Organization 41(4): 337-362.
- Arundel, A. and I. Kabla (1998). "What percentage of innovations are patented? empirical estimates for European firms." Research Policy 27(2): 127-141.
- Barney, J. (1991). "FIRM RESOURCES AND SUSTAINED COMPETITIVE ADVANTAGE." Journal of Management 17(1): 99-120.
- Billon, A. and P.-H. Bigeard (2001). Petroleum Refining, Technip, Paris.
- Bingham, C. B., K. M. Eisenhardt, et al. (2007). "WHAT MAKES A PROCESS A CAPABILITY? HEURISTICS, STRATEGY, AND EFFECTIVE CAPTURE OF OPPORTUNITIES." Strategic Entrepreneurship Journal 1(1-2): 27-47.
- Bingham, C. B. and J. Halebian (2012). "How firms learn heuristics: Uncovering missing components of organizational learning." Strategic Entrepreneurship Journal 6(2): 152-177.
- Bowen, S. (2012). "Testing Moderating Hypotheses in Limited Dependent Variable and Other Nonlinear Models: Secondary Versus Total Interactions." Journal of Management 38(3): 860-889.
- Butler, J. E. (1988). "THEORIES OF TECHNOLOGICAL INNOVATION AS USEFUL TOOLS FOR CORPORATE-STRATEGY." Strategic Management Journal 9(1): 15-29.
- Cohen, W., R. Nelson, et al. (2002). "Links and Impacts: The influence of public research on industrial R&D." Management Science 48(1).
- Danneels, E. (2002). "The dynamics of product innovation and firm competences." Strategic Management Journal 23(12): 1095-1121.
- Danneels, E. (2007). "The process of technological competence leveraging." Strategic Management Journal 28(5): 511-533.
- Davis, G. F. (1991). "AGENTS WITHOUT PRINCIPLES - THE SPREAD OF THE POISON PILL THROUGH THE INTERCORPORATE NETWORK." Administrative Science Quarterly 36(4): 583-613.
- Dierckx, I. and K. Cool (1989). "ASSET STOCK ACCUMULATION AND SUSTAINABILITY OF COMPETITIVE ADVANTAGE." Management Science 35(12): 1504-1511.
- Dimaggio, P. J. and W. W. Powell (1983). "THE IRON CAGE REVISITED - INSTITUTIONAL ISOMORPHISM AND COLLECTIVE RATIONALITY IN ORGANIZATIONAL FIELDS." American Sociological Review 48(2): 147-160.

