2013 | Faculteit Bedrijfseconomische wetenschappen

DOCTORAATSPROEFSCHRIFT

Research Open Innovation at the R&D Project Level

Proefschrift voorgelegd tot het behalen van de graad van doctor in de toegepaste economische wetenschappen

Jingshu Du

Promotor: prof. dr. Wim Vanhaverbeke - Copromotor: prof. dr. Bart Leten

D/2013/2451/30

universiteit hasselt

Promoter:

Prof. dr. Wim Vanhaverbeke (Hasselt University, ESADE Busienss School-Barcelona, National University of Singapore)

Co-Promoter:

Prof. dr. Bart Leten (Katholieke Universiteit Leuven, Vlerick Business School)

Chair:

Prof. dr. Piet Pauwels (Hasselt University)

Ph.D Committee / Jury Members:

Prof. dr. Henry Chesbrough (University of California at Berkeley, US)

Prof. dr. Ammon Salter (Imperial Colleage London)

Prof. dr. Frank Piller (RWTH-Aachen, MIT)

Prof. dr. Victor Gilsing (Tilburg University)

Prof. dr. Bart Van Looy (Katholieke Universiteit Leuven)

Prof. dr. Nadine Roijakkers (Hasselt University)

Dr. Ferrie Aalders (Koninklijke Philips Electronics)

Acknowledgement

Four years and half ago, at the age of 23, I packed my luggage, flew to a piece of land called "Belgium" in Europe, and started a Ph.D. At that time, my immediate knowledge about Belgium was Brussels, chocolates, and smurfs. Not knowing where to go and what would be the destination in life, I was happy to discover new things, to experience different cultures and to meet people from all over the world.

This happy and carefree life soon came to an end the third month after my arrival, when I was eager and could not wait to test my first work at Academy of Management (AoM). Two months later I got the feedback, and I remember it was the very first time I experienced "blows" in life when reading the comments from reviewers. As an award-winning student in China, I finally got to know how big the world is. My pride and confidence which had been with me for years, disappeared.

Struggled to find my way out and to re-build my confidence, I owe tremendous thankfulness to my promoter, Prof. dr. Wim Vanhaverbeke. We've been knowing each other for 7 years, and during these years, Wim has always been the one who gives me the strongest support in work. No matter how doubtful I was about myself and about the future, and whatever obstacles I've encountered, Wim keeps strong faith in me. As he always says "You can do it". Now, when looking back, with all the 4 papers in this thesis presented at both AoM and SMS respectively, and papers in the pipeline are heading to a promising direction for journal publication, more than I can say how much thankfulness I owe to Wim, for his constant support and encouragement.

In my Ph.D journey, Bart Leten, my co-promoter, also gave me lots of help and guidance. I enjoyed the discussions, conversations, as well as many lunches with Bart, and he is always there to consult when problems popping out. Bart is not only my co-promoter, but also a friend and advisor. From him, I learned not only various techniques in econometrics and tips in paper writing, but also the happiness, passion, confidence, priority, goals, and pursuit in work and life. Bart, Thank you.

My gratitude also goes to the jury members in my committee. Prof. dr. Henry Chesbrough, “father of open innovation”, who I’ve known for already some years and met in Twente, Barcelona, Boston and Lausanne, has witnessed my development from a novice in open innovation, to a knowledgeable student in this field. Prof. dr. Nadine Roijakkers, my colleague and friend at UHasselt, the lady with whom I shared the same office for several years, also gave me much patient help and advice during my Ph.D. Nadine, I also enjoyed the very sweet family pictures of you and your two lovely daughters— Ema and Lisa, thank you! Prof. dr. Frank Piller, who I met in Aachen and in Boston, gave me lots of encouragement and friendly support in my study. Prof. dr. Ammon Salter, who I met at HEC Paris, gives me lots of very valuable suggestions for my paper revision. Frank and Ammon, thank you for the very nice comments and advice for my thesis! Prof. dr. Victor Gilsing, who I met in Eindhoven, and Prof. dr. Bart Van Looy, who I several times bumped into in the corridor of KULeuven MSI department, both gave me very good suggestions and shared with me several valuable feedbacks, thank you! Prof. dr. Piet Pauwels, with whom I had the chance to co-supervise a master thesis, is a very caring and responsible scholar, and shared with me many sincere advice. Last but not the least, my thankfulness goes to Dr. Ferrie Aalders. I’ve always been touched by the patience, pursuit of accuracy, and the great sense of responsibility of Ferrie. Thank you so much for opening the doors to me and letting me work on the data, the experience and knowledge I’ve accumulated during my Ph.D process, will surely be a priceless asset in my whole life.

Also, my thankfulness goes to Prof. dr. Keld Laursen, Prof. dr. Thomas Asterbro, Prof. dr. Stefano Brusoni, Prof. dr. Rene Belderbos, Prof. dr. Alfonso Gambadella, among many other scholars, whose comments have directly or indirectly impacted my study and this thesis.

Besides many sleepless nights of hard working, there is also much excitement and happiness in pursuing a Ph.D ☺ I would never forget all the joyful moments I shared together with friends and colleagues in Diepenbeek, Hasselt, Leuven, Brussels, and Maastricht. I am also thankful to the help and nice accompany of friends and colleagues from Wuhan and Zhejiang, particularly to Prof.Xie Kefan, Prof. Chen Jin, and their teams. I would also like to thank

Cindy, Anita, Maria, Annemie, and Marleen for their great help and support during my stay in Hasselt, and for helping me organize the defense of this thesis.

Last but never the least, I am forever indebted to my grandparents, parents and other family members. Dear Mom and Dad, your encouragement and support helped me overcome several difficult moments in life, and I know no matter what happens, you are always there for me. Dear Grandma and Grandpa, thank you for all the love and great care you've invested in me for all the years. Dear Aunt Joan, Aunt Denise, and grandaunt Susan, thank you for your care, advice, and suggestions, and also thank you for hosting me every time during my US trips.

My dear family and friends, I love you all.

Table of Contents

TABLES

FIGURES

Chapter 1

Introduction

1.1 Introduction

The past decade has witnessed an up surging growth of open and collaborative innovation activities. Because of the changing competitive landscape, the shortened product development life cycle, the mobility of talents and knowledge workers, as well as the increasing complexity, risks, and costs of innovation activities, increasingly more firms embrace open innovation strategies in their daily operations. This trend in open and collaborative innovation activities has its root back into several decades ago (Trott and Hartmann, 2009), and recently it is re-examined, extended, systemized, and termed as "Open innovation", defined as the use of purposive inflows and outflows of knowledge to accelerate internal innovations, and expand the markets for external use of innovation, respectively (Chesbrough, 2003). Ever since the term is coined, open innovation has become one of the hottest research fields in innovation management (Laursen and Salter, 2006; Enkel et al., 2009; Van de Vrande et al., 2008).

Based on its definition, open innovation covers a wide range of activities, such as outside-in (inbound), inside-out (outbound), and coupled (inbound &

outbound) open innovation activities (Enkel et al., 2009)[1]. Consequently, a number of organizational modes are adopted to support these activities, including formal & informal collaborations, in-/out- licensing, contract research, outsourcing, spin- ins/outs and spin-offs. The present thesis will be mainly studying the *outside-in open innovation activities*, with a particular focus on the effects and contingencies of *R&D collaboration* in the open innovation process.

R&D Collaboration, as characterized by both knowledge inflows and outflows of the focal organization as well as of its external partners in the innovation process, is one of the mostly adopted organizational modes that underlie open innovation principals. Through joint problem-solving and co-creating innovations, it enables the focal organization to leverage external resources and expertise, to gain access to multiple outside knowledge sources and talents, to share costs and risks in the development of innovations, and to respond quickly to external environment (Hagedoorn, 1993; Powell et al., 1998). Consequently, R&D collaboration activities are heavily adopted by a variety of industries. It is observed that, in 2006-08, more than 78% of large innovative firms in Denmark and about 69% of the SMEs in the UK collaborated with external actors on innovation (ESCP Europe & Accenture, 2011). In the fast clock speed industries, the number of joint collaborative research projects comprises almost 50% of all research projects within a company (Enkel et al., 2009). Collaboration in open innovation became "a way of living" for business, and the percentage of firms which actively engaging in collaboration activities continues to increase at a considerable rate (Cosh and Zhang, 2010).

[1] Besides this categorization, other categories apply, see: Dahlander and Gann, 2010; Huizingh, 2010

A number of studies have investigated open innovation from theoretical perspectives (Chesbrough, 2003; Chesbrough et al., 2006; Lichtenthaler, 2011; Dahlander and Gann, 2010; Huizingh, 2010; Enkel et al., 2009). These studies assumed multiple benefits of being open with externals, based on conceptual assumptions or case studies (Mortara and Minshall, 2011; Chiaroni et al., 2011; Bianchi et al., 2011; Huston and Sakkab, 2006; Kirschbaum, 2005; Van den Biesen, 2008). Noticeable early adopters of open innovation principles include companies such as P&G, DSM, Unilever, Fiat, STMicroelectronics, and Philips (Huston and Sakkab, 2006; Kirschbaum, 2005; Mortara and Minshall, 2011; Di Minin et al., 2010; Cassiman et al., 2010; Van den Biesen, 2008). Despite its popularity and presumed benefits, a number of issues on open and collaborative innovation[2] remain unclear over the past decade. First, as a new paradigm of organizing innovation activities, there is a particular need to examine the actual effect of open innovation in more details. Although the mass media has been applauding towards the tremendous success of a few star firms in their open innovation practices (Huston and Sakkab, 2006; Kirschbaum, 2005; Van den Biesen, 2008) and the popular news press and academic reports have oftentimes detailed at length the advantages of open innovation strategies (Business Week, 2008; Financial Times, 2010; The Economists, 2007; OECD, 2008 & 2011; Cambridge IfM report, 2010; Vinnova report, 2010; UK-IRC report, 2011), the actual effects of open innovation are far from well understood. Two issues are of particular importance in this regard. In the first place, it is questionable whether the success distilled from the few case studies is truly representative of the real effect of open innovation on a larger and more diversified sample of organizations. Alongside the few star pioneering firms which are enjoying success in their open innovation practices, it is observed

[2] Hereafter, I use the single term "open innovation" to denote the general open and collaborative innovation activities.

that a great number of firms still remain closed in a large share of their innovation activities (Lichtenthaler, 2008). Within the firms that are open, a considerable number of them are struggling in their open innovation journey (Enkel et al., 2009) and some are even experiencing great difficulties or even failures (Lhuillery and Pfister, 2009). Hence, before being generalized to larger samples of observations, the prevailing optimistic evaluation on the effect of open innovation, as derived from a few star companies, should be treated with caution. Next, also unclear is whether or not open innovation is beneficial (or harmful) for only one/few particular goal of organizational performance (e.g.: innovation speed, technological/ financial performance), or it has proliferating effects on multiple organizational goals simultaneously. Recent advancement of open innovation include empirical studies that are primarily focusing on one particular performance dimension of open innovation outcome, such as financial returns (Belderbos et al., 2004; Faems et al., 2010), sales (turnover) of innovative products (Faems et al., 2005), or number of patent applications (Gulati, 1995), while lacking a full picture when multiple organizational goals are simultaneously brought into consideration. As innovation performance is essentially a multiple-dimension construct and trade-offs between different organizational goals commonly exist in firms' innovation activities (Swink et al., 2006), it deserves questioning whether the adoption of open innovation strategies favors only some goals, or has universal benefits on multiple goals altogether. Some very recent studies find a negative effect (Knudsen and Mortensen, 2010) or value-enhancing but also cost-increasing effects of open innovation (Faems et al., 2010; Belderbos et al., 2010). These studies suggest there is a great need to develop a comprehensive and complete framework in order to better understand the actual effect of open innovation on firm performance.

Second, there is a burning need to understand how open innovation is managed in organizations and what are the possible contingency effects that may affect its outcome, in order to maximally unlock its potential. As no panacea could cure all diseases, open innovation is also likely to have its contingencies to be successful. Besides its benefits, open innovation activities also entail considerable costs and risks which may hinder organizations from profiting from their open innovation initiatives. Examples include commitment of resources, re-structuring organizations, nurturing and adapting corporate culture, communicating and coordinating among partners, loss of control and higher complexity, difficulties in finding the right partner, opportunistic behavior of partners, as well as possible knowledge leakage to the externals (e.g.: Das and Teng, 1998; Malone, 1987; Becker and Murphy, 1992; Enkel et al., 2009). These possible costs and complexities, together with the potential benefits of open innovation, may exist on a case-by-case basis, depending on the practices adopted by the organization and the goals it aims to achieve. Given these complexities, a better understanding of open innovation is to look beyond the basic effect of open innovation, and take into account the contingencies that may shape its performance in different scenarios. The future lies in an appropriate balance of using the right open innovation approaches at the right time and to address the right organizational needs. Therefore, it is critical to understand *under which circumstances* open innovation will (or will not) play a beneficial role to the innovation performance of organizations. Instead of blindly embracing open innovation strategies in all circumstances, having a clear "roadmap" in mind before embarking on the open innovation journey, and preparing for the most suitable condition to maximally unlock the potential of open innovation activities, is important for firms, particularly in economic downturns and are faced with resource and budget constraints (Chesbrough and Garman, 2009).

Third, there is also a need to advance our understanding on open innovation at multiple levels, ranging from individual, project, program, to firm and ecosystem (West et al, 2006). Firm-level innovation studies have received the most scholarly attention, and have been dominating the existing research stream of open innovation for decades (e.g.: Gulati, 1995; Laursen and Salter, 2006; Faems et al., 2010). However, purely approaching the firm as research unit is insufficient in understanding the underlying dynamics of open innovation. As it is pointed out, neither the analysis nor the activities of open innovation should be limited to the firm (West, Vanhaverbeke & Chesbrough, 2006, pp. 287-301). Completing the existing firm-level studies with other levels of analyses will help to enrich my knowledge on open innovation. In the first place, there is a need to distinguish between different levels of practices for more accurate analyses. Because there can be an infinite number of patterns of network ties, a formal study of open innovation demands the articulation of an underlying set of meaningful dimensions along which the structures of networks at the project level and at the firm level can be distinguished and classified, but not mixed up together (Ahuja et al., 2012). As the majority of innovative activities are essentially initiated and implemented at the project level, when looking at the firm as research unit, the innovation input (mostly are conducted at the level of projects) may not strictly correspond to its output (measured at the level of the firm). For instance, it may be possible that within a firm, the majority of badly-performed projects are closed, but only few, very profitable projects are open. While an analysis at the firm level will mistakenly lead to the conclusion that a low level of open innovation is beneficial for a company, an analysis at the research project level might lead to opposite (but correct) conclusions. Thus, a mixture of one level of activities with another level of outcomes may produce misleading results. Secondly, as increasingly more innovation activities are conducted in research projects and a rising number of firms start to adopt project-based organizational structure (Hobday, 2000), there is also a practical need to study open innovation at other levels of analysis than the firm level. For instance, it is observed that the decision and implementation of open innovation in projects can be rather different from those that are in the firm (IfM report, 2010). Typically, some individual projects within a firm might be very open in the way they operate, while the firm as a whole may not be considered as an open innovation adopter (IfM report, 2010) — as it is remarked, "It is a gross generalization to label the whole company as being either an open or a closed organization. Some parts have always been more open than others and, to an extent, this will continue to be the case" (Hague, VP of Open Innovation, Unilever, 2010). Hence, applying research findings derived from a firm-focused approach to the project (or to other levels of open innovation studies), may not be applicable. In this study, I mainly focus on the project-level open innovation activities and outcomes.

Taken together, this thesis aims to address the following research question: *Does open innovation improve innovation performance at the research project level and what are the mechanisms leading to superior innovation performance when firms collaborate with partners in research projects?* In answering this question, I break it down into several sub-questions. In what follows, I discuss these questions in turn.

1.2 The Effects of Open Innovation

Ever since the term is coined, open innovation has been argued as a new imperative for modern innovative firms (Chesbrough, 2003). Based on case studies and interviews, theoretical contributions on open innovation indicate it has multiple advantages. However, most recently, anecdotal empirical research has casted doubts on the idealistic effects of open innovation activities. Besides the commonly accepted positive effect of open innovation (e.g.: Dodgson et al., 2006; Sivadas and Dwyer, 2000; Tether, 2002; Becker and Dietz, 2003; Shan et al., 1994; Belderbos et al., 2004; Sofka and Grimpe, 2011), some research found that open innovation activities have no (Campbell and Cooper, 1999) or even negative effect on innovation performance (Knudsen and Mortensen, 2011; Kessler et al., 2000; Lee et al., 2009; Bougrain and Haudeville, 2002; Schulze and Hoegl, 2008). The diverse body of research findings suggest that there is a need to investigate the benefits (and drawbacks) of the effect of open innovation. In sum, the current research findings suggest a more in-depth, systematic examination of open innovation activities on multiple performance dimension of organizational innovation performance, in particular, there is a lack of research on the efficiency side (e.g.: speed) of open innovation. In what follows, I'll mainly discuss the effect of open innovation on two performance dimensions at the project level (Brown and Eisenhardt, 1995): project financials and innovation speed.

1.2.1 Open Innovation and Financial Performance

The effectiveness of innovation has been a major theme in performance-based studies. Depending on the research focus, effectiveness of open innovation can be categorized as pecuniary or non-pecuniary (Dahlander and Gann, 2010). While the former mainly concerns the financial outcomes of the product innovation, such as revenues, sales, or turnovers, the latter refers to non-financially related indicators, such as patents, volume or quality. The early advocators of open innovation claim that open innovation strategies are effective and play important roles in improving product innovations and financial returns (Chesbrough, 2003; Chesbrough et al., 2006). However, these early studies did not provide large-scale empirical support for their arguments, nor did they identify the situations in which open innovation may (or may not) work. In fact, besides the assumptions on the benefits of open innovation, there are studies warning about the "flip-side" of open innovation, which makes the effectiveness of open innovation uncertain. For instance, open innovation may bring the problem of knowledge leakage, thus strategic protection of knowledge may undermine the effectiveness of external knowledge sourcing (Monteiro et al., 2012); other practical observations suggest that using pre-existing solutions within the firm, instead of blindly jumping out for new ideas, is more effective in the innovation process[3] (Steven Goers, VP of open innovation and R&D at Kraft Foods). Partly echoing to practices, in the existing literature, studies have also not reached consensus on the performance effects of open innovation (see Tsai et al., 2009 for an overview). These studies have been almost exclusively using firm-level data, leaving the actual locus of innovation—the projects—largely untouched. As there is large disparity in research findings, a systematic analysis on the effect of open innovation based on reliable data is greatly needed. This thesis aims to add to our understanding on the effectiveness of open innovation by empirically analyzing firms' open innovation practices and their outcomes. The project-level data further allows me to control for the peculiarities among different types of projects and to provide better reliable results.

1.2.2 Open Innovation and Innovation Speed

Besides the effectiveness in product innovation, open innovation is also argued to be time-efficient for the innovation process (Chesbrough, 2003; Enkel et al., 2009). Speedy innovation, such as reducing time to market for products, is considered as one of the most important competitive advantages in nowadays time-based competition, particularly for fast-moving consumer companies and electronics firms who require the fastest rate of innovation (Eisenhardt and

[3] Source: http://www.innovationexcellence.com/blog/2011/03/08/how-pepsico-kraft-mwh-accelerate-innovation/

Martin, 2000). A recent report from IfM Cambridge by surveying 36 companies found that the pursuit for time efficiency –"shorter time to market" – was ranked the 1st among all the advantages of open innovation, followed by access to new technologies and to additional competences (IfM report, 2010). This indicates there is a great expectation among firms in using open innovation as a powerful tool to speed up their innovation processes. In theory, by leveraging the external readily available resources and expertise, open innovators are able to "stand on the shoulder" of their collaborators and avoid to "reinvent the wheels", thus saving time compared to innovating on their own. However, such theoretical assumptions have not yet been confirmed (or challenged) by evidence based on empirical data. In fact, in reality what I observe is that although a number of open innovation firms indeed innovate much faster than their competitors, some others constantly struggle in the process of the tedious selection, evaluation, communication and coordination among partners (Birkinshaw et al., 2010). Some firms even have to abandon open innovation strategies as they experienced a greater length of time devoted in the innovation process as compared to innovating alone (Birkinshaw et al., 2010). Given the complexities of open innovation activities, there is a need to study the benefits and possible drawbacks of open innovation for the speed of firms' innovation process, and to understand under which circumstances open innovation activities play a role for it.