- Drnevic, P. L. and A. P. Kriauciunas (2011). "CLARIFYING THE CONDITIONS AND LIMITS OF THE CONTRIBUTIONS OF ORDINARY AND DYNAMIC CAPABILITIES TO RELATIVE FIRM PERFORMANCE." Strategic Management Journal **32**(3): 254-279.
- Eisenhardt, K. M. and J. A. Martin (2000). "Dynamic capabilities: What are they?" Strategic Management Journal **21**(10-11): 1105-1121.
- Ernst, H. (2003). "Patent information for strategic technology management." World Patent Information **25**: 233-242.
- Fleming, L. (2001). "Recombinant uncertainty in technological search." Management Science **47**(1): 117-132.
- Fleming, L. and O. Sorenson (2004). "Science as a map in technological search." Strategic Management Journal **25**(8-9): 909-928.
- Fontana, R. and M. Guerzoni (2008). "Incentives and uncertainty: an empirical analysis of the impact of demand on innovation." Cambridge Journal of Economics **32**(6): 927-946.
- Foss, N. and T. Knudsen (2003). "A Resource-Based T angle: Towards a Sustainable Explanation of Competitive Advantage." Managerial and Decision Economics **24**(4): 291-307.
- Gambardella, A. (2013). "The economic value of patented inventions: Thoughts and some open questions. ." International Journal of Industrial Organization Available online 6 March 2013 <http://dx.doi.org/10.1016/j.ijindorg.2013.02.007>.
- Gambardella, A., D. Harhoff, et al. (2008). "The value of European patents " European Management Review **5**(2): 69-84.
- Gibbert, M. (2006). "Generalizing about uniqueness - An essay on an apparent paradox in the resource-based view." Journal of Management Inquiry **15**(2): 124-134.
- Greve, H. R. (2009). "BIGGER AND SAFER: THE DIFFUSION OF COMPETITIVE ADVANTAGE." Strategic Management Journal **30**(1): 1-23.
- Hamel, G. and C. K. Prahalad (1993). "STRATEGY AS STRETCH AND LEVERAGE." Harvard Business Review **71**(2): 75-84.
- Harhoff, D., F. Scherer, et al. (2003). "Citations, family size, opposition and the value of patent rights." Research Policy **32**(8): 1343-1363.
- Henderson, R. M. and K. B. Clark (1990). "Architectural Innovation: The Reconfiguration of Existing Product Technologies and the Failure of Established Firms." Administrative Science Quarterly **35**(1): 9-30.
- Hoopes, D. G., T. L. Madsen, et al. (2003). "Guest editors' introduction to the special issue: Why is there a resource-based view? - Toward a theory of competitive heterogeneity." Strategic Management Journal **24**(10): 889-902.
- Jaffe, A. B. (2000). "The US patent system in transition: policy innovation and the innovation process." Research Policy **29**(4-5): 531-557.
- Kor, Y. Y. and H. Leblebici (2005). "How do interdependencies among human-capital deployment, development, and diversification strategies affect firms' financial performance?" Strategic Management Journal **26**(10): 967-985.
- Kraaijenbrink, J., J. C. Spender, et al. (2010). "The Resource-Based View: A Review and Assessment of Its Critiques." Journal of Management **36**(1): 349-372.
- Lanjouw, J. O. and M. Schankerman (1999). "THE QUALITY OF IDEAS: MEASURING INNOVATION WITH MULTIPLE INDICATORS." NBER Working Paper 7345.

- Leiblein, M. J. (2003). "The choice of organizational governance form and performance: Predictions from transaction cost, resource-based, and real options theories." Journal of Management **29**(6): 937-961.
- Lerner, J. (1994). "THE IMPORTANCE OF PATENT SCOPE - AN EMPIRICAL-ANALYSIS." Rand Journal of Economics **25**(2): 319-333.
- Levinthal, D. A. and B. Wu (2010). "OPPORTUNITY COSTS AND NON-SCALE FREE CAPABILITIES: PROFIT MAXIMIZATION, CORPORATE SCOPE, AND PROFIT MARGINS." Strategic Management Journal **31**(7): 780-801.
- Levitas, E. and H. A. Ndofo (2006). "What to do with the resource-based view - A few suggestions for what ails the RBV that supporters and opponents might accept." Journal of Management Inquiry **15**(2): 135-144.
- Leydesdorff, L. (2008). "Patent classifications as indicators of intellectual organization." Journal of the American Society for Information Science and Technology **59**(10): 1582-1597.
- Lockett, A., S. Thompson, et al. (2009). "The development of the resource-based view of the firm: A critical appraisal." International Journal of Management Reviews **11**(1): 9-28.
- Luque, A. (2002). "An option-value approach to technology adoption in US manufacturing: evidence from microdata." Economics of Innovation and New Technology
- Makadok, R. and J. B. Barney (2001). "Strategic factor market intelligence: An application of information economics to strategy formulation and competitor intelligence." Management Science **47**(12): 1621-1638.
- Makri, M., M. A. Hitt, et al. (2010). "COMPLEMENTARY TECHNOLOGIES, KNOWLEDGE RELATEDNESS, AND INVENTION OUTCOMES IN HIGH TECHNOLOGY MERGERS AND ACQUISITIONS." Strategic Management Journal **31**(6): 602-628.
- McGrath, R. G. (1997). "A real options logic for initiating technology positioning investments." Academy of Management Review **22**(4): 974-996.
- Meyer, M. (2000). "Patent citations in a novel field of technology - What can they tell about interactions between emerging communities of science and technology?" Scientometrics **48**(2): 151-178.
- Miller, D. (2003). "An asymmetry-based view of advantage: Towards an attainable sustainability." Strategic Management Journal **24**(10): 961-976.
- Newbert, S. L. (2008). "Value, rareness, competitive advantage, and performance: A conceptual-level empirical investigation of the resource-based view of the firm." Strategic Management Journal **29**(7): 745-768.
- Park, N. K., U. D. Park, et al. (2012). "Do the Performances of Innovative Firms Differ Depending on Market-oriented or Technology-oriented Strategies?" Industry and Innovation **19**(5): 391-414.
- Penrose, E. (1959). "Theory of the Growth of the Firm."
- Powell, T. C. (2001). "Competitive advantage: Logical and philosophical considerations." Strategic Management Journal **22**(9): 875-888.
- Priem, R. L. and J. E. Butler (2001a). "Is the resource-based "view" a useful perspective for strategic management research?" Academy of Management Review **26**(1): 22-40.
- Priem, R. L. and J. E. Butler (2001b). "Tautology in the resource-based view and the implications of externally determined resource value: Further comments." Academy of Management Review **26**(1): 57-66.

- Ragatz, G. L., R. B. Handfield, et al. (2002). "Benefits associated with supplier integration into new product development under conditions of technology uncertainty." Journal of Business Research **55**(5): 389-400.
- Reitzig, M. (2006). Valuing patents and patent portfolios from a corporate perspective: theoretical considerations, applied needs and future challenges. The Management of Intellectual Property. B. Derek and W. Elisabeth, Edward Elgar Publishing Limited
- Rouse, M. J. and U. S. Daellenbach (2002). "More thinking on research methods for the resource-based perspective." Strategic Management Journal **23**(10): 963-967.
- Schmidt, J. and T. Keil (2013). "WHAT MAKES A RESOURCE VALUABLE? IDENTIFYING THE DRIVERS OF FIRM-IDIOSYNCRATIC RESOURCE VALUE." Academy of Management Review **38**(2): 206-228.
- Sorenson, O. (2000). "Letting the market work for you: An evolutionary perspective on product strategy." Strategic Management Journal **21**(5): 577-592.
- Souder, W. E., J. D. Sherman, et al. (1998). "Environmental uncertainty, organizational integration, and new product development effectiveness: A test of contingency theory." Journal of Product Innovation Management **15**(6): 520-533.
- Teece, D. J. (2007). "Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance." Strategic Management Journal **28**(13): 1319-1350.
- Teece, D. J., G. Pisano, et al. (1997). "Dynamic capabilities and strategic management." Strategic Management Journal **18**(7): 509-533.
- Teece, D. J., R. Rumelt, et al. (1994). "UNDERSTANDING CORPORATE COHERENCE - THEORY AND EVIDENCE." Journal of Economic Behavior & Organization **23**(1): 1-30.
- Trajtenberg, M. (1990). "A PENNY FOR YOUR QUOTES - PATENT CITATIONS AND THE VALUE OF INNOVATIONS." Rand Journal of Economics **21**(1): 172-187.
- Tushman, M. L. and L. Rosenkopf (1992). "ORGANIZATIONAL DETERMINANTS OF TECHNOLOGICAL-CHANGE - TOWARD A SOCIOLOGY OF TECHNOLOGICAL EVOLUTION." Research in Organizational Behavior **14**: 311-347.
- van Zeebroeck, N. and B. van Pottelsberghe de la Potterie (2011). The vulnerability of patent value determinants.
- Webb, C., H. Dernis, et al. (2005). "ANALYSING EUROPEAN AND INTERNATIONAL PATENT CITATIONS: A SET OF EPO PATENT DATABASE BUILDING BLOCKS" STI WORKING PAPER 2005/9
- Wernerfelt, B. (1984). "A RESOURCE-BASED VIEW OF THE FIRM." Strategic Management Journal **5**(2): 171-180.
- Wernerfelt, B. (2013). "Small forces and large firms: Foundations of the RBV." Strategic Management Journal **34**(6): 635-643.
- Westphal, J. D., M. D. L. Seidel, et al. (2001). "Second-order imitation: Uncovering latent effects of board network ties." Administrative Science Quarterly **46**(4): 717-747.
- Wiersema, M. F. and H. P. Bowen (2009). "THE USE OF LIMITED DEPENDENT VARIABLE TECHNIQUES IN STRATEGY RESEARCH: ISSUES AND METHODS." Strategic Management Journal **30**(6): 679-692.
- Winter, S. G. (2003). "Understanding dynamic capabilities." Strategic Management Journal **24**(10): 991-995.