1.2.3 Innovation Speed and Financial Performance

In the research of new product development, a faster innovation speed is generally considered as desirable for innovative firms, and it is regarded as beneficial for achieving better project returns (Kessler and Chakrabarti, 1996). A study from McKinsey & Company of high-tech products found that new products that come to market six months late, but on-budget, earn 33% less profit than if they were on time, while new products which come to market on-time, but 50% over budget, earn only 4% less profit than if they were on budget (McKinsey & Co., 1983). A more recent study based on financial modelling shows that 12 months, 9 months, and 6 months reduction in time to market increases internal rate of return (IRR) by approximately 92%, 63%, and 39%, respectively, and these relationships are, for the most part, unaffected by changes in other variables including product life or product profitability (Douglass, 2011). With regard to market share, speed can help establish early segments and customer loyalty, gain first-mover advantage, as well as enjoy a wider range of strategic choices compared to slower innovators (Griffin, 1993; Kessler and Chakrabarti, 1996; Zirger and Hartley, 1994), moreover, fast product development is usually more productive and lower cost because lengthy time in product development tends to waste resources on peripheral activities and mistakes (Tabrizi, 2005). However, recent studies have also cast doubts on a (overly) speedy innovation process (Swink et al., 2003), as there may be potential tradeoffs between respective pairs of NPD performance outcomes: speed-quality (Calantone and Di Benedetto, 2000; Harter et al., 2000); time–cost (Graves, 1989; Mansfield, 1988); and time-quality (Karlsson and Ahlstrom, 1999). As such, it is questionable whether speed is "too much of a good thing" (Chen et al., 2008), and some previous studies reveal that speedy development is not universally welcome (Kessler and Chakrabarti, 1996). For instance, Crawford (1992) and Von Braun (1990) discussed several "hidden costs" or downsides of speed, such as more mistakes, heavy usage of resources, and disruptions in workflow. Some researchers also have pointed out the general disadvantages of innovating too quickly (Langerak and Hultink, 1996) and pioneering new technologies (e.g., Golder and Tellis, 1993; Lieberman and Montgomery, 1988). As it may need longer time to innovate "the next big thing", a pure focus on a fast innovation process may mislead the project team in incrementally improving its existing products (as it is more predictable and less risky), or impair product quality by an overly fast cycle of product development. A most recent study on the consequences of new product development speed shows that while in general, new product development speed is associated with improving success outcomes, those relationships may diminish or even disappear depending upon a number of decisions and research contexts (Cankurtaran et al., 2013). In line with the above-mentioned aspects, it is argued that speed is not universally appropriate in each industrial context. Firms must carefully determine the need for speed for different innovations within different task and regulatory environments before blindly pursuing faster development (Kessler and Chakrabarti, 1996). Speed leads to success primarily in more predictable contexts, which suggests that a fast-paced innovation strategy is best when "you know where you're going" (Kessler and Bierly, 2002).

1.3 The Organization of Open Innovation in Research Projects

Aforementioned examples show that there is vast heterogeneity among firms in their open innovation performance. Given the potential benefits of open innovation, their realization seems however to be far from ready and easy. Frequently asked questions are "how to implement open innovation strategies?" or "how does open innovation fit into my organization?" Typically, the existing studies have been focusing on the outcomes of being *open*, with strong differences in the definition on *what is open*, *how open a company is* and *what kind of open innovation practice is adopted*. Besides advancing our understanding on the effect of open innovation on different dimensions of organizational performance, it is also worth investigating the contingencies of open innovation strategies under different open innovation practices. Consider, for instance, in the same firm, two similar projects are both actively involved in open innovation practices, but they may generate quite different outcomes. Although both projects are labeled as "open innovators", they may differ in many aspects in their daily operations: the degree of openness, the choice of partners, the management of innovation process, the timing of openness, as well as the technology fields that are chosen to be open to external partners, may all vary from one to the other to some extent. Consequently, the effects of open innovation depend on the way it is managed. To better understand the role open innovation plays in research projects (and in the firm as a whole), it is necessary to consider a range of possible contingencies in implementing an open innovation strategy. In what follows I will discuss some of these contingencies from three different perspectives: the external factors to the firm, the internal factors of the firm, and the open innovation process. More in-depth analyses will follow in later chapters.

1.3.1 Partner Choice in Research Projects

External factors, such as the types of partners, may shape collaboration outcome in open innovation activities. A research project team may collaborate with different types of partners. Traditionally, R&D collaboration is characterized by formal collaboration deals such as strategic alliances (Hagedoorn et al., 2003; Gulati, 1995), based on data from public announcements and agreements (e.g.: MERIT-CATI database) and with strictly-defined rules, terms, tasks, and goals. More recently, in the context of open innovation, R&D collaboration also incorporates an increasing use of different types of less formal collaborations, such as collaborating with consultants, users, and crowds (Tether and Tajar, 2008; D'Este and Patel, 2007). Taken together, these external knowledge sources can be categorized as either market-based, or science-oriented (Danneels, 2002; Faems et al., 2005). Each type of partners has different capabilities and incentives to collaborate.

For instance, market-based partners (e.g.: suppliers and customers) have expertise and knowledge on market needs (von Hippel, 2002; Prahalad and Ramaswamy, 2004) and the latest technologies, parts and components that are available to satisfy these needs. They help a new product to establish a foothold in the market-place (Appiah-Adu and Ranchhod, 1998) by eliminating the likelihood of product failures (Harrison and Waluszewski, 2008) and meeting customer satisfaction (Ragatz, Handfield and Peterson, 2002; Gruner and Homburg, 2000). Science-based partners, on the other hand, are experts in (basic) scientific research and provide project teams with knowledge on the latest scientific developments, which may function as a "map" for scientific research and point R&D teams to the most profitable directions for applied research (Rosenberg, 1990; Fleming and Sorenson, 2004; Cassiman et al, 2008). Because of their distinct nature, collaboration with these two types of partners will likely have a varying impact on the different dimensions of project performance. As it is stated, partner selection is central for organizations in open innovation. The project (firm) needs to identify what each contributor does best – what is the specific expertise that the project (firm) requires and what is the competitive advantage that each potential partner might provide (IfM report, 2010) in order to better suit the project needs.

1.3.2 Technological Fields in Research Projects

The main driver of the focal project (or the firm in which the project is embedded) to adopt open innovation strategies is to serve its *internal* needs and demands. The *external* factors (e.g.: types of partners) that influence open innovation implementation should be combined with considerations that are made internally. There are a number of *internal factors* that may moderate or shape the impact of open innovation on the outcome of research projects. One of them is the technological fields that are involved in open innovation activities. Because collaboration in research projects is essentially an inter-organizational knowledge flow process, it is likely that collaboration outcome will be contingent on the abundance and direction of knowledge exchange between partners, and on the knowledge protection and leakage in collaboration activities. Over the years, the focal firm has developed a greater knowledge stock in some technological fields that constitute its core competencies, and a weaker pool of knowledge stock in some other technological fields that lie in its technological periphery (Praharald and Hamel, 1990). When it comes to R&D collaboration, a natural choice the firm faces is in which technological fields it collaborates with external partners. Because the focal firm builds up its core technologies over time (Nelson and Winter, 1982), it develops a specific position in the technology landscape vis-à-vis its (potential) partners. Consequently, collaboration activities take place in the technology core fields of the firm might function differently from collaboration activities that take place in its peripheral technology fields. Taken together, the collaboration fields involved in open innovation activities are likely to affect how collaboration has to be organized, and what the collaboration outcome will be.

1.3.3 Project Management in Research Projects

Besides the *external* (e.g.: partner choices) and *internal* (e.g.: technology fields) factors that may affect the implementation and the outcome of open innovation, the managerial approach that is adopted in the *process* of open innovation activities may also play a critical role in innovation outcome. Previous studies show that other things being equal, research projects that are managed in an appropriate way will be more likely to achieve satisfying results than projects that are mismanaged (Clark and Wheelwright, 1990; Cooper and Kleinschmidt, 1995). However, so far, most insights on project management are distilled from studying closed innovation projects, and it is not clear whether these insights can be generalized to the management of open innovation projects (Grönlund et al., 2010). In fact, opening up corporate boundaries implies that the research project may face many new managerial challenges which it does not face when it is developed in-house: the project may need tailored ways to facilitate communication and knowledge exchange, as well as to deal with communication and coordination barriers among different types of partners, the project may need better knowledge protection as it bears the risks of unwanted knowledge spillovers to an external party, the project may have to install more stringent monitoring functions as it is confronted with the issues of free-riding and opportunistic behavior of its partners, and the project may need to balance resources committed to both internal and external activities. All these factors may call for a different fashion of project management in open innovation practices, rather than what have been taken for granted in the existing project management literature (which is mainly summarized from practices of those “closed” projects). In the context of open innovation, project controls may need to be further strengthened to prevent knowledge leakage and free-riding, but at the same time the project may need to be allowed sufficient room for freedom and improvisation in order to stimulate partners in making further contributions and resource commitments. In sum, project management in research projects is another dimension which may affect the implementation and outcome of open innovation strategies.

1.3.4 Collaboration Timing in Research Projects

Besides the management of research projects, the timing of collaboration in the projects’ innovation process is also likely to have an impact on the success of open innovation projects. Collaborations may take place at different points of time in a research project. Typically, research projects go through four development stages in their life cycle: initialization (also called as “conceptualization” or “fuzzy front end”), planning, execution, and termination (e.g.: King and Cleland, 1983; Clark and Wheelwright, 1990). As projects dynamically evolve over time into further development stages, in each phase, its goals, needs, and activities are different. Research projects that adopt open innovation practices may collaborate in one, or several, of these phases, and for each of these phases, project performance is likely to be influenced by external partnerships in different ways. However, the majority of existing studies have a static view on the critical factors that affect project success: Success factors are considered to have the same impact on the success of research projects regardless their development phase (Pinto and Prescott, 1988). A number of questions are emerging: To better realize the potential of R&D collaborations, will it be better if the project opens up for its whole life span, or should the project also allow for some (shorter or longer) periods for “closed” innovation? Does it pay off if the project collaborates simultaneously with different types of partners all at the same time, or it is more preferable if the project collaborates with different partners in a sequential manner? Is it a better choice if a project conducts collaboration activities continuously, or it is more desirable if it allows for some “breaks” in the collaboration process? Will it be better if collaborations take place in the beginning of the project, or it is more preferable to postpone collaborations to later phases, when objectives and problems are better understood and defined? So far, our understanding in organizing the timing of collaboration is scarce. Some studies argue that external partners should be involved early in projects (Zahay et al, 2011), while others claim that partners can be integrated at any point of time (Rothwell et al., 1974; Ragatz et al, 1997). The aim of this thesis is also to investigate the optimal timing and sequence in collaboration with different types of partners in the course of research projects.

1.4 Conclusion

Open innovation as a new paradigm of organizing corporate innovation activities has been developed for almost a decade. Despite the inspirations it brings, so far, the actual effect of open innovation is far from well understood. Although the popular news press has been advocating its benefits at length, what we see in reality is that still a considerable number of firms are struggling in their open innovation journey. Some firms succeed in it, some are skeptical and hesitated about it, and still many others are either keeping closed, or get back from open to closed innovation practices. All these observations remind us that open innovation is not an easy approach; rather, it requires great caution in implementation.

To understand the actual effect of open innovation, it is necessary to research open innovation at multiple levels. Open innovation challenges the traditional way of thinking and organizing innovation activities (most of which are conducted inside of the firm): innovation activities are not necessarily centered at the firm, but also at other levels of locus. The prevailing firm-level studies have to be completed with observations from other levels, and this thesis aims to take the first step by shifting the focus of analysis from the firm to the research project level. By controlling for the peculiarities of each research project, I endeavor to develop a better understanding of the effect of open innovation.

To understand the actual effect of open innovation, it is important to examine how companies organize for their open innovation activities and how this moderates the effectiveness of open innovation. Experience shows that to harvest the benefits of open innovation, it is not sufficient to simply open up the boundaries of a firm. Rather, because of the risks and costs that are involved in open innovation strategies, the competitive edge of firms may lie in the thoughtful and skillful usage and combination of a variety of open innovation strategies under different circumstances, instead of simply being "open" (or not) per se. As open innovation activities are simultaneously affected by internal factors, external factors, as well as the coupled process of the firm (or the projects therein), it is critical to investigate the contingencies of open innovation under different circumstances to make it successful. This thesis aims to answer some of the contingency issues by examining the effects of internal, external, and process factors on the implementation and outcome of open innovation activities.

In sum, this thesis is among the very first studies that empirically test the effect and contingencies in adopting and implementing open innovation strategies at the research project level. It should be borne in mind, however, that neither the level of study, nor the influential factors that are identified in this study, are limited to the ones that are investigated in this manuscript. In fact, other levels of analysis, such as the level of the individual, the program, or the ecosystem, are of equal importance in developing a better and more comprehensive understanding of open innovation. Moreover, there are many other contingencies of open innovation that have not been covered in this thesis. Future research is therefore encouraged to take up this challenge and to advance this research avenue further.

This thesis is organized as follows: Chapter 2 gives an overview of the data and sample that are used in this thesis. Chapter 3 and Chapter 4 examine the effects of open innovation by focusing on the financials (Chapter 3) and speed (Chapter 4) of open innovation, respectively. Chapter 5 and Chapter 6 investigate the contingency effects of open innovation by studying the timing and the technology fields of R&D collaborations. Finally, the thesis is concluded with Chapter 7, where the conclusion and implications for future research are discussed.

Chapter 2

Data and Sample

2.1 Introduction

As in this thesis I focus on studying open innovation in research projects, I rely on project-level data to test my hypotheses. This thesis is based on a unique longitudinal dataset with detailed information on the operational activities of a large number of research projects that are conducted by a large multi-national multi-divisional European-based manufacturing company. This company has an annual R&D budget of more than 1.5 billion euros and is active in a variety of (mainly manufacturing) industries. It is also one of the industrial pioneers that actively embrace open innovation in its research activities. This dataset contains detailed information on all research projects that have been initiated and executed in the company's Research labs during the period 2003-2010. This longitudinal, multi-project, single-firm research setting enables me to investigate many details in the new product development process at the firm and compare multiple aspects of projects with similar characteristics. However, further research is needed to validate the results by surveying research projects from more firms in different industries and with a variety of open innovation experience.

2.2 Data Sources

The main body of the data used in this thesis is built upon first-hand company records, interviews, and archival data collected from multiple sources within the firm. Company visits, interviews, reports (early-, middle-, final- term), as well as email/ telephone communications are maintained frequently throughout the whole research period. Besides the data sources that I collected from the firm, other second-hand data sources, such as corporate annual reports, 10-K reports, as well as public patent databases are also employed in this study. I trace the annual mergers & acquisitions and subsidiary structure of the company to identify its knowledge base and patent stock on a yearly basis. I researched patents in the European Patent Office (EPO), the United States Patent Trade Office (USPTO), the Japanese Patent Office (JPO), the China State Intellectual Patent Office (SIPO) and the World Intelligence Patent Office (WIPO).

2.2.1 Company Dataset

The main body of the first-hand data is illustrated in the 4 boxes of Figure 1. Each box represents a unique set of tables (datasets) of the firm: *Project Table, Transfer Table, Potential Business Success (PBS) Table,* and *Business Score Board (BSB) Table*.

For each year there is an individual table recording each of the above mentioned four types of data. In total I have 49 tables together (for more detailed description regarding to the time aspect of these tables please see the next section). All these tables are then linked into one master table with all the basic information of the projects, their practices and evaluations across years. For an overview of the relation among these four types of tables, please refer to Figure 1.

The Project Table records projects dated earliest from the year 1990 onwards[4]. In the Project Table, in total there are 5170 projects (Full Sample) with completed proposal, among which, 3500 (Approved Sample) are approved by the corporate upper management, and are funded to get started. From the year 2003 onwards, the company started to record open innovation indicators for each project. As my focus is on open innovation in research projects, therefore I take all the projects for the year period 2003 ~ 2010 as my sample for research (2900 projects). Among those 2900 projects, 1451 were not approved and never get started, this leaves me with 1449 approved research projects, which may have subsequent open (or closed) innovation practices and outcomes, and 1336 projects (Valid Sample) that are with complete OI indicators throughout their life time. Among those 1336 projects, 876 of them have sufficient information to enter into the regressions[5], and 558 of them (Restricted Sample) have detailed record (at least for one year) on their project management practices[6]. For a detailed list of the number of observations according to different categories, please refer to Table 1. In this chapter, unless being specified, I will mainly discuss the data in the Valid Sample (1336 projects) and the Restricted Sample (558) projects.

---

[4] Not all the projects originated in/after 1990 are recorded, but mainly the ones that are still active from 1998 onwards.

[5] Which means they have at least one non-missing values in any of the regressors. For a detailed explanation of the regressors I use in this thesis, please refer to section 2.3: Variable Definition and Descriptive Statistics.

[6] For more details, please refer to the description of PMM in section 2.3: Variable Definition and Descriptive Statistics.

Table 1 Number of Projects in Each Project Category and Year Cohorts[7]

Abbreviation in this Thesis	Explanation	1990-2010	2003-2010
Full Sample	Full Data in my Dataset	5170	2900
Approved Sample	Approved Full Proposal (APP)	3500	1449
Valid Sample	APP+ OI indicators	1603	1336
Restricted Sample	APP+ OI indicators +Valid Project Management Scores	707	558

In the Project Table, *Project Year, Project Title, Project Status* ("approved full proposal" or other status such as "rejected" indicating disapproval of the project), *Project Full-Time Equivalent Researchers (FTE), Project Account(the department who sponsor the project), Project Costs* are recorded. Project Costs are recorded as Project Specific Cost and Project Total Cost, however, the recording procedure is not standardized and there are extensive missing values in both of the two variables.

[7] Note: The sample of projects is further detailed in each chapter, according to the specific research context and research question of the chapter.

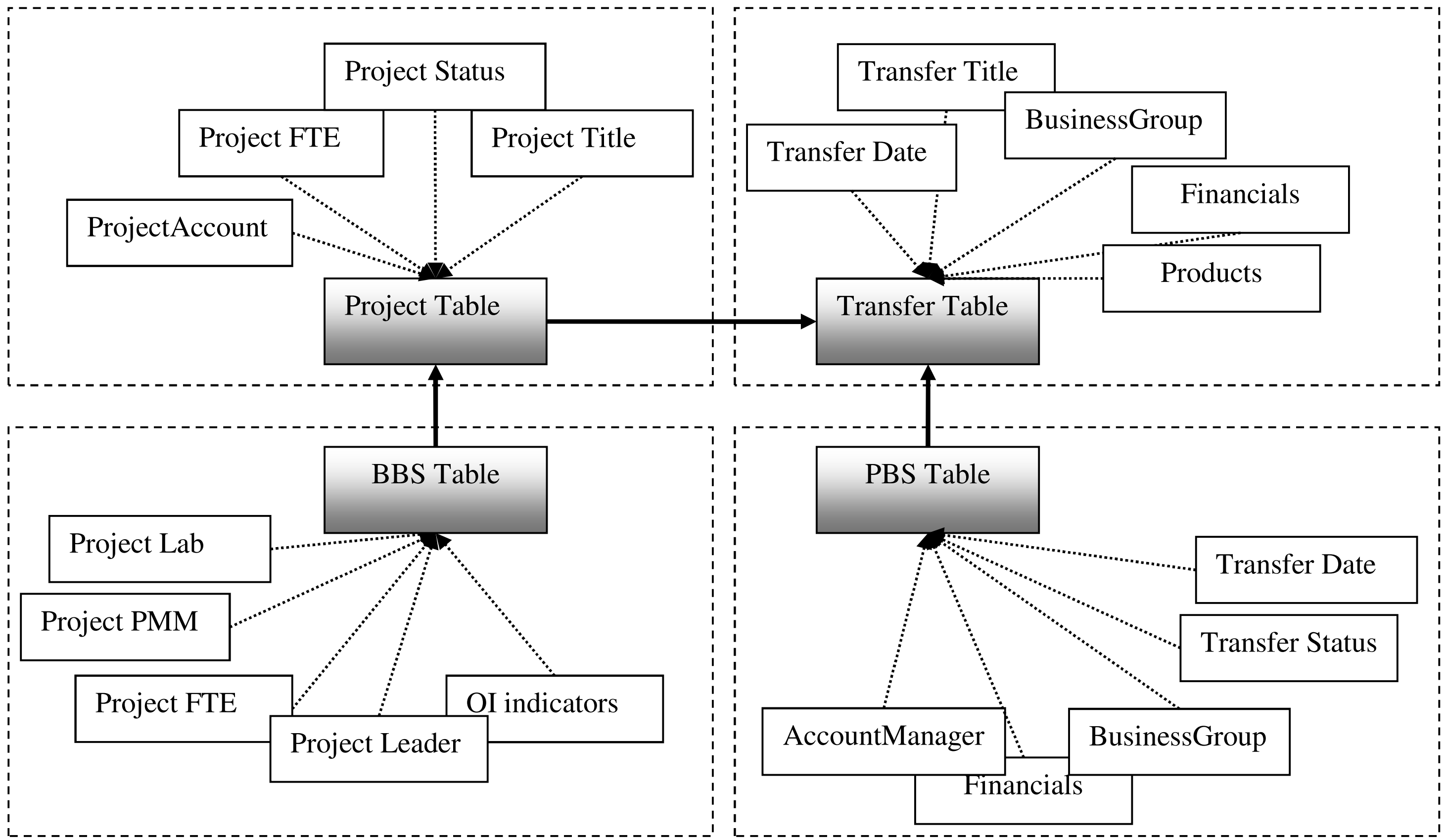


Figure 1 Main Elements of the Four Tables in the Company Dataset

The Business Score Board (BSB) Table records the annual operational activities of the projects, starting from year 1998 onwards. In the BSB table, *Project Lab, Project Division, Project Department, Project FTE, Project Leader, Project Open Innovation Indicators* (whether the project was executed in collaboration with science-based or market-based partners—will be discussed at length in section 2.3: Variable Definition and Descriptive Statistics), *Project Management Maturity* (PMM) are recorded. The Project Management Maturity (PMM) variable constitutes 6 elements: *Project Start-up, Project Ownership, Project Planning, Project Monitoring and Review, Project Business Rationale, and Project Closure* (if applicable) (for a detailed explanation, please refer to Appendix A-- Project Management Questionnaire and Score Guidelines). In total there are 11 broad project labs, which are mainly corresponding to the geography location of the lab. Project Account is the department which sponsors the research project, it contains 538 different values for all projects and 150 different values for the restricted sample. After extensive name cleaning and grouping with the consultancy to corporate management, I managed to summarize in total 11 broad project sponsor units (including "rest categories" as the minority of my data). For the resulting innovations, they mainly face two destinations: either stay in the lab and become something that "nobody wants" (in many cases such projects are stopped being financed), or their results are picked up by one or more business groups and be introduced into the marketplace. For the latter case, the recipient business group sees the value in the resulting innovation, and agrees to take it forward, commit to it (e.g.: financial investment in downstream activities such as manufacturing, production, marketing, etc.), and commercialize the innovation into the marketplace. Upon the "order(s)" received from business groups, Research labs deliver their finalized innovations to one or more business groups (In this thesis, a successful delivery from Research lab to business groups is called a "transfer", more details are followed in the next section—*The Transfer Table*). The innovations that do not receive any orders are therefore unable to reach the marketplace (thus no financial returns generated). Note, here the business groups not only represent the internal needs of the firm in the firm's own markets, but can also be other outlets to market via requests sent from externals (e.g.: IP & Standardization; Licensing, etc.). One project can be transferred to multiple business groups. For an overview of the business groups and their frequency of appearance in my sample data, please refer to Figure 2.

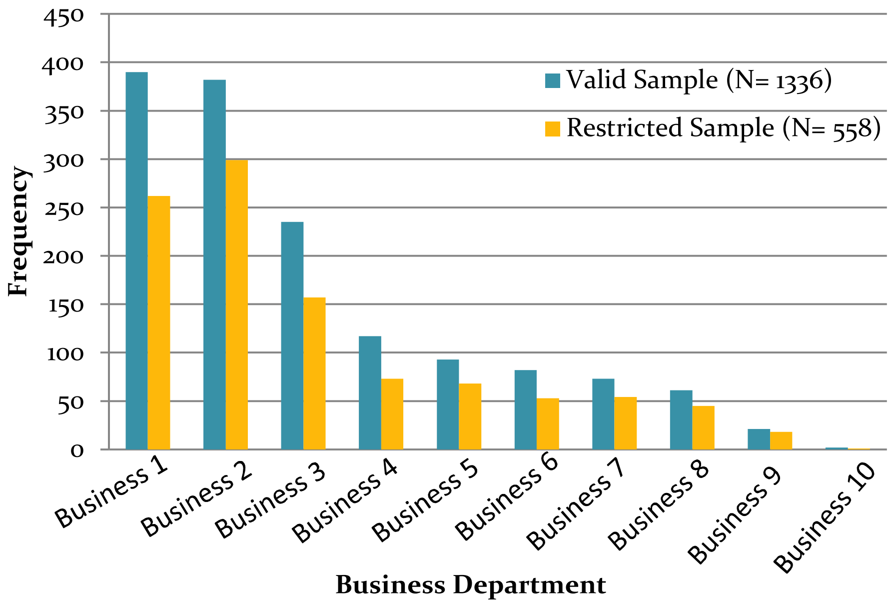


Figure 2 Frequency of Business Groups as Recipient of Transfers

The Transfer Table Research projects have different objectives. A major objective of research projects is to generate internal transfers to businesses groups. Research projects stay in research labs, and transfer their research results to the business, either internal, or external to the firm. When agreed upon a "transfer", the customer (a business group) will apply this knowledge in (pre) developing projects, products, processes or services or it will take action to absorb this knowledge to generate a new application. In this sense, transfers are an early and crucial indicator of the potential commercial value of a research project. Most transfers are delivered to the "sponsoring" business units (the one who pays for the research), but transfers can also be delivered to other business units if a fit in terms of commercial potential is foreseen. Moreover, the research results from Corporate Research, although are sponsored by research instead of business, are flexible to be picked up by business groups for further development. The Transfer Table records projects dated earliest from the year 1998 onwards. For my valid sample of approved projects and with OI indicators, in total there are 1456 transfers. In the transfer table, *Transfer Number, Transfer Title, Product, Business Group, Transfer Date, Financial Impact* and *Estimated Year* are recorded. The *Financial impact* is recorded annually by project managers, based on either the prediction of future financials that are foreseen to be generated by the transfer in the later years, or the real financials that have already been generated by this transfer in the current, or the past years. Corresponding to financials, the Estimated Year – the estimated year of financial generation – is recorded as well. Every year this information is adapted and updated, based on the actual performance of the transfer in the marketplace. As this information is recorded yearly, for the transfers that have an estimated year in or before the year of 2010, I am able to check whether or not the transfer lives up to expectation and indeed realizes its financials as estimated. In my data, the Financial Impact is a conservative indicator and only 79 projects (5,91 %) in my sample are estimated to achieve financial revenues, among which, 41 projects have an estimated year in or before year 2010, which I am able to compare the accuracy of the financial predictions with the fact. In most cases (90%), the estimation of transfer financials gives quite reliable information and realized their financial goals. Given the high accuracy of prediction, for the transfers that are predicted to generate financials but have not yet come to their estimated years (e.g.: in some cases, the estimated financial returns are supposed to be realized in year 2015 or in year 2016), it also serves as a good indicator for the potential of the financial of the research project.

For my valid sample, of the total 1336 projects, 414 projects (31,0%) generated at least one transfer. There are in total 1456 transfers generated for the period 2003-2010. Figure 3 gives an overview of the number of transfers per research project. The majority of projects (69,0%) generated no transfers and 179 projects (13,4%) generated only one transfer. The remaining projects (17,6%) generate multiple transfers. 8 projects produced more than 20 transfers. The project originated in year 2004 in the audio technology created 54 transfers – the maximum number in the database.

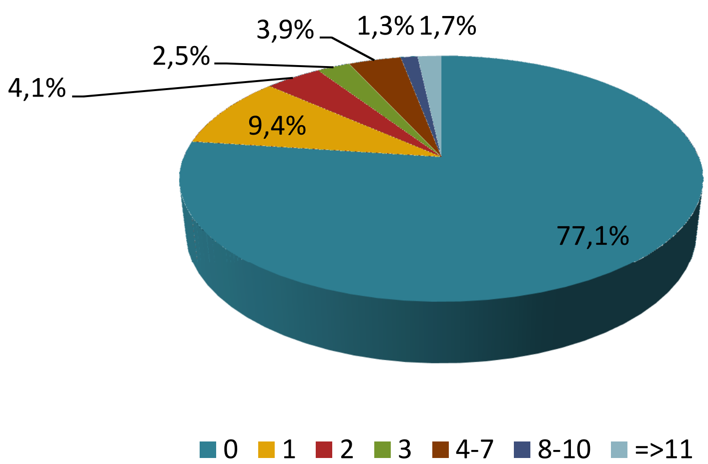


Figure 3 Number of Transfers Generated per Research Project (N = 1336 projects)

Of the total 558 projects in my restricted sample, 225 projects (or 40.32 %) generated at least one transfer. There are in total 1482 transfers generated for the projects started in the period 2003-2010. Figure 4 gives an overview of the number of transfers per research project. The majority of projects (59.7 %) generated no transfers and 13.6 % generated only one transfer. The remaining 26.7% of the projects generated multiple transfers.

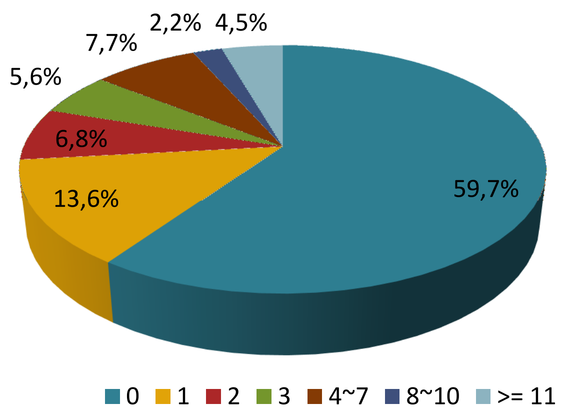


Figure 4 Number of Transfers Generated per R&D Project (N = 558 projects)

In my restricted sample, the majority of research projects (60 %) do *not* produce transfers. This seems to be inconsonant with their high patenting rate (64.34%, thus only 35.66% projects do *not* patent)[8]. However, I suppose compared to patent applications, project "transfer" actually serves as a more reliable indicator for project quality and its (intermediate) results. While firms, particularly those big and asset-abundant ones, can simply patent everything even though the resulting innovations are not promising enough or may not be able to generate profitable products, just for the reason of knowledge protection or for their strategic needs. Only those projects that are considered as profitable

[8] Will be detailed at length in the following section 2.2.2.

and valuable will be further taken over by business groups for further development and commercialization.

Research projects may produce transfers at different points in time. Some projects lead to a transfer within (or less than) a year but some projects continue to produce transfers even after a decade. New projects generate transfers relatively quickly. At the same time, some old projects continue to spawn transfers in later years. Therefore, transfers' portfolio in a particular year can be composed of projects that are initiated in the last 10-15 years. In the valid sample, 25% of the transfers are generated after 1 year, 50% before the end of the second year and 80% within the first 5 years. Most of the firm's research projects produce transfers in the first three years after a project started. In general, the average elapsed time between the start of a project and a transfer is 1.33 years. For instance, research project named "2002-029" (the # 29 project proposed in the year 2002), initially sponsored by Business Group *Consumer Life Style*, started one year after the project was proposed (thus initiated in year 2003). It already delivered its first transfer in the same year 2003 to *Consumer Life Style*; in January 2004, it delivered its second research result to *IP & Standardization*; in the following year 2005, it delivered a third research result to *External*, and finally in the year 2006, it delivered a fourth research result again to *IP & Standardization*.

The PBS Table records the actual performance of the transfers, starting from 1998 onwards. The PBS table includes *Business Groups* as the recipient of the transfer, the *Status of the Transfer* (In total there are 5 categories: Business Success, Potential Business Success, Old Business Success, Inactive, and Transfer), *Account Manager* (if any), *Transfer Date, Estimated Year* and *Financial Impact*. The information that is not complete in the Transfer Table, are recorded in the PBS Table. For the business groups, there are in total 417 different values for all projects. After extensive name cleaning, I managed to group those BGs into 11 broad groups. The names of these BGs are also corresponding to the names of the 11 Accounts (sponsor units). After the research project is finished, the project team is dissolved and people are allocated to different projects. For more details, please refer to section 2.3: Variable Definition and Descriptive Statistics). Of the 1456 transfers in my valid sample (1336 projects), 951 (65,3%) were transferred to a business group (BG) which is also its original sponsor (project account), and still 505 of them (34,7%) were transferred to a different BG rather than its original sponsor. Out of these 951 transfers, the vast majority (96,2%) were conducted for their original sponsors, while 505 transfers were delivered to a different BG rather than its original sponsor. Further, 282 transfers (55.8%) came from projects that were originally sponsored by “Research”. It seems that there is cross-fertilization between the original sponsor BGs and the actual beneficent BGs within the firm, and the corporate “Research” department plays a long-term and strategic role in investing in research projects, while the Business Groups are more practical and application-oriented.

In each year there is an individual table for each of the above mentioned four types of tables. Therefore, in total I have 54 tables (project table starting from 1996 onwards, which records the earliest projects initiated in 1990). All these tables are then linked into one master table, with all the basic information of all projects across years. Figure 1 shows an overview of the relation among these four types of tables.

Based on this master table, I created three types of data structure for my analysis: a cross-sectional structure, a panel data structure, and an event-history data structure (based on multiple events). I will discuss these data structures in more details in the data part of the following chapters. For the time aspect and the overall relation of the data I have, please refer to Figure 5. Project tables start from year 1996 onwards, transfer tables start from year 1998 onwards, open innovation practice tables start from year 2003 onwards.

Projects mainly follow two different, but inter-related paths to realize their value (the thick dark arrowed lines in Figure 5): the first path is mainly financially-oriented: results from the transfers to business units (either within or outside of the firm) are manufactured and commercialized, bringing the firm financial returns in the final markets. The second path is mainly science-driven: results from the research project are filed at the patent offices, which result in patent applications (and grants). Although these two paths are different, they are not strictly separated as the same project can both generate financial returns and apply for patents. In my valid sample (1336 projects), 214 projects (16,02%) applied for patent(s) as well as generated transfer(s), 328 projects (24,55%) only applied for patent(s), 200 projects (14,97%) only generated transfer(s), and the remaining 594 projects (44,46%) do not apply for patents nor generate transfers. As already mentioned before, the smaller percentage of the projects that generated transfers, as compared to those that applied for patents, also partly show that transfers may serve as a better and stricter indicator of (intermediate) project success.

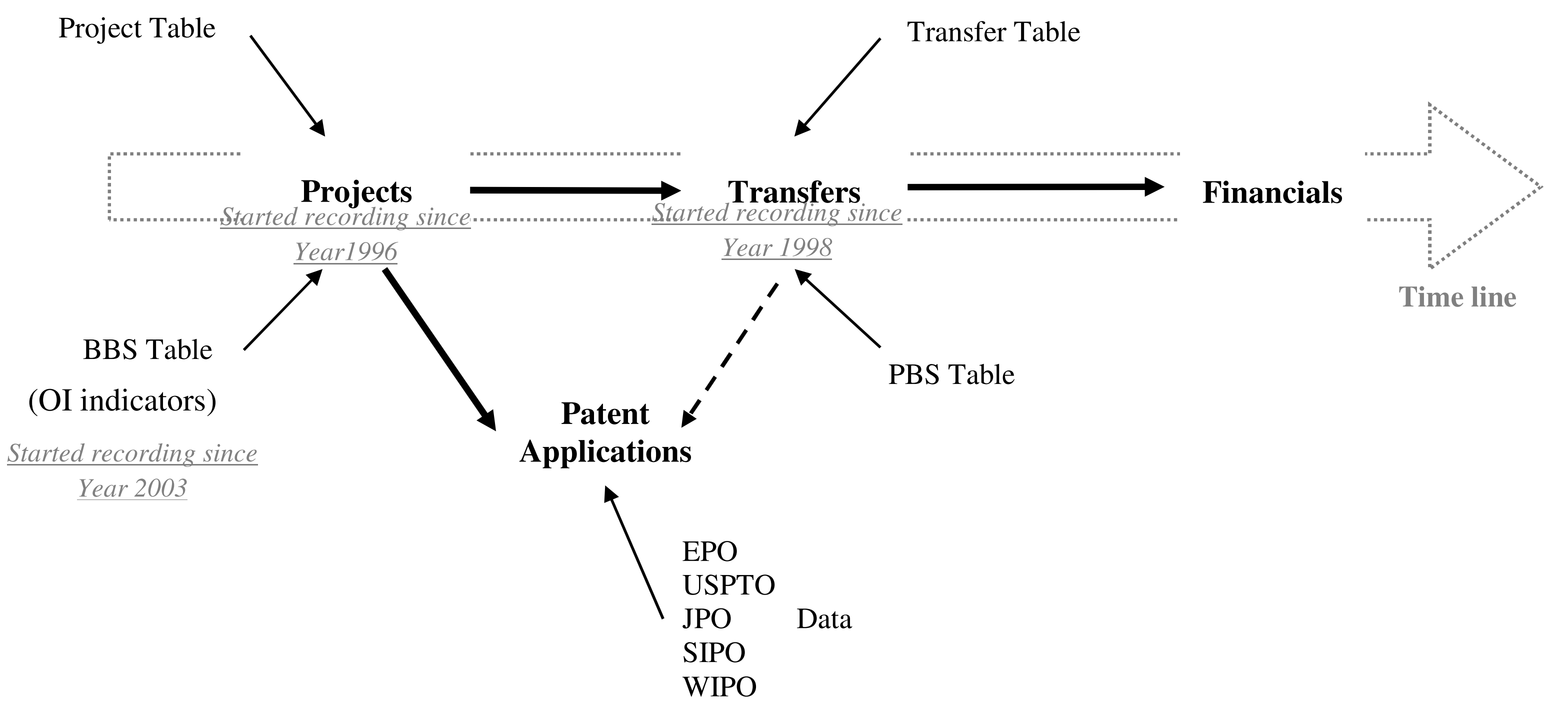


Figure 5 Relations among the Different Constructs in the Dataset

2.2.2 Patent Dataset

Because research projects are conducted in different technological fields of the firm, even within the same firm, their technology strength may differ dramatically. Besides the extensive information I collected from the Research department, I have also collected data from the Intellectual Property department on the patent(s) that each of the projects has applied for (if any). When a patent is filed, it is recorded and linked to the particular project that has been developing it. This results in a large project-patent database with all the research projects of the firm on the one hand and all their patent applications (at different patent offices, at international, regional, and country level) on the other hand. I managed to link each project to its patent application(s) filed at all the major public patent office such as European Patent Office (EPO), United States Patent Trade Office (USPTO), Japanese Patent Office (JPO), China State Intellectual Property Office (SIPO), as well as World Patent Office (WO) if EPO, USPTO, JPO, or SIPO patent applications are not available[9]. In total, of the valid sample (1336 projects), 542 projects have applied for at least one patent, which are corresponding to 26393 different patent filings in all public patent offices. The patent applications cover 45 different countries/ regions, and the majority of projects (1784 projects, 59,6% in the valid sample) filed at European Patent Office. Because the same invention derived from the same research project can be used to apply for multiple patents in different patent offices, therefore, besides collecting data on all the general patent filings of each project, I also looked into the *first filing* of each project in its patent family[10]. This thus results in patenting information of research projects in EPO

---

[9] In my sample, patents filed at other national/regional patent offices are also filed at one of the above-mentioned major patent offices.

[10] A patent family is a set of either patent applications or publications taken in multiple countries to protect a single invention by a common inventor(s) and

(69,9% of all projects, first filing, same for the following), USPTO (20,3%), SIPO (4,9%), British IPO (2,6%), and WO (1,9%). First filing in JPO is not found.

Hence, the patent filings are then further narrowed down to 2993 different patent families according to the first filing date of each invention applied (sequentially) in different regions. For the patent applications made by all the projects in my dataset, WO, USPTO, SIPO and EPO (in this order) are the four patent offices that are most heavily patented at (Figure 6); for the first filings of patent families of all the projects in my dataset, EPO, USPTO, SIPO and WO (in this order) are the four mostly patented patent office for my sample (Figure 7). For the restricted sample (558 projects), 359 of them (64.34%) have applied for patent(s), which are corresponding to 22459 different patent applications and 2560 different patent families filed at all public patent offices. For the analyses in my sample, I take the patenting information of the first filing each project made in its patent family. For all the projects that filed for (at least) a patent application at public patent offices, their technological fields are identified based on their patent filing documents (e.g.: for the EPO patent filings, the technological fields a patent covers is represented by its International Patent Classification (IPC) code, which are, in most cases, examined by patent examiners who are assigned to examine the patent application. In this thesis, I take it at the IPC-4 digit level). Further, because my sample firm is European-based and files for patents mostly at EPO (Figure 6, Figure 7), I therefore use project patenting information at EPO as the major source for my analysis.

---

then patented in more than one country. A first application is made in one country – the priority – and is then extended to other offices.

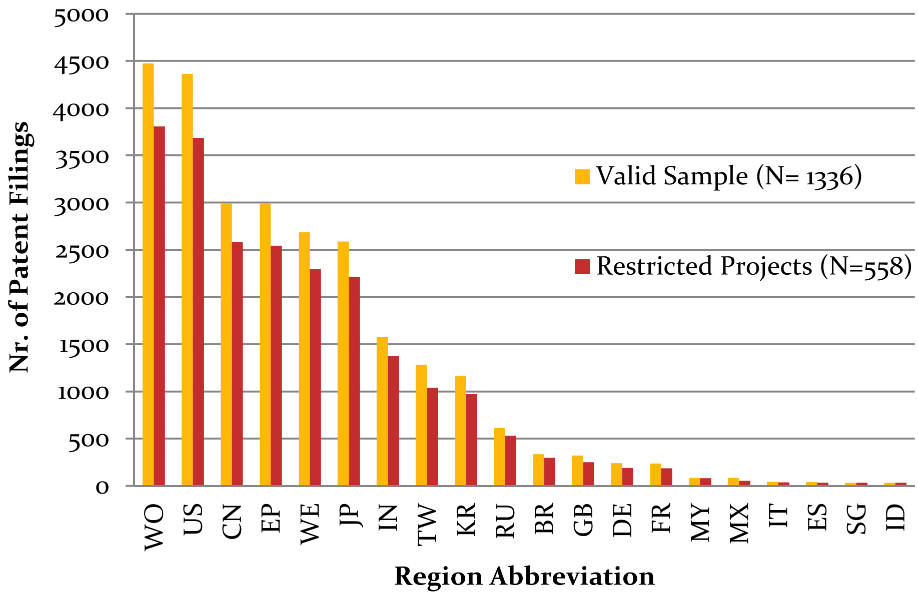


Figure 6 Top Regions for All Patent Filings of the Sample Firm

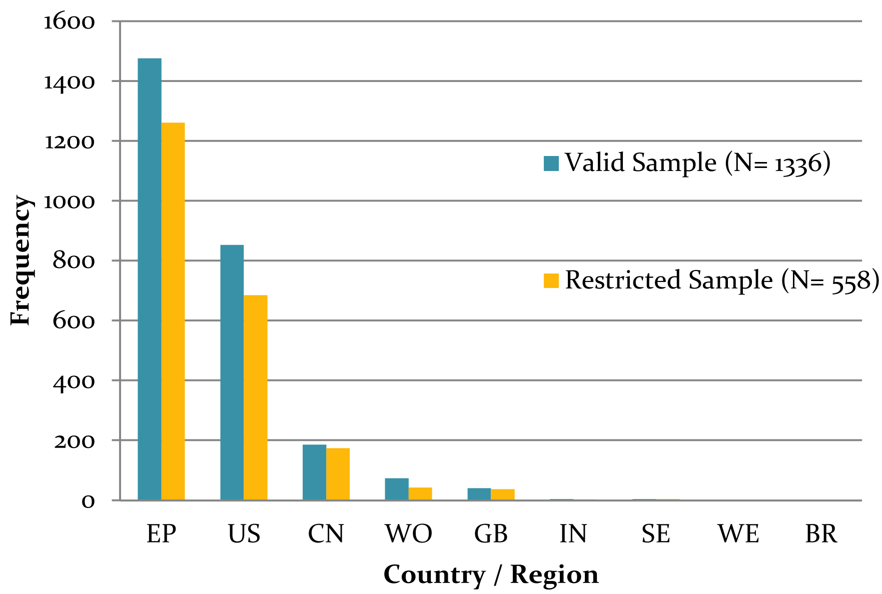


Figure 7 Top Regions for First Patent Filing of the Sample Firm

For the projects that did not apply for patents, I looked for all the relevant information in the company dataset, including project title, project description, project abstract, project department, as well as business department. I then match those details with the descriptions of International Patent Classification (IPC)[11] as listed on the World Intellectual Property Organization (WIPO) website[12]. The full IPC code is detailed at 8 digits[13]. Due to the limitation of the accuracy based on manual searching, the classification of IPC code for those projects that without patent application information is detailed at IPC 4-digit level[14]. In order to enhance the rate of accuracy, each of the matches was double-checked by me and experts from the sample company. For a detailed overview of IPC classifications in WIPO, please refer to Appendix B.