- Wooldridge, J. (2009). Introductory Econometrics - A modern approach, South-Western Cengage Learning.
- Wu, B., Z. Wan, et al. (2013). "Complementary assets as pipes and prisms: Innovation incentives and trajectory choices. ." Strategic Management Journal
- Zeebroeck, v. (2011). "The puzzle of patent value indicators." Economics of Innovation and New Technology **20**(1): 33-62.

Acknowledgements: The authors would like to thank Hans Christian Kongsted, Ulrich Kaiser, Keld Laursen, Finn Valentin, and participants in the internal seminar at CBS department of Innovation and Organizational Economics (2012), DRUID 2012 and EPIP 2013 for useful feedback. We are particularly grateful for the support received from anonymous patent experts and scientists in the Hydrocracking industry. Karin Beukel would like to thank H. Lundbeck A/S, Copenhagen University Faculty of Health and Science, Molecular Disease Biology and Copenhagen Business School for sponsoring her part of this research.

CHAPTER 6

6 CONCLUDING DISCUSSION, AND SOME LIMITATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

This PhD research aimed to improve our understanding of the determinants of valuable innovations. It departs from the notion in the extant literature in innovations studies that innovation is a journey into the unknown, and that the path that the innovating organization has to travel is characterized by uncertainty, path dependency, cumulativeness, irreversibility, technological interrelatedness, tacitness, and inappropriability (Koopmans 1957; Williamson 1975; Dosi 1982; Tushman and Anderson 1986; Green and Scotchmer 1995; Teece 1996; Scotchmer 2004). Technological innovations can be described as having properties that leave room for variety of utility. Empirical studies show that the distribution of the value of the individual technological invention follows a highly skewed distribution, meaning that most inventions have very little or no value, and very few inventions develop into very valuable inventions (eg. Jaffe 1986; Cockburn and Henderson 1996; Harhoff, Scherer et al. 2003; Giuri, Mariani et al. 2007; Harhoff and Hoisl 2007; Cassiman, Veugelers et al. 2008; Gambardella, Harhoff et al. 2008). This thesis research aimed at identifying modifying conditions under which valuable inventions are created by analyzing four modifying conditions. Each of the chapters in this thesis addresses one research sub-question and comprise standalone papers that contribute to addressing how organizations can generate more valuable innovations. The main research question of what determines valuable innovations is explored through the following four sub-questions:

1. How is science transformed into patents, and what actions affect the generation of valuable innovations?
2. How does search in science affect the value of innovations at different stages of R&D?
3. How does horizontal and vertical learning affect organizations generating complex innovations?
4. How does rarity and uncertainty affect organizations to generate valuable innovations?

6.1 Conclusions

In Chapter 2 the first sub-question was addressed about to how science is transformed into patents, identifying the micro-foundations for generating surplus patent breadth. I presented a small N-case study of 12 transformations of science into patented inventions. By examining in detail the reasons for observed variety in patent breadth outcome, I identified the actions where technical scope of scientific discovery would be broadened when transformed into a patent. The actions highlighted are three micro-foundations or organizational performance: interruption, cognitive variety, and abstraction. I also identified the main stakeholders mobilizing these value creating actions as the patent experts. This chapter provides a unique contribution by being the first study to examine how science is transformed into patents, highlighting the importance of the patent experts' role in creating patent breadth, and applying an innovative and novel combination of both qualitative and quantitative methods.