The innovations derived from one research project can be filed for one, or multiple patents at the same or different patent offices. The following graph (Figure 8) shows the frequency of the number of patent(s) a project applies for.

---

[11] The International Patent Classification (IPC) is a hierarchically-structured patent classification system used in over 100 countries to classify the content of patents in a uniform manner.

[12] http://web2.wipo.int/ipcpub/#refresh=page

[13] There are in total 4 different IPC digit-levels: 1-digit level, 3-digit level, 4-digit level, as well as 8-digit level. The less digits a IPC code has, the less accurate it is.

[14] IPC 4-digit classes are commonly used in economics studies (e.g.: Verbeek et al., 2002; Meyer, 2007).

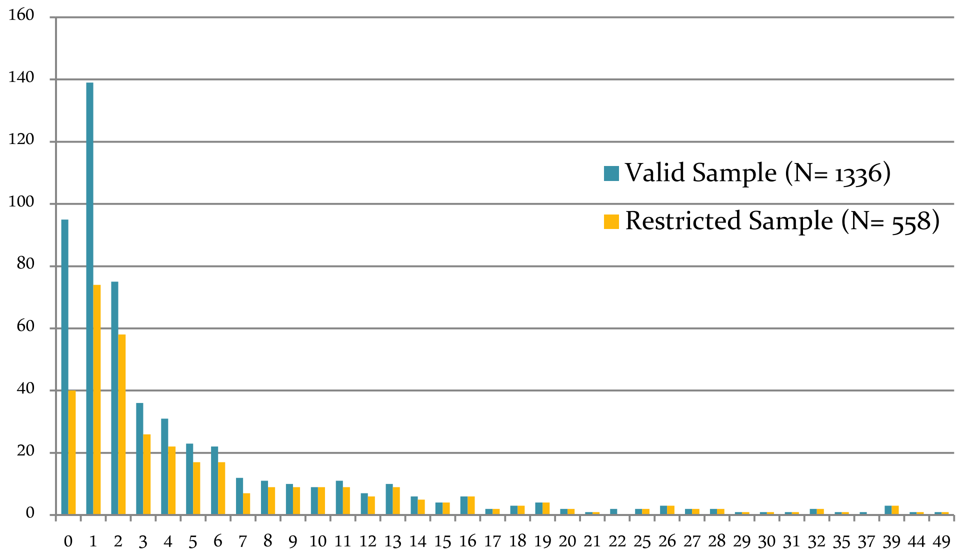


Figure 8 Number of Patent Applications Per Project (First Filing of Patent Families)

While the majority of projects (60,40%) in my sample applied for one or less than 5 patents, the most productive project applied for 49 patents in the public patent office.

2.2.3 Annual Structure of the Company

Besides using patent data to construct indicators of technological fields and to measure technical performance of *each project*, patent applications is also used to denote the technological strength (knowledge stock) of *the parent firm as a whole* in the field which the project is active in. In the latter case, the annual structure of the firm is needed for overall patent applications made by the firm (or its different subsidiaries / merged & acquired firms). I performed a large data collecting exercise to collect patent data at the consolidated firm level. Therefore I searched, for patent applications made by the parent firm, for patents applied under the names of the parent firm and its majority-owned subsidiaries, as well as patents relating to its divestments, on a yearly basis. First, for the patents that are applied for by the firm itself (or its subsidiaries), yearly lists of company's subsidiaries included in corporate annual reports are consulted and double checked. This is because company names in public patent database are not unified and patents may be applied by assignees fall under the name variations of the parent firm, or name variations of its subsidiaries and divisions. Thus, I searched for all the patent applications under the name of the parent firm and its majority-owned subsidiaries. Second, the consolidation was conducted on a yearly basis also to take into account changes in the group structure of the sample firm, due to acquisitions, mergers, green-field investments and spin-offs. Acquisitions are considered as part of the parent firm from the year the acquisition transaction is completed. The patent stock of the firm's divestments is taken out of the firm's whole patent stock from the year the divestment is made. Finally, in case I mistakenly included patent applicants that share the same (or partly the same) name of my sample firm, I went through all the names of the applicants that are included in my calculation. I further searched on the internet one by one their name clarifications to avoid mis-matches[15]. In total, 152 different name variants of the firm, its subsidiaries, and its acquired/ merged firms at EPO have been linked to the firm over the period 2003-2010.

2.3 Variable Definition and Descriptive Statistics

In this section, I describe briefly the main concepts that are used in this report and provide some descriptive statistics of these concepts. In what follows, I define the most important concepts and variables used in this thesis:

---

[15] For instance, company "ConocoPhillips" is headquartered in US and is in a completely different industry (oil and gas) from "Royal Philips Electronics", which also has a name of "Philips".

2.3.1 Definition of Transfer

Transfer is a key concept in this thesis. Research projects are conducted in research labs, when the research is completed or valuable research results are achieved, they can be "transferred" to one of the business departments of the firm for further development and commercialization. A transfer takes place when knowledge is purposefully disclosed to a customer of the research lab under specific conditions:

- When the "customer" agreed to apply this knowledge in his/her business in (pre) development projects, products, processes or services
- recognizes this knowledge as adding value
- takes action to absorb this knowledge in his/her operation to enable an application

A transfer is only completed when the "customer" confirms these conditions (Note: here the "customer" is not the customer in the traditional meaning, the "customer" here is usually one of the business groups which agrees to commit to the innovation and commercialize it into the marketplace). Transfers are registered in, and were initially linked to, the reports on project progress. Technology transfers can be realized in many ways in the firm, depending on the type of technologies and knowledge. Possible outlets are:

- Being realized in the firm's existing market
- Being incubated in the firm
- Entering new business development program of the firm
- Licensed to another firm/ organization who sees the value of the technology
- IP transacted to another firm/ organization who sees the value of the technology

2.3.2 Definition of Innovation Performance

The ultimate goal of research projects is to contribute to the performance of the company. Following prior studies that innovation success is a multi-dimensional construct, I adopt two sets of indicators to study innovation performance of both the innovation speed and project financials of the research project. These two sets of indicators are combined to jointly provide an evaluation of the innovation performance of research projects. In what follows, I will discuss them in turn.

1) Innovation Speed

This measure of open innovation success is defined in this thesis as the rate of how quickly an innovation is developed. In other words, it is the rate of the elapsed time of a project between its start to its transfer to a business group. Transfers are recorded on a yearly basis with detailed information on the starting date of the originating project, and the transfer date of each transfer, which enables me to do delicate calculations based on objective records accurate at the "day" level. Because research projects may deliver transfers several times in a year or throughout a number of years, to one or different business groups, I therefore consider two types of measurements to analyze innovation speed.: 1) the rate at which a research project generates its first transfer, and 2) the rate at which a research project generates multiple transfers. For the first measure, I look particularly at how "fast" a project can generate a transfer by considering only the first transfer of each project (if any); for the second measure, I measure the overall speed of the research project as I also take into account of all transfers the research project generated (if any) (for more detailed explanations on innovation speed and how it is calculated in this thesis, please refer to Chapter 4: *Accelerating innovation? –Open Innovation and Innovation Speed of R&D Projects*). I compare between different collaboration options – innovating with R&D partners and innovating in a closed manner – and their effect on innovation speed based on the above-mentioned two measures. For the former, innovating with R&D partners, I further distinguished between a) innovating with science-based partners, and b) innovating with market-based partners, and compare their effects on project performance.

2) *Project Financials*

Research transfers are reviewed annually on their Business impact as they generated in the marketplace (and the licensing/ IP transaction fees they get from external buyers). Account managers are responsible for collecting business information of these transfers, on which judgments/ predictions are made related to their account. Results of the research projects are firstly transferred to one of the business units (within or outside of the firm) and then the recipient business units further commercialize them into the final market. Thus, two types of indicators are used for project financial performance in this thesis: project transfers, and project financials. Transfers are later on expected to render financial returns of the project. Unlike patent applications (that a firm can simply file patents for everything that comes out of its research labs regardless whether it will be financially successful or not), only those commercially promising project results are transferred to, and accepted by, one of the business units, and also only those successful transfers are able to make revenues in the final market. Some further statistics checks show that the correlation between project transfer and financial returns is rather high, thus I use transfers as an alternative indicator for project financial performance, as they represent the intermediate performance of the project.

The other indicator, project financial returns serves as the ultimate indicator of project financial success. Project financials are made up of financial evaluations and financial realities. I will explanation them in turn:

Evaluations on business success of transfers can result in the following five statuses (financial status):

- *Business Success*: the transfer delivers €25 million or more in turnover in a given year. Turnover is taken as a measure of success (and value) of a transfer. The lower limit of €25 million is based on the overall situation of the firm, in which 1 euro turnover approximates 1 euro market value;
- *Potential Business Success*: the transfer is expected to become a Business Success in the foreseeable future (less than 5 years);
- *Old Business Success*: the transfer achieved a business success previously, but no longer so
- *Inactive*: the business opportunity is no longer pursued
- *Transfer*: the transfer does not have a direct prospect of becoming a business success

Information about the business impact of research transfers is collected on a case-by-case basis in order to understand the relevance or importance of technology for the business. Extensive efforts are made for collecting the data.

Besides the *general* five categories of business impact which account managers assigned to each of the transfers they are responsible for, the *detailed* financial performance of these transfers (either the predicted amount of money to be made in the market if the profit year is yet to come, or the amount of money really made in the real market if the turnover is already achieved in the given year, or year(s) before). The information is also updated and adjusted by the account manager on a yearly basis. This information is called "business impact". Corresponding to the financial impact of the transfer, the "estimated year" of the transfer is added alongside to its financial impact to denote in which year this amount of financial impact is expected to be achieved (or is already achieved). Based on the above-mentioned three types of financial information: *business impact*, *financial returns*, and *estimated year*, I then did an extensive exercise on data matching and manually reviewed each pair of matches in order to make sure that the "real" amount of money generated by the transfer is correctly assigned to its "real" year of generation. The initial work is done via a set of extensive programming, which is then double checked via manual screening.

I aggregate all the yearly financial information of those transfers which are spawn from the same originating project into a single value, and then allocate this value to their originating project in the same year (if the project has generated more than one transfer and (some of) these transfers are running in parallel with each other). This then leads to the "project financials" in my dataset. I have this variable in two different forms: 1) project yearly business impact, and 2) project overall return (all the financials the project generated across all years). For a brief overview and example of the relationship between the project, its transfer(s), (yearly) financial returns, and its (yearly) estimated year, please refer to Figure 9. In this thesis I use the aggregated financials of each project as the indicator of project financial performance.

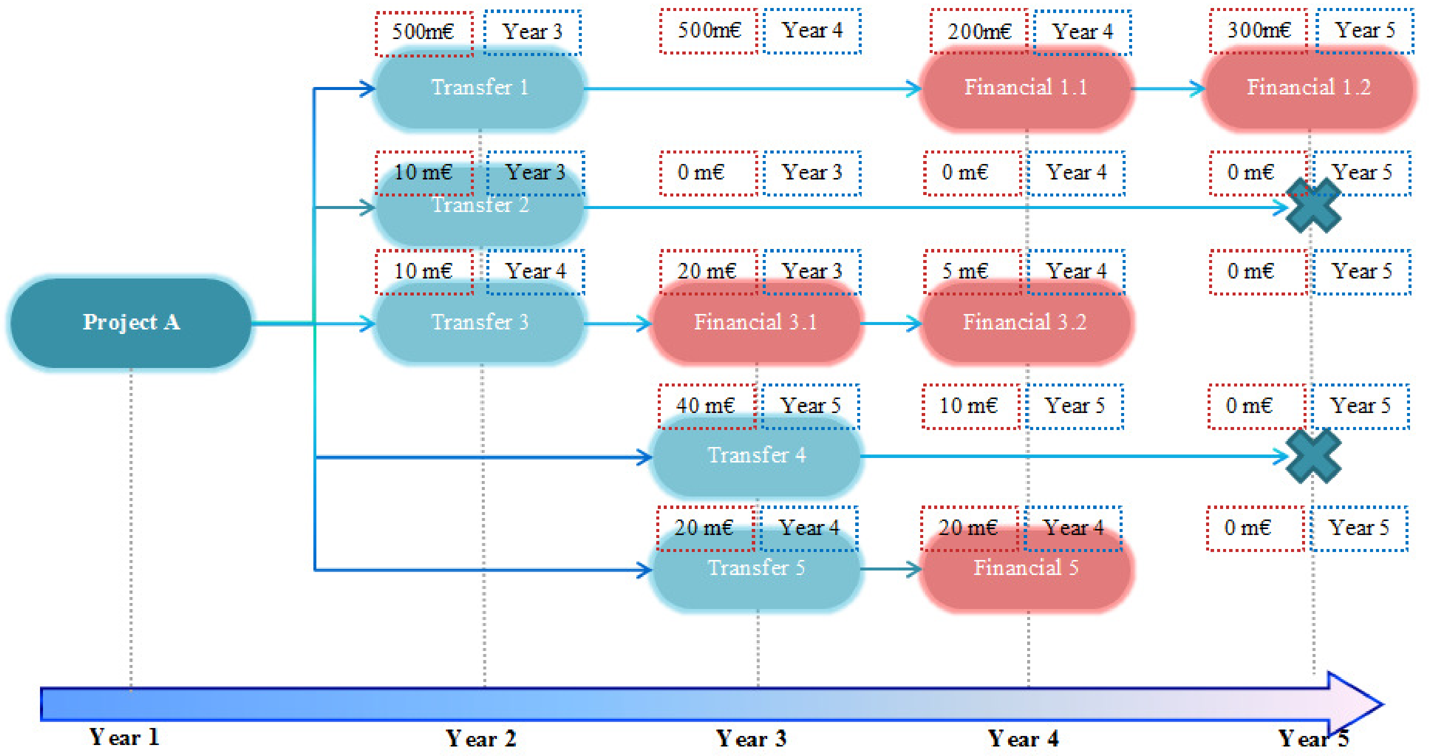


Figure 9 Project, Transfer, Financial Impact and Estimated Year

In Figure 9, Project A which was originated in Year 1 has generated 5 transfers in its lifetime. Which are labeled as Transfer 1, Transfer 2, …, Transfer 5. Among which, Transfer 1, 2, 3 are delivered in Year 2, and Transfer 4, 5 are delivered in Year 3. For each of these transfers, there is a possibility of generating financials in the marketplace, and the *Estimated Year* (in boxes bordered with blue dots) of financial generation is recorded alongside the *Financial Impact* (in boxes bordered with red dots). Transfer 1 generated its first financial (Financial 1.1) in Year 4, and then a second Financial (Financial 1.2) in Year 5. Same situation applies to Transfer 3, which delivered its first financial returns (Financial 3.1) in Year 3, and a second financial returns (Financial 3.2) in Year 4. Transfer 2 and 4 generated no financials. Transfer 5 has its first but also the last financial (Financial 5) in Year 4.

I aggregate the financials generated to Project A. Hence, for my panel dataset, Project A has Financial 3.1 in Year 3, Financial 1.1 + Financial 3.2 + Financial 5 in Year 4, and Financial 1.2 in Year 5. For my cross-sectional dataset, Project A thus has Financial 1.1 + Financial 1.2 + Financial 3.1 + Financial 3.2 + Financial 5 for its whole lifetime.

For an example, Transfer 1 was predicted to generate 500 m€ in Year 3, when it comes to Year 3, the prediction remains 500 m€, but was changed to be in Year 4 to realize this amount of financial. When it comes to Year 4, the prediction reduces to 200 m€, which is also the real money generated for Transfer 1 (e.g.: financials recorded in Year 4 reports the real financials generated in Year 4 (if any), and predicts the evaluated financials of Year 4+ t, if there is no financials generated for Year 4). In Year 5, the financial is reported as 300 m€, which is also the real money generated in the marketplace. Same rules apply to the financial impact and estimated year recorded for the other transfers. Hence, in this case, for the panel dataset, Project A has 20 m€

for Year 3, 225 m€ for Year 4, and 300 m€ for Year 5. For observations in the cross-sectional dataset, Project A generated 545 m€ during its whole lifetime.

2.3.3 Definition of R&D Collaboration Variables

I make a distinction between different types of research projects by categorizing them into open or closed projects[16]. In this thesis, open projects denote those projects that have collaborated with partners in its lifetime, while closed projects are those that do not collaborate with any partner in the research project. I further distinguish between two types of open projects according to the type of partners the project collaborates with: science-based partnership projects, and market-based partnership projects. I assume that once the collaboration takes place, the effect remains for the following years. Therefore, collaboration with science-based and / or market-based partners is captured by dummy variables. More specifically, a collaboration variable gets a value of 1 if collaboration (with the particular type of partner) took place in at least one of the previous years.

Science-based Partnerships signal whether the project is executed in cooperation with research-oriented partners, e.g. academic institutes, government agencies or other industries. This variable is entered yearly for each project in the database. This data on open innovation has been gathered in a systematic way for the period 2003-2010. This is a 0/1 variable that takes a value "1" when during a research project the company collaborates with science-based partners in one of the previous years or in the current year.

[16] I take both formal and informal collaborations into account in defining R&D collaboration. In this way, I use a broader definition of partnerships than what has been commonly used in the extant literature, which has focused mainly on the effects of formal partnerships. As Link and Bauer (1989) reported a percentage as high as nearly 90% of the research partnerships in their sample were actually informal in nature (Hagedoorn et al., 2000; Link and Bauer, 1989). Therefore I look not only at publicly announced alliances or collaboration deals, but also take into account the informal collaborations at the project level that are not revealed in alliance or collaboration data.

Market-based Partnerships denote the other type of external partnership which is more market-oriented. They signal whether the project is executed in cooperation with market-based partners such as customers, users, communities, or suppliers [17] of the firm's businesses. In line with the science-based collaboration variable, this is a dummy variable with value "1" if the project team collaborates with market-based partners in the current year or in any of the previous years, and "0" otherwise.

Open Innovation Projects takes a value of "1" if any of the value "Science-based Partnerships" and "Market-based Partnerships" takes a value of "1", and takes a value "0" otherwise.

2.3.4 Control Variables

As mentioned before, there are several factors that may influence project performance. I operationalize a number of variables to control for possible confounding effects at the project level.

Project Management. Prior literature in product development has highlighted project management as an important factor that underlies project success or failure (Kahn et al., 2006; Griffin, 1997; Cooper et al., 2004). Scholars identified key project management factors including project planning (Dwyer and Mellor, 1991; Zirger and Maidique, 1990), project regularly revision, evaluation, and adjustment (Cooper, 1990; Cooper, 2008), which has been termed as "stage-gate" model (Cooper, 1990). It is argued that successful projects are the ones that have implemented stage-gate processes in a more systematic way than the rest (Kahn et al., 2006; Griffin, 1997). Following

[17] The "horizontal" type of partners, such as competitors are labeled as either market-based collaboration or technology-based collaboration according to the type of knowledge they provide in the innovation process. However, this type of collaboration is seldom adopted by research projects in my sample.

previous studies, in this chapter I introduce the variable "project management maturity" (PMM) indicating to which extent the projects has followed a formalized management process. I further distinguish between two dimensions of the management process: project planning on the one hand and project monitoring and review on the other hand. These two indicators are evaluated on a yearly basis with a scale from 0 to 5 (for a detailed description of how these variables are composed, see Appendix A).