Chapter 3 discusses the distribution of search in science and technology during different stages of R&D. It is the first large-N empirical study to confirm the shift in search approaches during R&D – that is, search towards science decreases along the R&D cycle, whereas search towards technologies increases along R&D cycle. Using a unique algorithm based on semantic structures and IPC, an identification of different types of patents each

belonging to different parts of the drug discovery process was conducted to demonstrate this shift empirically. In the second part of the chapter, we theorized about the differences between a science based and a technology based search lens, emphasizing how the value of either types of search should be considered in R&D. In early R&D processes, where firms seek to transform scientific invention into stable and industrial applicable innovations, search in technology is infrequent compared to late R&D stages, but one-sided search for problem solving in science has a penalizing effect on invention value. At the opposite end, at late stage R&D, search in science occurs less often but is associated with an increase in invention value as firms can use science to avoid being trapped in familiarity traps. The results in this chapter highlight the importance of considering individual stages of the R&D cycle when examining the value of search lenses, and add to the search discussions in the organizational literature.

In Chapter 4 the focus shifts towards understanding how types of learning affect organizations by generating different levels of complex innovations. Understanding the determinants of complex innovation creation have been neglected in the management literature. Based on a framework that considers learning as vertical and horizontal learning, we examined individual mechanisms within each type. The results highlight the difficulties organizations face in moving beyond the current levels of complexity of their knowledge bases. We also analyzed types of horizontal learning; results show that related and unrelated learning have a positive effect on generating medium complex inventions, while a specialized knowledge base has a direct negative effect for generating medium and highly complex inventions.

In Chapter 5 the focus shifted to the topic of innovation strategies in different environments for creating more valuable inventions. The Resource Based View emphasizes rare capabilities for generating superior performance. However, Chapter 5 proposes that firms should

consider both rare and less rare capabilities since both can be converted into valuable innovations, suggesting a u-shaped relationship between rarity and invention value. This result was confirmed. This chapter contributes also by examining the relationship between uncertainty and invention value, and uncertainty as a moderating effect on the relationship between rarity and invention value. The results show that uncertainty and invention value follow an inverted u-shaped relationship, in conditions of low uncertainty, high predictability and low levels of differentiation and that incremental inventions emerge under conditions of high uncertainty when prediction is difficult and firms then tend to imitate successful practices, which lead to less radical innovation. We proposed and confirmed an inverted u-shape between uncertainty and invention value. Finally, we showed that during periods of low uncertainty, innovation strategies needs to be rethought since low uncertainty has a negative moderating effect on rarity, suggesting that both rare and non-rare capabilities are less important in these conditions. This chapter contributes to the recent vibrant discussion in strategic management research on the limitations of the Resources Based View.

The main outcome of the research presented in these four chapters is that intra-organizational processes play a significant role in explaining innovation value. The results in Chapter 4 indicate that organizations can become trapped at a certain level of complexity: organizations can combine a certain number of individual technological domains but become trapped because they find it difficult to increase the level of complexity by integrating more technologies. The literature identifies science as a map to circumvent familiarity traps (Fleming and Sorenson 2004), however, the results in Chapter 3 provide a more nuanced picture of when science should be used to avoid familiarity traps. Two related findings in Chapter 3 can be highlighted: that the stage of R&D in which the invention process is taking place needs to be

taken into consideration (is it early or late in R&D), and that not only science, but the balance between using science as a map and use of a technology as a map should be incorporated into these considerations. Chapter 3 argues that organizations should ensure a balance between a science based and a technology based cognitive map in order to achieve superior performance. The notion of cognitive variety not only shows superior higher valued inventions when part of the overall search pattern in an invention process, but also when it is part of the process that occurs post scientific invention, that is, in the process of transforming the scientific invention into a patented invention. In Chapter 2 we found that during this particular transformation process, patent experts exploiting cognitive variety or abstraction can result in inventions occupying a broader patent landscape, and therefore with more value. Taken together, the chapters in this thesis show that not only are intra-organizational learning and processes important during scientific work on invention, but also in the processes post scientific invention. In addition also the uncertainty of the technological environment showed to be influential on intra-organizational practices. The research in Chapter 5, shows that the surrounding environment has an influence on which innovation strategies are superior, and the results confirm that pursuing an innovation strategy that focuses on rare capabilities will not compensate for low uncertainty.