Project Resources. "Project resources" is another factor that may affect project performance (Cooper et al., 2004; Griffin, 1996). Projects with a bigger budget and more resource allocation may be intrinsically more important and more complex than the others. Therefore, such projects have a bigger chance in generating higher financial impact but at the same time they may take more time to develop. Moreover, it has been argued that projects with higher internal resource endowment perform better than the ones that do not (Cooper et al., 2004). I use the number of full time equivalent researchers (FTE) working on a research project as a proxy of project size and internal resource endowment. This information is available on a yearly basis. In line with the R&D collaboration variables, this variable is calculated as a cumulated variable over the past years. Moreover, this variable is highly correlated with project costs, and thus I use it as an alternative to the cost of the project.

Project Technological Fields. I use a set of dummy variables to denote the technology fields in which research projects are executed. Prior literature has pointed out there are significant differences among industries in their motivation (Tether, 2002), practices (Knudsen, 2007) and outcomes (Belderbos et al., 2004) of collaborations. Projects in different technological fields are likely to pursue distinct types of innovations. For instance, consumer products may be developed quicker, generate higher volume, but may generate less revenues and profits, while drug development may be riskier, take a longer time to develop, but finally achieve higher financial results once the project is successfully developed. Therefore, differences between the industries are an important factor which I need to control for. I have followed a two-step process to classify research projects into technological fields. First, for projects that have made patent applications, I use the technology class information on the patent applications. If a patent contains multiple technology classes (IPC4-digit level), a project is assigned to multiple fields. Second, the remaining projects are assigned manually to IPC technology classes by using information on the project content from the project titles and descriptions. To reduce the probability on misclassifications, I work at the level of IPC 4-digit classes. Technology classes with a low number of projects in my sample are grouped together in a rest category.

Project Technical Strength (Firm Patent Stock). This variable represents the technological strength of the company in the technology fields that are relevant for the research project. It measures to what extent the company has a strong technical expertise in the technological field(s) of the research project. These competences are expected to be (at least partly) accessible to the project team. This variable represents the previous 5-year patent stock of a project, which is measured based on the total number of the relevant 4-digit IPC code (5 years prior to the project year) of the patent applications the firm has made in EPO. If projects are in the technological fields in which the company has built a strong position it may have better absorptive capacity, stronger reputation vis-à-vis its partners, and a greater knowledge stock, which all positively contribute to project performance. The technological fields of a project are identified based on its 4-digit IPC code of the firm's patent stock. I have collected patent data for the sample firm at the consolidated level, including both the parent firm and their majority-owned subsidiaries. The consolidation was done on a yearly basis (2003-20010) to take into account changes in the firm group structure due to acquisitions, mergers, green-field investments, spin-offs and divestments. Based on the technological fields of each research project, I extracted the relevant patent stock in the same technological fields of the firm five years prior to project origination. I also calculated previous 3 years and 10 years patent stock as robustness checks.

Corporate Research. To sustain survival and growth, firms have to develop ambidextrous capabilities and balance the exploitation and exploration of their innovation activities (Tushman and O'Reilly, 1996; March, 1991). In this study, research projects can be initiated from two types of sponsor units, i.e. corporate research, or the business groups which are in different business divisions. Corporate research may display distinct characteristics compared to business divisions, as the latter are usually faced with budget limitations or fierce market competition (Chesbrough, 2003). In contrast, projects that are initiated by corporate research are typically focused on the long term development of the firm and, therefore, these projects can be strategically important. They may get priority from senior managers. These projects may also be more explorative and promise higher returns, but they may also take more time to accomplish. Projects that are initiated by business groups, on the other hand, may be more application-oriented and usually have a short-term focus. Therefore, I control for such differences by adopting a dummy variable with value "1" representing a project initiated by corporate research, while "0" suggesting that a project is sponsored by business divisions.

Project Patent. A dummy variable (0/1) is added to control for whether a research project has resulted in patents applications. The purpose of this variable is to control for the novelty of the technological results of the project, as novelty is one of the criteria for patentability. Novel inventions are expected to be more likely to result in large financial revenues.

Project Transfer. A first condition for a research project to generate financial returns is a transfer of the project results to one, or multiple, business departments; called development departments hereafter. I use a dummy variable (0/1) to indicate whether a research project has generated a transfer.

Sponsor Departments. Research projects can be initiated by corporate research (49% of projects) or any of the business departments (51% of projects). As explained before, research projects that are initiated and sponsored by different departments are likely to differ in characteristics. I therefore add a set of 11 dummies that indicate the sponsor departments.

Development Departments. After the results of Research projects are transferred to a business department (which is about 50% of the cases also the sponsor department), the further development and commercialization of the project results are taken care of by the development department. The capabilities, reputation, and experience of the business departments which take the responsibility in commercializing the project results also affect the final market success of the research project. To control for this, I add a set of 11 dummies that indicate which business departments have requested a transfer of project results.

# of Projects Under Management. The more projects a project leader is actively managing, the less time and energy he/she may devote to each individual project, which may affect project outcomes. Projects that receive more attention from their project manager may enjoy timely feedback, and receive more managerial support, and be ultimately more successful. In this study, I use number of projects that the project leader is managing concurrently during the project's life span as a proxy for (a possible lack of) managerial attention.

Length of the Project. Project length may be another important factor influencing its innovation performance as longer projects might have had more possibilities in solving technological issues, generating patent applications, and building up competencies.

Project Initiating Years. Finally, I control for the year in which the project started. The "project originating year" may signal the macroeconomic situations at a particular point in time, but it may also embody the effects of changes in corporate level strategy on the research projects. I use a range of dummy variables to control for effects related to specific external and internal conditions when research projects were initiated.

Chapter 3

Does Open Innovation Improve the Performance of R&D Projects?

3.1 Introduction

Open innovation has triggered considerable scholarly attention in recent years (e.g.: Laursen and Salter, 2006; Vanhaverbeke et al., 2008). Open innovation is advocated to lead to a number of benefits such as better adaptation to market needs, shared resources and risks in the innovation process, and higher commercial returns for innovation activities (Chesbrough, 2003; Chesbrough et al., 2006). As such, open innovation is contended to be an imperative for innovative firms, and increasingly more companies have embraced open innovation as part of their innovation strategy (Huston and Sakkab, 2006; Kirschbaum, 2005; Van den Biesen, 2008; Hagedoorn, 2002; Roijakkers and Hagedoorn, 2006). However, despite its popularity, empirical analyses on open innovation are scant, and the actual effects of open innovation are not yet well understood. Existing research on the performance effects of openness or collaboration with external partners has generated mixed results: some authors found positive effects of being open (e.g.: Laursen and Salter, 2006), while others found no, or even negative effects of open innovation activities (e.g. Lhuillery and Pfister, 2009; Un et al., 2010; Coleman, 1988).

A possible reason for the mixed research findings on open innovation is that most of the studies are conducted at the firm level, comparing and analyzing the performance of firms that differ in terms of their overall openness to external partners. However, innovation activities in firms are conducted via research projects. Recent estimates show that 80 percent of firms organize their R&D activities in projects (Sydow et al., 2004) and that increasingly more organizations adopt project-based forms of innovation (Gemünden, 2009; Hobday, 2000; Sydow et al., 2004). Research projects, even those conducted within the same firm, are different in many respects, such as the type of technologies that are developed, the resources that are available and the way projects are managed. To determine the performance of open innovation approaches it is important to control for the peculiarities of research projects, which, in turn, calls for a switch of the unit of analysis from the firm to research projects. Responding to the call of Chesbrough et al. (2006, p. 287), that "neither the practice of nor research on open innovation are limited to the level of the firm", and that "the sub firm level of analysis is particularly salient in understanding the sources of innovation" (2006, p. 287), this chapter is among the very first contributions that examine open innovation at a sub-firm level, being the research project level. More specifically, in this chapter I examine the effect of (outside-in) open innovation practices on the financial performance of research projects. Following prior literature (e.g. Danneels, 2002, Deeds and Rothaermel, 1999, Faems et al., 2005), I distinguish between two types of open innovation partnerships – science-based partnerships (including universities and knowledge institutions) and market-based partnerships (including customers and suppliers) – and I examine their distinctive effects on the financial performance of research projects.

Switching the unit of analysis from the firm to the research project does not only allow for a more precise estimation of the performance effects of open innovation, it also offers an opportunity to identify and study a new set of variables that moderate the open innovation – performance relationship, which are only available in project level datasets. One such variable is project management. Project management refers to the process and tools that are adopted to monitor and control the execution of research projects (Clark and Wheelwright, 1990; Cooper and Kleinschmidt, 1995). Project management has been widely studied in the new product development (NPD) literature. A formal "stage-gate" monitoring process, with regular reviews and a strict planning has been put forward as the "golden rule" of project management (Slevin and Pinto, 1986; Cooper, 1990; Barczak et al, 2009; Cooper and Edgett, 2008; Griffin, 1997; Kahn et al., 2006). Most insights on project management are however distilled from studying closed innovation projects, and it is not clear whether these insights can be generalized to managing open innovation projects (Grönlund et al., 2010). A few observations seem to suggest that strict monitoring may not be the best management approach for all types of research projects. First, although companies have increasingly formalized their project management process, the success rate of research projects has stagnated over time (Griffin, 1997; Barczak et al, 2009). Second, there are examples of projects that were monitored in a less formal way but were highly successful (Munns and Bjeirmi, 1996). The second purpose of this chapter is therefore to study whether project management, and more specifically the extent to which a formal monitoring process is used, moderates the effectiveness of open innovation partnerships with science-based partners and market-based partners. As such, my work fits in the literature that posits that the effect of open innovation is contingent on a number of factors, such as breadth and depth of openness (Laursen and Salter, 2006), absorptive capacities (Tsai, 2009), and searching directions (Sofka and Grimpe, 2010).

To examine the impact of open innovation on the financial performance of research projects, I rely on a unique longitudinal dataset (2002-2009) that records annual information on the open innovation practices, project management and financial performance of 489 research projects from a leading multi-national European manufacturing company that is active in a variety of industries and has an annual R&D budget of more than 2 billion euros. My results show that that research projects that open up and form external partnerships have a higher financial performance conditional that they are managed in the right way. Market-based partnerships have a positive effect on performance if a formal monitoring process is used; but these partnerships have negative effects for loosely monitored projects. In contrast, science-based partnerships have beneficial effects on performance only for loosely monitored projects.

The remainder of the paper is organized as follows. First, I provide a literature review on open innovation and the management of research projects. Next, I develop my research hypotheses. Section four describes the data and methods, and section five reports the empirical findings. In the final section I discuss the main findings and draw several conclusions and implications for both academicians and practitioners.

3.2 Literature Review

3.2.1 Research Projects and Open Innovation Partnerships

Most companies innovate by setting up a stream of research projects. Projects and project management are at the heart of implementing corporate strategies (Brown and Eisenhardt, 1995). Research projects can be considered as temporary entities which conduct a series of complex and interrelated activities and which operate with relatively limited resources and have pre-defined goals

(Clark and Wheelwright, 1990; Cleland and Kerzner, 1985; Pinto and Prescott, 1988). Innovations are created by groups of individuals in research projects and the essential processes of knowledge creation and dissemination accrue at the interface between projects and the environment in and through which they operate (Grabher, 2004). Firms undertake research projects to address a wide range of innovation needs: as the pilot fish to explore a new research area, as the visible entity to attract external resources and investments, or as the working unit to address a particular research goal. In any of these cases, projects act as the focal point of firms' innovation activities (Clark and Wheelwright, 1990). As a result, research projects assume an indispensable role in innovation strategies. Despite some similarities, there are also considerable differences between firms and projects as unit to study innovation activities: in contrast to firms which can be characterized as long-established and rigid institutions, projects allow for a much more flexible and task-specific allocation of resources (Grabher, 2004). While firms usually possess a portfolio of projects, which help them to hedge from the possible losses of any single project failure, projects are much more task-oriented and time-pressured as they have only limited resources and relatively short timelines. As such projects entail different characteristics from firms (Gemünden and Turner, 2012).

One possible way to infuse research projects with new knowledge and to improve their performance, as suggested in the open innovation literature, is to open up and establish R&D partnerships (Chesbrough, 2003; Hagedoorn et al., 2000). R&D partnerships have been primarily studied at the firm level, where it is argued that they help organizations to access and leverage external complementary resources (Eisenhardt and Schoonhoven, 1996; Grant and Baden-Fuller, 2004; Tether, 2002; Miotti and Sachwald, 2003), to reduce costs and risks in development (Belderbos et al., 2004; Hagedoorn, 1993), to achieve synergetic effects among partners (Hagedoorn, 1993), to adapt to dynamic environments (Eisenhardt and Martin, 2000; Dittrich and Duysters, 2007) and to generate higher revenues (Faems et al., 2005).

Prior studies have stressed that science-based partners and market-based partners provide the innovating organization access to diverse types of knowledge (Baum et al., 2000; Danneels, 2002; Faems et al., 2005). Although there are debates over which type of knowledge is more beneficial for R&D activities, studies have shown that both science-based and market-based knowledge play significant but different roles in firms' R&D activities (Chidamber and Kon, 1993; Danneels, 2002; Faems et al., 2005; Hoang and Rothaermel, 2005).

3.2.2 Research Projects and Science-Based Partnerships

Basic scientific research conducted at universities and knowledge institutes, is an important input for many industrial innovations (Jaffe, 1989; Mansfield, 1995 & 1998; Klevorick et al., 1995; Cockburn and Henderson, 1998; Narin et al., 1997). Surveying samples of US firms across different industries, Mansfield (1995 & 1998) found that, during the period 1975-1985, 11% of firms' new products and 9% of new processes could not have been developed (or with substantial delay) in the absence of academic research. The numbers are even higher for the period 1986-1994, with respectively 15% of new products and 11% of new processes. New basic research is in many cases of an experimental and tacit in nature. It is embedded in the lab and scientist specific routines. By collaborating with science-based partners, research project teams get access to this tacit scientific knowledge (Cockburn and Henderson, 1998). Furthermore, these collaborations may provide access to relevant codified knowledge of scientists that is not yet published, allowing firms to build fast on recent research findings (Fabrizio, 2009). Scientific knowledge functions as a “map” for applied research (Rosenberg, 1990; Fleming and Sorenson, 2004) by providing the research project teams a better understanding of the technological space in which they search for solutions for the technical problems that they are working on. Besides access to latest scientific knowledge, science-based partnerships can also provide access to the most advanced scientific equipment and facilities, and broad scientific networks in which individual scientists are embedded.

Because of the escalating expenditures and risks in R&D activities in many industries (Mowery, 1998), science-based partnerships are increasingly seen by companies as an inexpensive and low risk source of specialist knowledge (Tether, 2002), and science-based partnerships have been growing considerably in both scale and scope over time (Hagedoorn, 2002; Liebeskind et al., 1996; Link and Scott, 2005). The growing number of science-based partnerships has also been stimulated by the installment of government policies to promote ‘translational research’ and public-private research partnerships (Perkmann and Walsh, 2007; Link and Siegel, 2005). Science-based partnerships are considered useful by firms both in exploratory research projects in which they experiment with new technologies and exploitative, application oriented, research projects in which existing products are refined (Perkmann and Walsh, 2007; Cohen et al., 2002)

While there are clear benefits of science-based partnerships, the benefits may only surface in the long run and may be hard to appropriate at the individual project level (Ahrweiler et al., 2011). For example, Feller and Roessner (1995) studied what industry expects from university partnerships, and stated that from the firm’s perspective, “efforts to quantify benefits may not be worth the cost”, and “what firms get from university partnerships are ‘methods and tools’… it is hard to estimate the economic return from their partnership” (p. 84). Their study also pointed out that firms value their relationships with science-based partners over the whole innovation cycle and not just for the initial supply of inventions within a short timeframe (Perkmann and Walsh, 2007). In fact, from the viewpoint of the firm, the role of ‘ready-made’, university-generated technology is moderate compared with the knowledge that is accessed through market-based partnerships. This is underlined by the fact that firms’ expectations towards collaboration tend to be informed by capacity-building and learning motives (Harryson et al., 2008; Mowery, 1998) rather than tangible outcomes. Further, research projects are usually executed by small teams which are temporary entities that work together during the lifetime of the project, and which are dismantled afterwards (Pinto and Prescott, 1988). Therefore, there may be insufficient opportunities for project teams to reflect on the learning from previous science-based partnerships (Hobday, 2000; Brady and Davies, 2003; Grabher, 2004). As such, project teams are restricted by their absorptive capacity (Grabher, 2004), which might constrain their learning from science-based partners (Tsai, 2009; Escribano et al., 2009). In sum, it is unclear whether the potential benefits of science-based partnerships will manifest themselves at the project level (Ahrweiler et al., 2011).

3.2.3 Research Projects and Market-based Partnerships

Market-based partnerships consist of players that have a close link with markets, such as suppliers and customers (Danneels, 2002). There is a substantial literature on market-based partnerships. Relationships with external market players are labeled in different ways: market orientation (Jaworski and Kohli, 1993; Narver and Slater, 1990), customer (or supplier) involvement (Song and Thieme, 2009), customer (or supplier) interaction (Gruner and Homburg, 2000), customer empowerment (Fuchs and Schreier, 2011), collective customer commitment (Ogawa and Piller, 2006), or marketing-R&D

interfaces (Griffin, 1993; Song and Parry, 1997). Besides the traditional market partners such as customers and suppliers, recent studies on open innovation proposed that projects can benefit also from sourcing market information from broader channels, such as communities (Dahlander and Wallin, 2006) and communities of practice (West and Lakhani, 2008).

There are various reasons for firms and research project teams, to collaborate with market-based partners (for a review of the relevant literature, see Greer and Lei, 2012). First, suppliers have expertise and knowledge on the latest technologies, parts and components that are available on the market (Sun et al., 2010). Partnerships with suppliers allow research projects to identify potential technical problems early in the process (Kessler and Chakrabatri, 1996), therefore improve product reliability and performance (Dyer, 1996; Langerak and Hultink, 2005). Second, partnerships with customers provide project teams with first-hand information on market needs (von Hippel, 2001; Prahalad and Ramaswamy, 2004) and help to establish a foothold in the market-place (Appiah-Adu and Ranchhod, 1998) by eliminating the likelihood of product failures (Harrison and Waluszewski, 2008) and meeting customer satisfaction (Ragatz, Handfield and Peterson, 2002; Gruner and Homburg, 2000). It is argued that timely and reliable knowledge about market preferences and requirements is the single most important type of information necessary for product development (Ogawa and Piller, 2006; Cooper and Edgett, 2008). Many new products fail not because of technical shortcomings but because they simply have no market (Ogawa and Piller, 2006). Therefore customer value is regarded as “the next source for competitive advantage” (Woodruff, 1997, Dyer, 1996).

Prior research has shown that there is also a dark side to market-based relationships. First, intense relationships with customers may result in the rejection of new technologies that initially don't meet the needs of mainstream customers (Bower and Christensen, 2005), and which have the potential to become breakthrough innovations (Gassmann et al., 2010). Furthermore, buyer-supplier relationships can reduce the buyer's ability to make objective decisions and it can increase the supplier's opportunistic behavior, and ultimately reduce the performance of the research project (Villena et al., 2010; Song and Thieme, 2009). Finally, as R&D teams are temporarily entities, they may not have the time to absorb the knowledge from their market-based partners. Limited absorption capability of the R&D teams limits their learning from both science-based partners as well as from market-based partners. However, I expect that this effect will be smaller for market-based relations as the focal firm is collaborating with market partners for several reasons among which learning is only one dimension of the relationship. In contrast, relations with universities and research labs are almost exclusively focusing on co-creation and transfer of knowledge.

A significant number of papers have examined the impact of market-based partnerships on the performance of research projects. However, the findings are mixed. While most studies found positive net effects of partnerships with market partners on project performance (Ragatz et al., 1997; Lettl et al., 2006; Calantone et al., 2010; Song and Di Benedetto, 2008), some studies found no (Un et al., 2010) or even negative effects (Knudsen, 2007; Song and Thieme, 2009). This chapter will add to the extant literature on market-based and science-based partnerships by taking both types of partnerships simultaneously into account, and performing a full analysis of open innovation strategies with different types of external partners at the project level.

3.2.4 Research Project Management

The crucial role of project management in research projects has been widely emphasized in a number of studies (e.g.: Griffin, 1993; Griffin and Page, 1997; Cooper and Kleinschmidt, 1995; Ernst, 2003; Slevin and Pinto, 1986; Pinto and Prescott, 1988). Project management is the process that is followed by company executives and project managers to monitor and control the execution of research projects, via the adoption of management tools and techniques (Clark and Wheelwright, 1990; Pinto and Prescott, 1988). In the new product development (NPD) literature, it is generally agreed that having an efficient process that is able to manage the ambiguity of the new product development process is critical to project performance (Globe et al., 1973; Adams et al., 2006).

New product development is a risky process, and many research projects can and do easily "go wrong" during development (Cooper et al., 2004; Wheelwright and Clark, 1990). To reduce the failure rate of research projects and to achieve their goals within the planned budget and time, a formal monitoring process, with a strict planning and regular reviews, has been put forward as the best project management approach (Slevin and Pinto, 1986; Cooper, 2000; Cooper and Edgett, 2008; Griffin, 1997; Kahn et al., 2006; Barczak et al., 2009). An example of a formal monitoring process is the "stage-gate" model, firstly introduced by Cooper (1990). The stage-gate model emphasizes the regular monitoring, reviewing and evaluating of research projects at pre-defined stages between idea conception and market launch. A set of deliverables is specified at each stage, which a project team has to fulfill in order to get the approval to proceed to the next development stage (Cooper, 1990; Cooper and Edgett, 2008).