This thesis adds to the literature on patent value measures. The prior literature has been challenged since good measures are hard to find. In the management literature the trend is to use number of forward citations as a measure, although it is acknowledged that this measure has limitations and carries noise. The chapters in this thesis contribute to work on patent value indicators by suggesting three ways to deal with this issue. They suggest a solution to the issue through use of a combined measure inspired by Lanjouw and Shankerman (2004). The measure

includes both number of forward citations, a measure of how the market assesses the value of the invention, and family size, an indicator of the importance given by the individual firm to each patent. The measure was tested and results were similar to those obtained from applying the measures individually except for Formulation patents, where the sample was small (108 patents). Considering the type of industry and cumulativeness between patents, could suggest that multiple indicators are appropriate in small samples. Hereby initiate future studies to use several measures to indicate patent value, this goes hand in hand with the recently published database ‘OECD Patent Quality Indicators database – July 2013’ which includes several value measures that combine multiple value indicators, and also draws on the work of Lanjouw and Shankerman (2004).

6.2 Limitations

All research has limitations, and the research presented in this PhD thesis is no exception. The four chapters that present the four studies include related research limitations, but there are others that become apparent only when looking at all the chapters together. For instance, none of the studies that form this doctoral research provide joint analysis and evaluation of a bundle of patents protecting a final product. For example, protection of a drug can involve several different types of patents. Chapter 3 showed that in relation to the drug discovery process the patent types involved include platforms, compounds, utility, delivery, formulation and processing which firms need to combine in order to increase the barriers to competition in the market. However, none of the studies takes account of this although undoubtedly the value of an individual invention relies on the scope, types, and the breadth of the bundle of patents related to it. Unfortunately the structure of our data do not allow such an investigation, and to my knowledge, no other studies take account of this effect using a precise measure. In the chapters

in thesis we rely on a rather imprecise way of controlling for the effect, by analyzing firms' total patent portfolios at a given point in time.

A second limitation related to the studies in Chapters 3, 4 and 5, is use of patent data to identify sources of knowledge, learning types, and rarity of inventions. As I show in Chapter 2 not all inventions are patented, as organizations which do not have structures which impose interruption may overlook potential patented inventions. Use of patent data, as in Chapters 3, 4 and 5, allows us to observe only the patented output of R&D; organizational learning from projects that ultimately were not protected by patents are excluded from these estimations. We try to minimize this effect by careful selection of the industries we investigated and collaboration with industry patent experts to guide the selection of patents and check the validity of the results, e.g. the patent categories generated by the algorithm.

6.3 Future research

This doctoral research contributes to our understanding of how intra-organizational issues and uncertainty affect generating valuable inventions, and contributes to the relevant literature. It also opens new research questions many of which I plan to investigate in future research. Some directions for future research are outlined below.

We showed in Chapter 3 that search in science changes along the R&D process, but we need perhaps to be more precise. Is it only the overall dominance of search in science that changes? Does the type of science search change, e.g. the shift from searching in basic science in early R&D to searching in applied science at late stage R&D? Are there differences in the value science contributes depending on the type of science? The theoretical lens of cognitive mapping suggests that there are some differences. However, we need more information on

individual NPL citations, which might be derived by linking NPL citations to their subfields and journal classifications (e.g. CHI classification). However, I would argue that combining an econometric study of NPL citations along R&D with case studies of specific search processes would provide more thorough knowledge about the influence of types of science on innovation.

Since we know that patent experts can generate patent breadth during the process of transformation from science to patent (results from Chapter 2), a large-N study challenging the results would be adequate to pursue. It would be interesting to investigate whether the inclusion of patent experts in parts of the R&D process would have an effect – not only on patent volume, as evidenced by Somaya, Williamson (2007) but also in terms of greater patent breadth? Subsequently, our knowledge of patent experts role in R&D would raise other questions, for example, does the presence of patent experts working closely with R&D have an effect on other patent indicators? It might be expected that the number of X citations a patent receives during patent examination is not only a measure of the competitive environment of the patent, e.g. in the form of blocking patents, but also correlated to organizational practices on patenting, as having done in-depth novelty searches could enable precise scope of the patent, thereby limiting number of X citations.

The study in Chapter 3 provides evidence of the stages of R&D that have a strong influence on whether a science and/or technology based cognitive map would be more advantageous. This could be used to extend the results in Chapters 4 and 5 for example, through an investigation of whether the stage of R&D moderates the relationship between rarity and invention value and whether complex learning is more important during early versus late stage R&D?

Finally, in the Introduction I suggested that a limitation of this thesis was the one-sided focus on technological inventions. In future research I want also to investigate core organizational processes to examine the effect on additional IP appropriation mechanisms. More specifically, I am interested in whether interruption, cognitive variety, and abstraction play a role in other IP appropriability mechanisms, and analyzing whether these affect design registrations (in the US design patents) or trademarks, or firms' combinations of uses of the various available IP mechanisms.

6.4 References

- Aiken, M. and J. Hage (1971). "ORGANIC ORGANIZATION AND INNOVATION." Sociology-the Journal of the British Sociological Association **5**(1): 63-&.
- Cassiman, B., R. Veugelers, et al. (2008). "In search of performance effects of (in)direct industry science links." Industrial and Corporate Change **17**(4): 611-646.
- Cockburn, I. and R. Henderson (1996). "Public-private interaction in pharmaceutical research." Proceedings of the National Academy of Sciences of the United States of America **93**(23): 12725-12730.
- Collins, P. D., J. Hage, et al. (1988). "ORGANIZATIONAL AND TECHNOLOGICAL PREDICTORS OF CHANGE IN AUTOMATICITY." Academy of Management Journal **31**(3): 512-543.
- Dosi, G. (1982). "TECHNOLOGICAL PARADIGMS AND TECHNOLOGICAL TRAJECTORIES - A SUGGESTED INTERPRETATION OF THE DETERMINANTS AND DIRECTIONS OF TECHNICAL CHANGE." Research Policy **11**(3): 147-162.
- Fleming, L. and O. Sorenson (2004). "Science as a map in technological search." Strategic Management Journal **25**(8-9): 909-928.
- Gambardella, A., D. Harhoff, et al. (2008). "The value of European patents " European Management Review **5**(2): 69-84.
- Giuri, P., M. Mariani, et al. (2007). "Inventors and invention processes in Europe: Results from the PatVal-EU survey." Research Policy **36**(8): 1107-1127.
- Green, J. R. and S. Scotchmer (1995). "ON THE DIVISION OF PROFIT IN SEQUENTIAL INNOVATION." Rand Journal of Economics **26**(1): 20-33.
- Hage, J. T. (1999). "Organizational innovation and organizational change." Annual Review of Sociology **25**: 597-622.
- Harhoff, D. and K. Hoisl (2007). "Institutionalized incentives for ingenuity - Patent value and the German employees' inventions act." Research Policy **36**(8): 1143-1162.
- Harhoff, D., F. Scherer, et al. (2003). "Citations, family size, opposition and the value of patent rights." Research Policy **32**(8): 1343-1363.
- Jaffe, A. B. (1986). "TECHNOLOGICAL OPPORTUNITY AND SPILLOVERS OF RESEARCH-AND-DEVELOPMENT - EVIDENCE FROM FIRMS PATENTS, PROFITS, AND MARKET VALUE." American Economic Review **76**(5): 984-1001.
- Koopmans, T. (1957). Three essays in the state of economic science, McGraw-Hill, NY.
- Lanjouw, J. O. and M. Schankeman (2004). "Patent quality and research productivity: Measuring innovation with multiple indicators." Economic Journal **114**(495): 441-465.
- Ruef, M. (2002). "Strong ties, weak ties and islands: structural and cultural predictors of organizational innovation." Industrial and Corporate Change **11**(3): 427-449.
- Scotchmer, S. (2004). Innovation and Incentives, Cambridge, Massachusetts: The MIT Press.
- Somaya, D., I. O. Williamson, et al. (2007). "Combining patent law expertise with R&D for patenting performance." Organization Science **18**(6): 922-937.
- Teece, D. J. (1996). "Firm organization, industrial structure, and technological innovation." Journal of Economic Behavior & Organization **31**(2): 193-224.
- Tushman, M. L. and P. Anderson (1986). "TECHNOLOGICAL DISCONTINUITIES AND ORGANIZATIONAL ENVIRONMENTS." Administrative Science Quarterly **31**(3): 439-465.
- Williamson, O. E. (1975). Market and Hierarchies, Free Press, NY.

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