The importance of formal project management approaches has also been stressed in the process management literature (Ishikawa, 1985; Deming, 1986). Process management views an organization as a system of interlinked processes, which involves concerted efforts to map, improve, and adhere to organizational processes. Two elements are of the central importance in this literature: 1) adhering to documented systems and procedures, and eliminating variations in processes and outputs (Harry and Schroder, 2000) and 2) standardization and generalizability across projects (Hackman and Wageman, 1995). To achieve these goals, a formal review process is needed. During the past two decades, firms have increasingly implemented project management techniques (such as elements of the stage-gate product development process) and they have increasingly formalized their project monitoring process (Kahn et al., 2006; Griffin, 1997; Barczak et al., 2009).

Although formal project management techniques are widely used, several recent findings and observations cast doubts to such an approach as a universal rule in project management. First, Griffin (1997) and Barczak and colleagues (2008) found that, although increasingly more companies have formalized their project management process, the failure rate of research projects remains considerably high and has stagnated across the past years. Second, Munns and Bjeirmi (1996) provided examples of projects that resulted in huge market success, but which were managed in a less formal way. Hence, a formal monitoring approach does not necessarily lead to successful project outcomes, or vice versa. In other words, projects that are managed in a more “loose” way can still achieve final successes, while those projects that are managed in a formal way may turn into big failures (Munns and Bjeirmi, 1996). Third, several scholars have argued that there are differences across research projects and that the standard, formal project management approach may not be applicable to all projects (Adams et al., 2006; Benner and Tushman, 2003;

Shenhard and Dvir, 1996). Adams et al. (2006) pointed out that because the product development process is complex and in several cases uncertain, “it is clearly possible that innovation processes will differ to some degree, across organizations and even within organizations on a project-by-project basis” (p. 36). In a similar vein, Shenhar and Dvir (1996) propose to categorize projects into different types when choosing the best matching project management approaches. One of the goals of this chapter is to examine whether a formal monitoring process is beneficial for research projects that have open innovation partnerships with science-based or market-based partners.

3.3 Hypotheses

3.3.1 Open Innovation Partnerships and Project Performance

The ultimate goal of research projects conducted in large, innovation driven companies is to generate new business opportunities with a strong impact on the long-term growth of the firm’s revenues. Revenues generated in the marketplace compensate for projects’ development costs, and are fed back into R&D for the continuation of existing and initiation of new research projects. In order to maintain a certain growth rate, to keep up their stock market value, and to compensate for their large research budgets, large R&D intensive companies need to find new business opportunities. To become a market success, a research project has to cope with two challenges: first, it has to survive the development process and be able to reach the market. Second, the project outcome has to become widely accepted in the market place. I argue that research projects can increase their financial revenues by opening up and forming open innovation partnerships with external partners for the following reasons:

First, open innovation partnerships may increase the likelihood that a project will survive the product development process and be launched on the market (Du et al., 2013). New product development is a highly risky and error-prone process (Cooper, 1990; Cooper et al., 2004). It is estimated that 35 to 80 percent of all product development endeavors are failures (Tidd et al., 2005). One reason for the high failure rate is that many research project teams lack the necessary resources and expertise to successfully complete the NPD process internally (Griffin, 1997; Barczak et al., 2009). A potentially promising project may be stopped early in the development process because the required resources are not available within the firm, or the project team is unable to solve problems which hinder the further development of the project. By working together with external partners, the project team is able to access and leverage the resources that its partners possess, which, in turn, increases the success rate of the research project.

Second, establishing open innovation partnerships may be instrumental in improving the innovativeness and quality of the products and solutions that are developed in research projects. Product innovativeness and quality are found to be among the major determinants of customers' purchasing decisions (Cooper, 1979; Cooper and Kleinschmidt, 1987). Compared to products which entail slight improvements, innovative products have larger market impacts and could sustain higher prices (Gjerde et al., 2002). Innovation is a process of knowledge (re-)combination, in which new inventions are created through combining different sets of knowledge together (Schumpeter, 1939; Tidd et al., 2006; Singh and Fleming, 2010; Schilling and Phelps, 2007). The basic premise is that experimentation with new components increases the variability that can result in novel inventions (Fleming, 2001). By collaborating with external partners, research project teams can access partners' knowledge stock, which may reside in industries or disciplines that it is less familiar with, and therefore expand its knowledge base and increase the possibility to create novel innovations.

Third, the exposure to different arrays of knowledge that may be (partially) new to a project team may help to overcome "local search" tendencies (Katila and Ahuja, 2002). The Not-Invented-Here (NIH) syndrome prevents scientists and engineers from looking for ideas outside the boundaries of the firm (Katz and Allen 1982). The NIH syndrome leads companies to local search behavior which finally stifles their competence to explore new technologies. However, the ability to exploit external knowledge is a critical component of innovative performance (Cohen and Levinthal 1990, p. 128). Empirical studies have shown that search processes have to span both organizational and technological boundaries to develop new, explorative and less incremental research (Katila and Ahuja 2002, Laursen and Salter 2006, Rosenkopf and Nerkar 2001). Partnership with external partners is a way to overcome the local search trap. External partners bring in new opinions and perceptions to the project team and may act as counterforces to the non-invented-here tendency. Partnerships with external partners enable the project to make better recognition and usage of diverse knowledge sources it may access, and the integration of new technologies its partners possess will help to rejuvenate the project's technology base and make the project outcome more innovative and competitive. Advanced innovation partnerships may also help to expose the research project to the newest or emerging technologies, and thus enable the research project to stay ahead of its competitors in the product it aims to develop. Therefore, I hypothesize:

H 1: Open innovation partnerships increase the financial returns of research projects

3.3.2 Science-Based Partnerships, Market-Based Partnerships and Project Performance[18]

The project team may collaborate with science-based or market-based partners. Both types of partners are different in nature, but both may help to generate larger financial revenues. Market-based partnerships are conducted with partners that provide the project team with the latest market insights. In this way they ensure that market requirements are taken into account, and that the innovations under development create value for the customers. Satisfying market needs is an important key to market success, and there is a strong positive relation between new products' ability to satisfy customer needs and their eventual financial success (Cooper and Kleinschmidt, 1987; Maidique and Zirger, 1990). Often customers are not able to articulate their needs, nor are they able to suggest solutions (Woodruff, 1997). In order to reveal and correctly understand customers' needs it is necessary to partner and develop new innovations in a co-creation process (Ulwick, 2002).

Partnerships with market-based partners can also help to identify novel business models. A business model explains how one can create value for customers and capture part of that value. It is an offering that helps customers to satisfy an important job-to-be-done which is superior to alternatives or at a better price (Chesbrough and Rosenbloom, 2002). Novel business models may increase revenues generated by the project team by unlocking multiple applications of the same technology.

[18] Science-based partnerships may be intended to create technology options, while market-based partnerships are intended to exercise those options. This may therefore imply different success rates in the financials generated, as most science-based options may not be exercised. However, this does not mean that science-based partnerships were a waste of investment. More to be discussed in the section of endogeneity in the data part.

Unlike market-based partners, science-based partners are at the forefront of scientific research and bring the latest scientific knowledge to the research project. Early access to new scientific knowledge may put the research project team in an advantageous position to be the first to turn this scientific knowledge into patentable innovations that can be launched on the market (Rosenberg, 1990; Fabrizio, 2009). This may lead to the creation of a (temporary) uncontested market space, or blue ocean (Kim and Mauborgne, 2005) in which firms can reap monopoly profits. Science-based partnerships may also be used by research project team to get access to advanced but costly scientific equipment and research facilities, which may be needed for state-of-the-art research. Finally, projects with science-based partnerships may also leverage academic networks in which the involved scientists are embedded (Liebeskind et al., 1996). Network theories claim for instance that partners spanning "structural holes" play a bridging role connecting two essentially different knowledge groups together (Ahuja, 2000). Collaboration with academia thus provides the project team with valuable learning opportunities to develop innovations that are innovative and generate higher revenues.

In sum, based on the above arguments, I hypothesize the following:

H2: Both science-based and market-based open innovation partnerships increase the financial returns of research projects.

3.3.3 Project Management, Market-Based Partnerships and Project Performance

Project management is an important determinant of project final success (Cooper et al., 2004). Although prior literature has placed much emphasis on strict project management, I argue in the context of open innovation different types of partners may require different management approaches. I argue that research projects with market-based partnerships (suppliers and customers) benefit most from a formalized project management approach, characterized by regular monitoring and adherence to a strict planning, for the following set of reasons:

First, some market-based partners, in particular suppliers, are business organizations themselves which are used to, and are familiar with, a formal way of project management in their daily operations (Barczak et al., 2009). Prior literature pointed out that goal divergence is a factor that undermines the use of formal rules and regulations in partnerships (Lorange and Roos, 1992). In a partnership with a supplier, both the supplier and the firm share a similar goal, namely to (directly or indirectly) serve the end market and to make profits in the marketplace. Suppliers have similar objectives and working procedures as industrial firms, and are therefore expected to operate well in a work environment of formal monitoring and a strict up-front planning.

Second, when partnering with suppliers, there is a need to clearly define the scope of the collaboration up-front and to strictly monitor the development process of a joint research project. A firm may have a co-opetitive relationship with some suppliers, and therefore it is needed to protect the research project from unwanted knowledge spillovers during the collaboration process. Studies have shown that there may be confidentiality issues in buyer-supplier relationships (Brockhoff, 2003), and that suppliers might eventually compete with customers (Schultze et al., 2007). A survey of R&D partnerships, with different types of partners, reported that 11% of firms identified R&D partners becoming future competitors as a major risk (Littler et al., 1995). A formal project management approach with a strict monitoring of the research directions that are taken in an research project can help to protect against unwanted knowledge spillovers in areas that fall outside the scope of the partnership. This creates a fertile ground for the R&D partnership and increases the likelihood to successfully co-develop innovations.

Third, market-based partnerships may also involve customers (including crowds), in which case a formal way of project management is also preferred. High levels of project monitoring and control are required to enhance the feasibility of the solutions that are proposed by customers and crowds. It is found that connections to external innovation communities provide access to a broad range of expertise, and thus are good for capturing and filtering large numbers of existing ideas. However, the more focused and professional innovation communities have less breadth but more understanding of context (Birkinshaw, et al., 2011). Clearly, the external community may be far less useful for tackling company-specific or situation-specific problems (Birkinshaw et al., p. 47) if are not guided and monitored in a timely and strict manner. Recent research on the value of crowd-sourcing (Poetz and Schreier, 2012) further shows that ideas that are suggested by customers score high on novelty and customer benefits, but low on feasibility (compared to ideas and suggestions from professionals). Feasibility refers to the ease in which ideas can be implemented and developed into products for the market. Suggestions from customers score low on feasibility because customers are not fully aware of the technologies and processes that a firm has in place. Customers and crowds often lack a conceptualization of the possible resources in need for their proposals, and are unable to articulate the underlying tacit knowledge related to the potential innovation, something which their counterparts— the science-based partners— are much better at (Katila and Mang, 2003). The large number and the diverse backgrounds of the possibly involved customers and crowds further make it difficult to set collaborations free and easy. A formal project management approach with regular and strict monitoring is important to make sure that a project develops according to plan and that unfeasible suggestions are not given too much attention. Further, formal project management approaches enable the project to cope with volatile market needs and to improve strategic decision making in the project development process. Customer preferences are dynamic and may change rapidly (Cooper, 1979; Cooper et al., 2004). Therefore, a high level of monitoring is required to ensure that the dynamic market needs are well understood (von Hippel, 1989) and that the project develops according to the latest market needs. Finally, products which manage to first serve a market void will enjoy first-mover advantages (Lieberman & Montgomery, 1988). In order to realize a first-mover advantage, an efficient product development process is key, as a formal project management approach with clear milestones and regular monitoring enhances the overall efficiency of the new product development process (Harry and Schroder, 2000; Hackman and Wageman, 1995). In sum, research projects are expected to benefit more from market-based partnerships when a formal project management approach is used:

H 3a: Formal project management positively moderates the relationship between market-based partnerships and the financial returns of research projects.

3.3.4 Project Management, Science-based Partnerships and Project Performance

In contrast to market-based partnerships, I argue that science-based partnerships require a less formal project management approach to be effective, for the following reasons:

First, science-based partners have different incentives and targets, and operate in a different working environment than industrial firms. While industrial researchers work in an environment characterized by regular monitoring and strict control, scientists operate in environments where there is more autonomy, academic freedom and room for improvisation. It is found that academic institutions and industrial firms differ in their focus on creative control versus focus (Aghion, et al., 2008). Scientists value creative control and academic freedom (Aghion et al., 2008), and are found to be willing to accept lower wages in return for the freedom to pursue own research agendas and to publish research findings (Stern, 2004). Science-based partners may find themselves uncomfortable working in partnerships that are managed in a formal and strict way, with a focus on attending meetings and reporting (Cooper et al, 2004) and less room for autonomy and experimentation. This is expected to result in a lower motivation to cooperate and a lower success rate of the partnership.

Further, science-based partners are not directly competing with industrial firms in the marketplace for revenues of the jointly created products. Science-based partners value scientific reputation and non-profit oriented goals more than monetary benefits (Mowery, 1998), although recently – due to declining government budgets for scientific research - there are increasing pressures to find extra sources of revenues. Since, both partners are no direct competitors, there are fewer concerns for unwanted knowledge spillovers and thus a lower need to formal monitor and control the scope of the partnership.

Finally, formal monitoring stifles experimentation, and reduces the benefits of partnering with science-based institutions. One of the main reasons for research projects to collaborate with science-based partners is to get a window on the latest scientific developments and to experiment with new technologies and methods (Cockburn and Henderson, 1998). Formal monitoring and control are project management techniques that are used to ensure that research projects stay on track and proceed according to plan (Cooper, 1990; Pinto and Prescott, 1988). To achieve these goals, research projects are well planned beforehand and there is a strict monitoring and follow-up. A strict monitoring however rules out experimentation with new technologies and reduces the possibility to make serendipitous discoveries. Experimentation (Eisenhardt and Tabrizi, 1995) and serendipitous discoveries (Doz et al., 2001) play critical roles in developing innovations, and are two core research strengths of science-based partnerships (Rosenberg, 1990), which might be hampered by formal project management.

Based on the above arguments, I hypothesize the following:

H 3b: Formal project management negatively moderates the relationship between science-based partnerships and the financial returns of research projects.

The different research hypotheses are summarized in Figure 10. In the first hypothesis, I test the effect of open innovation (in general, regardless of types of partners) on the market performance of the research project (as measured by financial returns), in the second hypothesis, I look into each different type of partners, and test their effect of project market performance, respectively. The third hypothesis is on the role of project management on open innovation and project market performance, where a positive (for market-based partners) and a negative (for science-based partners) relation are expected.

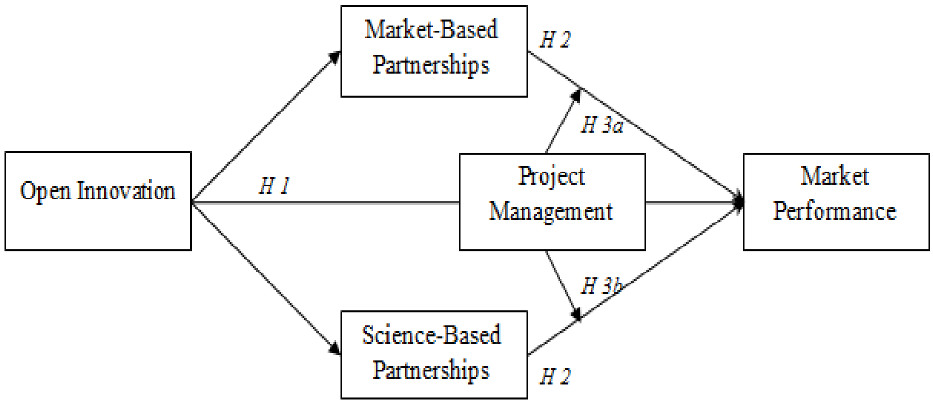


Figure 10 Conceptual Framework & Hypotheses

3.4 Data and Sample

To test my hypotheses, I use a unique longitudinal dataset on research projects that are conducted by a large multi-national, multi-divisional European-based manufacturing company. This company has an annual R&D budget of more than 1.5 billion euros and is active in a variety of industries. The dataset contains detailed information on all research projects that have been initiated in the company's R&D labs during the period 2003-2009 and were finalized before the end of 2010. The company adopts a global R&D structure which is typical for large technology-based companies (von Zedtwitz and Gassmann, 2002). Research projects are conducted in central R&D laboratories, and are initiated by either one of the company's business departments or by Corporate Research, which is the central R&D unit. Corporate Research overviews the R&D activities of the firm as a whole, and mainly sponsors research projects that are highly explorative, which have a long-term orientation and are of strategic importance to the firm. Business departments, on the other hand, being restricted by the need to show (quick) returns on R&D investments and a regular evaluation of business achievements, mainly sponsor research projects that are application-oriented and have a shorter time window.

The R&D laboratories execute the research projects and transfer the outcomes to the business departments that express their interest in taken up these outcomes for further development and commercialization. There are different types of business departments: the majority of them –which are organized around product groups - address the firm's existing markets; two departments (IP and Licensing) deal with external third parties and are responsible for facilitating inside-out project outcomes deliveries; the new business development department explores the use of technologies that can lead to a promising application, but which fall outside the score of the existing business lines of the firm; last but not the least, technologies with applications that fall outside the company's roadmap can be transferred to the incubator department and spun-out eventually. The different departments illustrate that the sample company uses both internal and external paths to bring its technologies to market.

In the project initiation phase, the R&D lab gets an "order" to start an research project as well as a R&D budget from Corporate Research or the sponsoring business department, and then a research project starts. During the course of a research project, the project team may collaborate with market-based (customers and suppliers) or science-based (universities and knowledge institutes) partners. Upon the finalization of the research project, if it satisfies expectations, the results of the research projects are delivered to its original sponsor (in most cases an existing business department), or to another department which is different from its original sponsor, but which perceived an opportunity to further develop and commercialize the outcome.

Each project is evaluated on a yearly basis from its start to termination (and to the latest year of data collection, 2012, for the financials). From the start of a research project, there is annual information about R&D partnerships, project management and financial revenues. After excluding the projects that are still running by the end of 2010, I have information on 489 completed projects. This dataset is a cross-sectional dataset with 489 observations.

3.4.1 Open Innovation Partnerships

The company who provided the data was amongst the first large R&D intensive companies to widely open up their R&D activities and to actively partner with external actors in R&D. The company has an explicit policy in promoting open innovation activities in its daily operations (e.g.: research projects), but as the actual effect of open innovation was unknown at the time when this concept was coined, and since both academicians and practitioners were/are still debating the benefits of open innovation (see, for instance, Campbell and Cooper, 1999; Knudsen and Mortensen, 2010; Faems et al., 2011), the firm started to record its practices on open innovation activities (at the project level), together with corresponding project characteristics and project performance from year 2003 onwards.

While my sample company promoted open innovation partnerships during my period of investigation, final decisions whether or not to engage external parties in research projects are made by the managers of individual projects. Project managers make these decisions based on project characteristics (such as characteristics of technology fields, and the availability of internal resources), but also have individual preferences. Some managers prefer closed innovation approaches, while others are "strong believers" of open innovation and frequently engage external partners in the research projects that they manage.

Preferences of project managers are based on their own beliefs, and experiences gained in prior projects.

I have annual information on the open innovation practices of the research projects. More specifically, I know – for all project years - whether a project collaborated with science-based partners (universities and knowledge institutes) or market-based (customers and suppliers) partners. I have no information on the identity (names) of the R&D partners. Out of the 489 research projects, 67 (13.70%) are "closed" projects and did not collaborate with any external partner. Of the open innovation projects, 70 (14.31%) are projects where the company only collaborates with market-based partners, 70 (14.31%) only with science-based partners, and 282 (57.67%) are projects where both types of partners are involved. The relatively high collaboration percentage in my data can be explained by the overall corporate policy that stimulated open innovation partnerships, as well as the fact that I take both formal and informal collaborations into account. In this way, I use a broader definition of partnerships than what has been commonly used in the extant literature, which has focused mainly on the effects of formal partnerships. As Link and Bauer (1989) reported a percentage as high as nearly 90% of the research partnerships in their sample were actually informal in nature (Hagedoorn et al., 2000; Link and Bauer, 1989). Therefore I look not only at publicly announced alliances or collaboration deals, but also take into account the informal collaborations at the project level that are not revealed in alliance or collaboration data.

The open innovation partnership variable gets a value of 1 if there was a partnership with either a market-based or science-based partner in at least one of the project year. The science-based partnership and market-based partnership variables follow the same logic and take a value of 1 if there was a partnership with the respective partner in at least one project year.

3.4.2 Moderating Variable

Project Management. The project management indicator measures to what extent a research project was monitored and controlled in a formal way by the project manager, the project sponsor and the responsible overviewing managers. Each project manager has to evaluate the management process of each project on an annual basis. More specifically, the project manager has to evaluate the formality of the project management process by providing a score from 0-5 (a score of "0" means that the activity is not performed; a score of "5" means that high importance is given to the activity) on the following three activities:

- Regular review of the project process, involving management, project owner (= manager), customers, and project sponsors (e.g. corporate research or business unit)
- During project reviews, corrective actions are identified, documented and tracked through to project completion
- Progress reports are made available at the project level on a regular basis, including information on project termination and transferred results

The project management score is calculated as the average score on these three questions. For projects that last longer than 1 year, the average project management score over time is used. A higher score on the project management indicates that a project is managed in a more formalized way, with regular project reviews and a strict project control. Although I do not have further-refined information on how project management is conducted for each single partnership, project management indicates how project teams are managed, including both internal researchers and external partners. My interviewees at the firm also state that typically one management approach is taken towards the project.

3.4.3 Dependent Variable and Empirical Method

Financial performance is the most frequently used measure of the performance of research projects (see Cooper et al., 2004, for a review of project-level performance indicators). The research project aims to develop new products in R&D labs. Its research outcome will be either transferred to business "recipients" (development departments, both within and outside of the firm) for further commercialization, or not transferred if none of the development departments is willing to commercialize the new product. Only the projects that are transferred to development departments are able to generate financials in the marketplace. Financial performance is measured as the total revenues that are generated by the "transferred" outcomes of a research project to one, or multiple business departments between the project termination and the latest year of data collection, i.e. 2012. R&D partners share development costs and risks, but they also share innovation revenues (Belderbos et al., 2010). I measure the revenues that accrue to the sample company; they include both revenues generated through internal and external paths to markets (e.g. licensing or IP sales).

Financial performance is a continuous variable that takes an average value of 8.76 million euros, and ranges between 0 and 800 million euros. The variable is truncated at a value of 0. To account for the truncation, Tobit regressions are used (McDonald and Muffit, 1980; Greene, 2000). As the Tobit model requires the assumption of normality, I prefer to use the log of my dependent variable to reduce skewness of the distribution. Not all projects generate financials, so some observations have a value of zero. As I cannot take the log of zero, I impute the smallest observed value (i.e. a value of 1 for my dataset) for these censored observations. I control for heteroskedasticity by using robust standard errors.

The data and empirical specification has several features that alleviate concerns of potential endogeneity and biases stemming from unobserved factors. First, I use project-level data from one firm, thus possible confounding effects at the firm level, such as innovation policy, corporate culture, etc. are taken care of. Second, I use a large number of control variables in my regressions that contain detailed information on the research projects. Despite these actions, there may still be unobserved factors that make my focal variables (open innovation partnerships and project management) endogenous. I have checked for potential endogeneity of the open innovation and project management variables using the Smith and Blundell (1986) test. The procedure is as follows. First, I regress the potential endogenous variables on all exogenous variables and a set of instrumental variables, and I obtain residuals from these estimations. Second, I add the residuals as additional variables in the basic tobit regressions and check whether they are jointly significantly different from zero.

To conduct this test, I need a good set of instrumental variables for open innovation partnerships and project management. I base my selection of instruments on theoretical reasoning, interviews with managers of the sample company, and a number of statistical tests. To instrument for open innovation partnerships, science-based partnerships and market-based partnerships, I constructed variables (one for each type of partnership) that indicate how frequently project managers use external partners in projects that are managed contemporaneous to the focal project. These variables are likely correlated with choices at the focal project, but are unlikely to be correlated with project performance. Using the same logic, I use the project management approach of project managers in other contemporaneous projects as instrument for project management. As additional instrument for the external partnership variables, I use project duration. Project duration is likely to be associated with the use of external partnerships since the sample company has an explicit policy of encouraging open innovation partnerships, therefore the longer a project lasts, the higher (random) probability it has to engage external partners. However, project duration is not directly related to project performance as both successful and failure projects can last for either a short or a long period of time: companies continue to invest in successful projects till the project get launched in the market, but they also invest in unsuccessful projects in the hope to bring the project back on the right track (Patzelt et al., 2011; Keil, 1995; Bowen, 1987). As final instrument for open innovation partnerships, I use "technology new fields" which indicates whether a technology field is new-to-the-firm (i.e. the firm didn't patent in the technology in the prior 2 years). When a firm conducts a project in a new field, it is more likely to engage external partners; there is however no apparent direct relationship between the newness of a field and the financial outcomes of research projects.

After identifying the set of instruments for my potential endogenous variables, I check for their validity and quality as potential IVs. I first conducted an under-identification test to examine whether the instruments are strong (quality): sufficiently correlated with the potentially endogenous variables. The first stage regressions (reported in Table 2) report partial F-values for the instruments of the four focal variables between 21 and 31, substantially above the cutoff point of 10.

Table 2 Instrumental Variable Analysis and Endogeneity Test

	OI Partnership	Project Mgmt.	MB Partnership	SB Partnership	Project Mgmt.
Project Resources	0.0735**	0.093	0.0635	0.156***	0.091
	(0.033)	(0.071)	(0.042)	(0.044)	(0.071)
Firm Patent Stock	-0.0025	-0.005	-0.0017	-0.004	-0.005
	(0.010)	(0.019)	(0.013)	(0.012)	(0.019)
Project Patent	0.0794**	-0.016	0.101**	0.096**	-0.014
	(0.035)	(0.077)	(0.043)	(0.043)	(0.076)
# Projects under Management	0.0437**	0.050	-0.008	0.056*	0.053
	(0.021)	(0.049)	(0.029)	(0.030)	(0.049)
Excluded Instruments					
Project Duration	0.025**	-0.011	0.060***	0.020	-0.0135
	(0.012)	(0.031)	(0.016)	(0.018)	(0.031)
Technology New Fields	0.0486	-0.420*	0.037	0.178*	-0.423*
	(0.084)	(0.244)	(0.114)	(0.107)	(0.241)
Project Leader Choice OI Partnerships	0.832***	-0.012			
	(0.091)	(0.164)			
Project Leader Choice MB Partnerships			0.945***	0.063	-0.138
			(0.090)	(0.093)	(0.159)
Project Leader Choice SB Partnerships			-0.018	0.847***	0.116
			(0.095)	(0.096)	(0.168)
Project Leader Style Project Mgmt.	-0.042	0.977***	-0.013	-0.046	0.987***
	(0.032)	(0.092)	(0.043)	(0.045)	(0.095)
# of Observations	489	489	489	489	489
Overall Model Fit: R-Square	0.3175	0.3854	0.3300	0.3477	0.3866
Excluded IVs- F(4, 453)	21.15***	30.94***			
Excluded IVs- F(5, 452)			29.17***	22.74***	26.31***
Wald test of Exogeneity	Chi-sq(2)= 1.67 (P-val: 0.4349)		Chi-sq(3)= 2.03 (P-val: 0.5662)		
Cragg-Donald Wald F Statistics for Weak Identification	21.75		13.18		
Amemiya-Lee-Newey Statistics for Overidentification	Chi-sq(2)= 2.089 (P-val: 0.3519)		Chi-sq(1)= 2.511 (P-val: 0.2849)		

Note: 1. Standard Errors are listed below coefficients (between brackets);

2. Technology Fields, Sponsor Departments, Development Departments, Year Dummies are all included.

The instruments also have a clear discriminatory effect, with the instruments based on managers' preferences for particular partnerships or management approaches affecting only the corresponding focal variable. Project duration has a positive effect on open innovation partnerships. Technology new fields have a positive effect on science-based partnerships and a negative effect on project management formality. Further, I performed over-identification tests to check whether instruments are valid (i.e. exogenous). The Amemiya-Lee-Newey minimum chi-square test statistics for both sets of instruments (chi-sq(2) = 2.089, p-value = 0.35; chi-sq(1) = 2.51, p-value = 0.28) cannot reject the null-hypothesis that the instruments are exogenous. With strong and valid instruments, I can test for the presence of potential endogeneity problems. The Wald tests for exogeneity on both sets of potentially endogenous variables (chi-sq(2) = 1.67, p-value = 0.43; chi-sq(3) = 2.03, p-value = 0.56) cannot reject the idea that the open innovation partnerships and project management variables are exogenous in my empirical setting. In other words, I find no evidence that there are remaining unobserved factors that simultaneous drive my focal variables and project financial performance, and confound my results in this empirical setting. Control variables are described in Chapter 2.

3.4.4 Descriptive Statistics

Descriptive statistics and correlations for the variables are provided in Table 3. As mentioned above, most of the research projects have open innovation partnerships (86.3%); they actively partner with market-based as well as science-based external partners. The average project management score is 3.96, which indicates that, on average, a formal process is used to follow-up research projects in the sample company. Most of the research projects (64.8%) apply for patents. None of the reported correlations are high. The variance inflation (VIF) score is 1.5, which is well below 10; hence multi-collinearity is not an issue in my analyses.

Table 3 Correlation Matrix

	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11
1. Project Financials (Logged)	0.280	1.063	1.00										
2. Open Innovation Partnership	0.863	0.344	0.09	1.00									
3. Market-Based (MB) Partnership	0.720	0.450	0.04	0.64	1.00								
4. Science-Based (SB) Partnership	0.720	0.450	0.09	0.64	0.29	1.00							
5. Project Management	3.959	0.774	0.05	0.11	0.20	0.05	1.00						
6. MB Partnership * Project Mgmt.	2.918	1.914	0.05	0.61	0.95	0.28	0.42	1.00					
7. SB Partnership * Project Mgmt.	2.868	1.893	0.10	0.60	0.33	0.95	0.31	0.39	1.00				
8. Project Resources	2.070	0.625	0.09	0.31	0.28	0.36	0.14	0.29	0.38	1.00			
9. Firm Patent Stock	5.787	2.205	0.04	-0.04	0.03	-0.01	0.05	0.02	0.01	0.04	1.00		
10. Project Patent	0.648	0.478	-0.04	0.14	0.16	0.12	0.05	0.13	0.12	0.22	0.21	1.00	
11. # Projects under Mgmt.	2.506	0.648	0.00	0.09	0.02	0.08	0.09	0.04	0.09	0.18	-0.07	-0.11	1.00

(Number of observations = 489 Projects)

Table 4 Descriptive Statistics on Partnership Categories

VARIABLES	Closed Innovation	SB Partnership	MB Partnership
Project Financials (Logged)	0.051 (0.051)	0.371 (0.148)	0.306 (0.059)
Project Management	3.753 (0.126)	3.680 (0.094)	4.054 (0.037)
Project Resources	1.587 (0.053)	1.981 (0.063)	2.180 (0.033)
Firm Patent Stock	5.985 (0.268)	5.399 (0.283)	5.826 (0.116)
Project Patent	0.478 (0.061)	0.571 (0.060)	0.696 (0.025)
# Projects under Management	2.358 (0.060)	2.616 (0.066)	2.512 (0.037)

- *Note*:
  -- Standard Errors are listed between brackets.
  -- N= 489 Projects.

Table 4 reports average values for the dependent variable, project management and the control variables for closed innovation projects, and both types of open innovation partnerships. The figures show that both types of open innovation projects generate, on average, more financials than closed innovation projects. Further, the statistics show that projects with science-based partners are managed, on average, in a less formal way than projects with market-based partners or closed innovation projects. Also interesting is that open innovation projects have, on average, more internal resources than closed projects.

3.5 Empirical Results

The results of the regression analyses are shown in Table 5. Model 1 is the baseline model which includes only the control variables. The coefficient estimates for the control variables indicate that research projects that have more internal resources and apply for patents record, on average, higher financials. Furthermore, I find that research projects perform better when the company has a larger relevant patent stock, and the project managers manages a smaller number of projects at the same time. The coefficient for project management is insignificant. Finally, the different sets of dummy variables are each jointly significant.

Table 5 Tobit Regressions on Project Financial Performance

VARIABLES	(1) model	(2) model	(3) model	(4) model
Open Innovation Partnership		2.606***		
		(0.398)		
Market-Based (MB) Partnership			-0.557	-8.150***
			(0.368)	(0.393)
Science-Based (SB) Partnership			2.657***	17.67***
			(0.377)	(0.398)
Project Management	0.134	0.0769	0.119	2.106***
	(0.0941)	(0.0958)	(0.0958)	(0.0980)
MB Partnership * Project Management				1.976***
				(0.0921)
SB Partnership * Project Management				-3.798***
				(0.0956)
Project Resources	2.078***	1.951***	2.019***	1.959***
	(0.159)	(0.162)	(0.162)	(0.165)
Firm Patent Stock	0.575***	0.529***	0.447***	0.262***
	(0.0588)	(0.0597)	(0.0596)	(0.0605)
Project Patent	1.683***	1.533***	1.739***	2.218***
	(0.350)	(0.355)	(0.356)	(0.368)
# Projects under Management	-1.550***	-1.572***	-1.650***	-1.674***
	(0.139)	(0.141)	(0.141)	(0.144)
Constant	-13.26***	-14.97***	-14.12***	-22.87***
	(0.397)	(0.405)	(0.404)	(0.412)
Sigma	4.714***	4.697***	4.632***	4.572***
	(0.148)	(0.149)	(0.148)	(0.150)
Observations	489	489	489	489
Log Likelihood	-162.1	-161.7	-160.8	-159.2
Pseudo. R-squared	0.267	0.269	0.273	0.280

- *Note: Technology Fields, Sponsor Departments, Development Departments and Year Dummies are all included.*
  Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

The open innovation partnership variable is added to Model 2. The results of the other variables remain unchanged when including this variable. The coefficient of the open innovation partnership variable is positive and significant. Hence, Hypothesis 1 is supported: research projects that open up and set-up R&D partnerships realize, on average, a higher financial performance. In Model 3, I make a distinction between market-based and science-based partnerships. Both coefficients are positive, but only the coefficient for science-based partnerships is significant. This means that, on average, only science-based partnerships increase the financial performance of research projects. Therefore, Hypothesis 2 is only partially supported for its effect for science-based partners, instead of for market-based partners. The results of the control variables remain relatively unchanged in Model 3.

In Model 4 I add interaction terms between the two open innovation partnership models and research project management to test for moderation effects. For market-based partnerships, I find a negative and significant main effect and a positive interaction with project management. The positive interaction coefficient confirms Hypothesis 3a: formal project management positively moderates the relationship between market-based partnerships and research project performance. An analysis of the size of both estimated coefficients shows that, for low values of project management, the net effect of market-based partnerships on project performance is negative, while for high values of project management, the net effect is positive. The break-even point occurs at a value of 4.12 of project management, with 44% of the sample observations having values for project management larger than 4.12. For science-based partnerships, the main effect is positive and significant, while the interaction effect with project management is negative and significant. The negative interaction effect implies that formal project management negatively moderates the relationship between science-based partnerships and research project performance, confirming Hypothesis 3b. An analysis of the estimated coefficients shows that, for high values of project management, the net effect is negative, while for high values of project management, the net effect is positive. The break-even punt occurs at a value of 4.65, with 80% of the observations beyond this value. The coefficient of project management is positive and significant. This indicates that for closed innovation projects, a formal management approach is preferred.

To get an indication of the "importance" of the estimated effects for my focal variables I have calculated average marginal effects for partnerships with market-based and science-based partners across the sample observations. They are reported in Table 6. Since the partnership variables are dummies, the marginal effects represent changes in the predicted financial performance of projects. The predictions are based on the conditional mean function of the tobit regression E(Y| X_i) that equals to $\Phi\ (X\beta/\sigma)X\beta+\ \sigma\ \emptyset(X\beta/\sigma)$. As project management moderates the effectiveness of both types of open innovation partnerships, marginal effects are calculated for different values of project management formality: minimum, low (25th percentile), average (median), high (75th percentile) and maximum. The reported values relate to non-log transformed financials. The marginal effect of market-based partnerships fluctuates between -0.65 (minimum project management) and +0.14 (maximum project management) million euros; the marginal effect of science-based partnerships fluctuates between +0.56 (minimum project management) and -0.12 (maximum project management).

Table 6 Marginal Effects of MB and SB Partnerships for Different Values of Project Management

Type of Partnerships	Project Management				
	Minimum	Low	Average	High	Maximum
Market-Based Partnership	-0.653	-0.070	-0.019	0.059	0.145
Science-Based Partnership	0.558	0.226	0.169	0.047	-0.121

3.6 Robustness Checks

1) Exclusive Categories of Open Innovation Partnerships

As my variables of market-based and science-based partnerships are non-mutually exclusive (the correlation between both variables is 0.2902), I checked the robustness of my results to the categorization of the open innovation partnership variables by re-estimating my regressions with three mutually exclusive partnership variables. The results are reported in Table 7. The variables “only MB partnership” and “only SB partnership” have the same sign and significance levels as the non-exclusive MB and SB partnership variables in my basic model (Table 5). The coefficients of the main and interaction effects for the variable “both MB and SB partnerships” take values in between the coefficients of the “only MB” and “only SB” partnership variables, and the interaction terms of “project management” and “both MB and SB partnerships” turns to be insignificant. Hence, I can conclude that my results are robust to the exact categorization of the open innovation partnership variables.

2) Project Transfers and Project Financial Returns

Considering the links between project transfers and project financial returns, in this chapter I also empirically investigated the relationship between these two variables. As project transfer is an intermediate result of project financials (only those projects that are successfully transferred to the development department, e.g.: Business Groups, are able to be commercialized and generate financial impact in the marketplace). I estimated Heckman 2-stage models, which separate the likelihood of project transfers and financials conditional on transfers. The Heckman 2-stage regression results are reported in Table 8. The key variables of interest (open innovation partnerships and project management) take similar signs in both steps of the Heckman models. However, the coefficients are larger, and become significant, in the second stage of the Heckman models. This indicates that open innovation partnerships and project management approaches have a stronger effect on the generated project financials (conditional on a transfer) than on the probability to generate transfers. This result can also be interpreted as evidence that project financials are a better indicator of project performance than project transfers, although project transfers are equally valuable particularly in the earlier phase of project development (before financials are generated). I regard project transfers as an intermediate, although imperfect, indicator of project performance, and project transfer is an alternative dependent variable to financials.

Table 7 Tobit Regressions on Project Financial Performance with Mutually Exclusive Open Innovation Variables

VARIABLES	(1) Model	(2) Model	(3) Model	(4) Model
Open Innovation Partnership		2.606***		
		(0.398)		
Only Market-Based (MB) Partnership			0.772***	-17.07***
			(0.297)	(0.489)
Only Science-Based (SB) Partnership			3.893***	10.37***
			(0.323)	(0.628)
Both MB & SB Partnership			2.971***	3.214***
			(0.370)	(0.414)
Project Management	0.134	0.0769	0.139	0.357***
	(0.0941)	(0.0958)	(0.0947)	(0.0961)
Both MB & SB * Project Management				-0.137
				(0.0970)
Only MB * Project Management				4.326***
				(0.116)
Only SB * Project Management				-1.800***
				(0.157)
Project Resources	2.078***	1.951***	2.010***	1.991***
	(0.159)	(0.162)	(0.160)	(0.162)
Firm Patent Stock	0.575***	0.529***	0.435***	0.240***
	(0.0588)	(0.0597)	(0.0592)	(0.0598)
Project Patent	1.683***	1.533***	1.684***	2.212***
	(0.350)	(0.355)	(0.351)	(0.360)
# Projects under Management	-1.550***	-1.572***	-1.653***	-1.647***
	(0.139)	(0.141)	(0.140)	(0.143)
Sigma	4.714***	4.697***	4.630***	4.566***
	(0.148)	(0.149)	(0.147)	(0.147)
Constant	-13.26***	-14.97***	-15.04***	-16.53***
	(0.397)	(0.405)	(0.401)	(0.406)
Observations	489	489	489	489
Log Likelihood	-162.1	-161.7	-160.7	-159.1
Pseudo. R-squared	0.267	0.269	0.274	0.281

- *Note: Technology fields, Sponsor Departments, Development Departments, as well as Year Dummies are all included in the regressions.*

Robust standard errors in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8 Heckman Two-Steps Model on Project Transfers (intermediate result) and Project Financial Returns (final result)

VARIABLES	Model 1		Model 2		Model 3		Model 4	
	Step 1	Step 2	Step 1	Step 2	Step 1	Step 2	Step 1	Step 2
Open Innovation Partnership			0.574	0.564				
			(0.684)	(1.260)				
Market-Based (MB) Partnership					-0.0343	-3.669***	-2.619	-12.68***
					(0.353)	(0.502)	(1.778)	(1.050)
Science-Based (SB) Partnership					0.452	1.693***	3.677	4.259***
					(0.402)	(0.329)	(2.980)	(1.455)
Project Management	0.0520	0.603***	0.0408	0.631***	0.0429	1.608***	0.294	1.084***
	(0.197)	(0.202)	(0.199)	(0.211)	(0.201)	(0.178)	(0.781)	(0.308)
MB Partnership * Project Management							0.663	2.917***
							(0.443)	(0.331)
SB Partnership * Project Management							-0.817	-1.283***
							(0.720)	(0.471)
Project Resources	0.460**	-0.172	0.434*	-0.114	0.443*	0.335**	0.441*	-0.251**
	(0.229)	(0.228)	(0.232)	(0.260)	(0.237)	(0.140)	(0.237)	(0.107)
Firm Patent Stock	0.130	0.797***	0.123	0.632	0.108	1.870***	0.0543	1.657***
	(0.155)	(0.220)	(0.154)	(0.431)	(0.157)	(0.245)	(0.169)	(0.127)
Project Patent	0.485	3.187***	0.461	2.799***	0.488	2.149***	0.636	1.257***
	(0.364)	(0.450)	(0.366)	(0.449)	(0.371)	(0.424)	(0.392)	(0.428)
# Projects under Management	-0.324	-1.729***	-0.327	-1.707***	-0.344*	-1.845***	-0.359*	-2.014***
	(0.200)	(0.303)	(0.199)	(0.304)	(0.204)	(0.162)	(0.210)	(0.112)
Constant	-3.284**	11.38***	-3.701**	10.39**	-3.473**	5.987***	-4.755	8.420
	(1.354)	(3.204)	(1.481)	(4.420)	(1.375)	(1.975)	(3.428)	(0)
Sigma	0.340***		0.339***		0.201***		0.104***	
	(0.0392)		(0.0390)		(0.0228)		(0.0133)	
Observations	489	489	489	489	489	489	489	489
Log Likelihood	-87.45	-87.45	-86.93	-86.93	-67.22	-67.22	-39.67	-39.67

- *Note: Technology fields, Sponsor Departments, Development Departments, as well as Year Dummies are all included in the regressions.*

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

3.7 Discussion and Implications

This chapter investigates whether open innovation partnerships improve the financial performance of research projects. Hereby, I distinguish between two types of partnerships: science-based partnerships with universities and knowledge institutes, and market-based partnerships with customers and suppliers. Furthermore, I analyze the moderating role of project management on the impact of both types of partnerships on the financial performance of research projects. In exploring these issues, the paper sheds light on a number of tightly related issues in the open innovation literature: Is it possible to provide hard evidence that open innovation is indeed improving the financial performance of projects and companies? How does the analysis of open innovation change when we move from the traditional firm-level analysis to the research project level? Do the project management approaches that are traditionally designed for closed innovation projects still work for managing open innovation projects? How to manage open innovation projects with different types of partners?

Responding to the call of Chesbrough et al. (2006), I analyzed open innovation no longer at the firm level, but switched to research projects as the unit of observation. I investigated the effect of open innovation partnerships on the financial performance of research projects based on a unique longitudinal dataset on R&D partnerships, project management and financial performance of 489 research projects of a large R&D intensive firm. To my knowledge, this is one of the first empirical studies that examine the relationship between external R&D partnerships and financial performance at the research project level. I compare "open" projects — those in which R&D teams collaborate with external partners, with "closed" projects — those in which R&D teams do not collaborate with external partners. Within the group of "open" projects, I further compare projects where market-based partnerships or science-based partnerships play a role. I examined their respective effect on R&D projects' financial impact. I further investigated how project management practices may moderate the effect of open innovation partnerships on the financial performance research projects.

This study contributes in different ways to the literature. Open innovation as a field of research needs hard empirical evidence to show that openness can or cannot improve the performance of R&D activities. First, previous studies, which enumerate the benefits of open innovation, are mainly based on case studies (e.g.: Huston and Sakkab, 2006; Kirschbaum, 2005; Van den Biesen, 2008), conceptual contributions (Chesbrough and Appleyard, 2004; Chesbrough and Schuwalds, 2007), or firm-level data (e.g. Laursen and Salter, 2006). In contrast to these studies, this chapter provides empirical evidence about the effect of open innovation at the research project level. I found that large companies can benefit from applying open innovation in their research projects under a range of conditions. These results provide support for the potential benefits of open innovation, and the analysis at the research project level enriches the existing research on open innovation. Second, I test the effect of open innovation based on an extensive dataset of research projects. I can therefore rely on accurate data about the formal and informal partnerships of each research project. Prior studies on this topic are mainly based on survey data such as the CIS survey (e.g. Belderbos et al., 2004; Knudsen, 2007; Faems et al., 2005 & 2010), or publicly announced collaboration data, such as the MERIT-CATI database (e.g. Hagedoorn, 2002; Gulati, 1995), again with primary focus on the firm as unit of analysis. Instead of relying on subjective and usually retrospective evaluations of managers, or relying on publicly announced collaboration deals which only capture the formal partnerships, I believe this study provides in-depth insights on the effect of open innovation at a micro level with more finely grained information about innovation processes in companies. Third, by examining open innovation at the research project level, this study gives a detailed view on how innovation is managed within big companies, and how outside-in open innovation can help them in improving their performance. Fourth, I make a distinction between science-based partners and market-based partners. Different types of partners have a different effect on project performance, and they further call for different managerial approaches to unlock their best potential in the innovation process.

My results show that the effectiveness of market-based and science-based open innovation partnerships depends on the way how projects are managed. Market-based partnerships have a positive effect on performance if a formal monitoring process is used; but these partnerships have negative effects for loosely monitored projects. In contrast, science-based partnerships have beneficial effects on performance only for loosely monitored projects. This result is interesting and at the same time challenging for project team leadership. Collaboration with science-based partners has to be loosely managed. This may seem counterintuitive at first sight but a more careful inspection of R&D partnerships with universities and other science lab partners shows why this is the case. First, firms collaborate with universities and research labs in a research project, when they want to explore a new technology in greater depth or when they want to get a better idea about the technical feasibility of a particular application of a technology. Research with universities or a science lab will therefore need to be managed in a loose manner to allow for sufficient room for experimentations. This calls for a looser project management approach. Second, science-based partners have their own expertise and objectives which may be completely different from the R&D team: researchers at universities follow an institutionalized way of doing (scientific) research and they have their own academic (slow) clock-speed which is hard to be influenced from the outside. Scientists also rely on their scientific autonomy and neutrality, which should be respected by companies that undertake science-based partnerships. Collaborating with science-based partners will therefore lead to contracts defining stages in which the former can work fairly independently, after which partners discuss the outcomes and define the next steps to take.

In contrast, collaboration with market-based partners has to be managed in a tight way. First, market-based partners are usually more involved in project phases where the market potential of the project is obvious and where speed to market is an important value driver. Second, developing and introducing a new product in the market requires more than just a technological partnership. Partners have to figure out how to create joint value, how to capture part of that value, how to convince complementors and other actors in the ecosystem to back the product with their own offerings, etc. Developing a product is thus a complex management task where partnerships have to be managed tightly in order to obtain the intended results. Project leaders who team up with market-based partners have thus to think carefully about these partnerships since they have to be managed in different ways to optimize the performance. An additional implication of the result of this study is that the benefits of the standard approach of project management as suggested by the new product development literature is contingent to the type of partners a company is working with. Collaboration with science-based partners requires a reconsideration of project management.

In sum, this study adds to the open innovation literature by providing a better understanding of how partnerships affect the performance of research projects. The results support that outside-in open innovation can, under certain conditions, improve the performance of research projects.

3.8 Limitations and Future Research

This study contributes to the open innovation literature by analyzing a critical but yet unexplored topic, i.e. whether collaboration with external partnerships improves the performance of research projects. Informative as it is, this study has also several limitations.

First, despite the richness of the data, the analysis is constrained to a single company. Therefore, a more encompassing dataset with data from different companies will be helpful to check the external validity of my conclusions. Second, compared to studies analyzing R&D collaboration at the firm level, this study does not capture the benefits of a research project portfolio approach or any potential synergies between projects, as a research team that learned from external partners in one project may use this knowledge in other research projects. The focus on research projects has the advantage that I get a detailed picture how companies benefit from open innovation, but I do not test how portfolios of projects and prior strength in collaborating with particular partners may contribute to the firm's overall innovation performance. Third, I use dummy variables to code whether a project is open or not. However, some scholars pointed out (e.g. Barge-Gil, 2010) that openness should be considered as a continuum. A research project is never fully open or completely closed: there is always some openness and there is always a need to fend off partners from particular parts in the project. In this way, it would be interesting to use indicators that reflect the degree of openness of research projects. I encourage scholars to examine how different levels of openness may affect the performance of research projects. Next, openness of research projects can also be examined over time - at different stages of a research project. R&D teams not only have to figure out whether they will open up a project to partners or not, but also when and for how long. Therefore, it is interesting to examine with longitudinal datasets the effect of external collaboration on project performance in each stage of the research project. Finally, the database does not allow me to quantify the number of external partners, nor to identify the individual partners with whom the research project collaborates. These limitations of the database prevent me to come to a more finely-grained categorization of different open innovation partnerships. My data does only allow me to differentiate between two broad categories of external partners: science-based partners and market-based partners. I believe that further splitting these two types of partnerships into more finely-grained sub-categories will help me to further improve our understanding on open innovation partnerships and project management styles. Moreover, the interplay between the number of open innovation partnerships and project management style is another interesting avenue for future research.

Despite these shortcomings of the current analysis, there are several areas for future research that emerge from my paper. First, empirical findings about the impact of open innovation on firm level performance are mixed. In contrast, the results in the current study indicate that analyzing open innovation at the research project is a promising way to understand under which conditions it is useful to collaborate with partners in research projects. Project level analyses provide several opportunities to further analyze, and understand, open innovation activities: First, the impact of openness on the research project performance can be measured in different ways: I focused in his paper on the financial performance of projects, but the success of research projects can also be measured in terms of successful transfers to the businesses in the company, the speed of the project, and the number of patents they generate. Second, an research project is managed by a team: team (leader) characteristics which are beneficial for closed innovation projects may be detrimental for open innovation projects. Third, projects are temporary constructs and they evolve and change over time: that brings me to the intriguing question when partners should be involved in the project and for how long?

The analysis at the research project level is interesting as a new approach for existing open innovation research. At the same time, introducing collaboration with different types of partners is fairly new to the research project management literature. Collaboration with suppliers and customers has received attention in the past, but less attention is given to science-based partnerships, nor to the comparison of both types of partners. Further, to the best of my knowledge, prior work has not made a clear comparison of the project performance effects of different types of partners. Moreover, this study provides the first evidence that the collaboration with different types of partners has to be managed in different ways. This observation may encourage scholars to reconsider how to manage research projects when a firm is collaborating with different types of partners. The classical research project management approach has been developed for closed innovation projects and might not be useful for particular types of open innovation projects. Studies investigating these different themes on the research project level may advance both a stronger theoretical understanding of open innovation as well as managerial practice.

Chapter 4

Accelerating innovation? –Open Innovation and Innovation Speed of Research Projects

4.1 Introduction

Chesbrough (2003; 2006) explains that "open innovation is the purposive use of inflows and outflows of knowledge to accelerate internal innovation … (and) assumes that firms can and should use external ideas as well as internal ideas, and internal and external paths to market, as they look to advance their technology". As open innovation strategies efficiently use resources both within and outside of the firm, it is supposed to bring multiple benefits to firms (Chesbrough and Garman, 2009). Until now, despite there is burgeoning research on the benefits of open innovation and external knowledge acquisition (Cassiman and Veugelers, 2006; Dahlander and Gann, 2010), some recent studies find negative effect of being open in innovation (e.g.: Knudsen and Mortensen, 2010), some other studies question the "universal benefits" of open innovation as it was supposed (Faems et al., 2010).

Among the multiple measures of innovation performance, innovation speed is a rather important but yet under-estimated aspect. A recent study based on financial modelling shows that 12 months, 9 months, and 6 months reduction in time to market increases internal rate of return (IRR) by approximately 92%, 63%, and 39%, respectively, and these relationships are, for the most part, unaffected by changes in other factors including product life or product profitability (Douglass, 2011) . However, speed is also frequently mentioned as a challenging dimension in new product development (Griffin, 1997; Barczak et al., 2009). According to a large-scale global survey, 42% of the companies reported an overly slow pace in their product development process. Combined with the increasing financial and operating pressure, the average company discontinued 15 new products. Some better performing firms point that the traditional approaches in innovation management do not guarantee a faster innovation speed, and there may be possible use of external resources (Accenture report, 2009).

Speeding up innovation is critical in nowadays pace-based competitive environment. However, despite its generally-recognized importance, product development speed has been consistently remarked as “one of the least explored aspects in organizational activities” (Griffin, 1997; Barczak et al, 2009). Due to the difficulties in collecting first-hand data on project start and termination in a real-time fashion, most existing studies rely on the subjective and retrospective evaluations of project managers, which can be inevitably error-prone and questionable in accuracy. Moreover, a clear definition on innovation speed is far from well developed. Within the limited literature body, innovation speed has been used interchangeably with product development speed (e.g.: Kessler and Chakrabarti, 1996; Kessler et al., 2002), product development time (Lilien and Yoon, 1989), and innovation time (Mansfield, 1988). While the product development process usually starts after the research phase, innovation typically covers a much longer time frame, from project start all the way down to production and market-launch— in most cases in the firm’s own current market (Kessler and Charkrabarti, 1996). In this chapter, I focus on the research phase of new product development, and measure innovation speed as from project starts till the research project delivers a marketable entity (Stalk and Hout, 1990) to the development department (business units). Particularly in the context of open innovation, clarifying this concept is needed because the resulting innovation not always necessarily ends up in the focal firm's own market, but may also be in someone else's. Figure 11 provides a visual conceptualization.

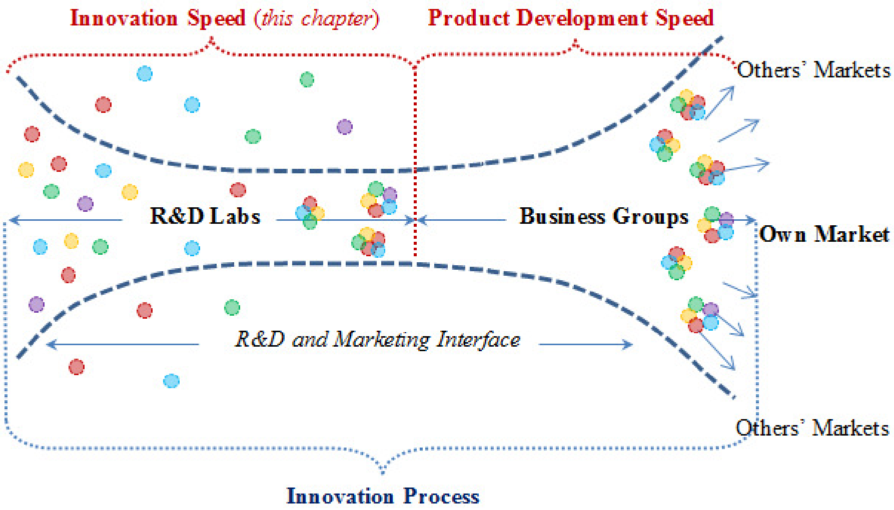


Figure 11 Innovation Speed and Product Development Speed

Besides vague definition of innovation speed (Cankurtaran, Langerak and Griffin, 2013), so far, most research on innovation speed has been focusing on the *intra-firm factors* such as cross-functional development teams and concurrent engineering (e.g.: Griffin, 1997; Millson et al., 1992; Chen et al., 2010; Kessler and Chakrabarti, 1996; Menon et al., 2002; Langerak and Hultink, 2008). "As techniques like cross-functional development teams and concurrent engineering become widespread, these approaches to shortening development cycles lose their competitive edge. Decisive advantage is likely to come from techniques that competitors are not using. There are other untapped sources of cycle time reduction for R&D managers to exploit…" (Smith & Reinertsen, 1992, p. 44). On the other hand, a faster innovation speed usually requires a greater investment of resources into the development process (Kessler and Charkrabarti, 1996), being constrained by their own resources, companies may choose to adopt open innovation strategies[19] in accessing resources outside of the firm, and thus accelerate their innovation speed. Nevertheless, being open in innovation is not risk-free, various factors that are both internal to the firm (e.g.: project characteristics) and are external to the firm (e.g.: types of partners) may play critical roles in determining the effect of open innovation on innovation speed. So far, little empirical evidence has been developed in this regard (e.g.: Faems et al., 2005; 2010). It is unclear whether open innovation indeed helps to accelerate firms' innovation speed, and under which circumstances the firm will benefit from adopting open innovation strategies in accelerating its innovation speed.

In this chapter I seek to investigate the above-mentioned research aspects on open innovation and innovation speed in new product development. To address these issues, a large dataset with 558 research projects from a multi-divisional Global 100 manufacturing company is employed in this study. I use R&D collaboration activities that are conducted in the research project as the proxy of open innovation, and test the effect of R&D collaborations on the innovation speed of research projects. More specifically, I distinguish between two types of partners, namely, market-based partners and science-based partners, and compare their effect on project innovation speed. I further introduce *project technical strength* as a moderating variable on the contingency effect of the different types of partners. Finally, I investigate the effect of project innovation speed (in its Research phase) and project performance. My findings show that,

[19] Hereafter I mainly refer to R&D collaborations.

being open to external partners generally pays off for accelerating innovation speed, but the positive effect comes mainly from collaborating with market-based partners, rather than from partnering with science-based partners. Moreover, I find that projects will accelerate their innovations more if having already possessed some levels of in-house technical capabilities. Finally, the findings suggest that there is an inverted U-shaped relationship between innovation speed and project performance (measured by project financial returns).

4.2 Background Literature

4.2.1 Innovation Speed –Research Perspectives

Innovation speed is generally referred to as the "(a) initial development, including the conceptualization and definition of an innovation, and (b) ultimate commercialization, which is the introduction of a new product into the market place (Kessler & Chakrabarti, 1996)". It has become a cornerstone for firms' innovation strategy (Eisenhardt & Martin, 2000; Kessler & Bierly, 2002) as it benefits a) faster internal product development (Chen et al., 2010; Eisenhardt & Tabrizi, 1995); and b) market internationalization (Ramos et al., 2011).

So far, studies on innovation speed typically examine the overall process of product development, and investigate a wide array of *intra-firm factors* that differentiate faster from slower innovation processes (e.g.: Griffin, 1997; Millson et al., 1992; Chen et al., 2010; Kessler and Chakrabarti, 1996; Menon et al., 2002; Filippini et al., 2004; Karagozoglu and Brown, 1993; Langerak and Hultink, 2008). In general, two major sets of factors have been proposed in the existing new product development literature as critical in influencing project innovation speed: 1) Characteristics of the product team and its parent firm (in most cases are within the organization), and 2) Connections and transitions from one phase of product development to the other. The first set of factors, namely, intra-organizational characteristics, mainly refer to the capability, strategy, and organization of the product development team and its parent firm. Critical factors such as team member and leader capability, shorter and longer tenure among team members (Kessler and Chakrabarti, 1999), team leadership style (McDonough and Barczak, 1991), team member motivation (Zirger and Hartley, 1994), incentives (Menon et al., 2002), upper management support (McDonough and Spital, 1984; Gupta and Wilemon, 1990), strategic orientation of the firm, clear time goals and delineation of product specifications (McDonough and Spital, 1984), emphasis on speed, strict planning and monitoring (Cooper et al., 2004), organizational culture (Menon et al., 2002), as well as organizational capability (staffing and structuring) (e.g.: Griffin, 1993 & 1997; Kessler and Chakrabarti, 1996 & 1999) have been investigated in a number of studies. The general finding is that a project team with dedicated team members and an experienced team leader, which set a time target as an explicit goal and clearly delineate product specifications, develops incentives linked to time targets, recognizes and rewards team members based on team time performance, which is embedded within a non-bureaucratic and risk-tolerant organizational culture, and enjoys high levels of information technology (e.g.: ICT, CAD), is more likely to achieve a fast product development speed.

The second set of factors in the existing literature, which focus on smoothening the transitions of the product development from one phase to the other, are considered to be another critical source of fast project development (Millson et al., 1992; Song and Parry, 1996; Griffin, 1997). A number of techniques have been proposed to smoothen the transition from one phase to another, such as the adoption of R&D-marketing interfaces (Barczak et al., 2009; Griffin and

Page, 1993), cross-functional teams (Song and Parry, 1996; Zirger and Hartley, 1994), R&D and operation cooperation (Olson et al., 2001), R&D and manufacturing team co-location (Zirger and Hartley, 1994), early involvement of marketing professionals into the R&D process (Kessler and Chakrabarti, 1996), process concurrency, parallel development within the firm (Swink, 2003), as well as eliminating steps (approvals) that are unnecessary to move from R&D to manufacturing (Millson et al., 2002). As in this chapter I only research innovation speed in one particular phase of product development, being *the Research phase*, I will not detail the transitions between multiple phases at length.

Besides these two sets of factors, prior studies have pointed out that the speed at which a product is developed, is also affected by a number of moderating factors, such as project characteristics, product complexity (Zirger and Hartley, 1994), product innovativeness (Langerak and Hultink, 1996), and environmental (un)certainty (Kessler and Bierly, 2002; Cabonell and Rodriguez-Escudero, 2009). Projects that are more innovative, more complex, and are operating under high uncertainty, take more time to develop. Consequently, besides the absolute time measure, a number of relative speed measures have been proposed in the New Product Development (NPD) literature. For instance, speed relative to schedule, or "on-time performance" (McDonough and Barczak, 1991), speed relative to similar, previously completed projects in one's organization (e.g.: Gupta and Wilemon, 1990; Millson et al., 1992; Zirger and Hartley, 1994), and speed relative to similar projects of competitors (e.g.: Stalk and Hout, 1990; Vesey, 1992). The basic idea is to compare innovation speed of projects with similar nature, instead of overly emphasizing the absolute time each project takes to develop its products.

In general, although the importance of research phase in project development has been highlighted in several studies, and it is likely that in the context of open innovation, external partnerships may affect the speed of innovation, however, little understanding has been developed regarding to the effect of external partnerships and their possible contingencies on the research phase of innovation.

4.2.2 R&D Partnerships[20] and Innovation Speed

As projects become increasingly open, they actively interact with external partners in the R&D phase (Cassiman et al., 2009 & 2010). Prior studies in the innovation literature identified two general types of partners: market-based partners (e.g.: customers and suppliers) and science-based partners (e.g.: universities and research institutions) (Danneels, 2002; Deeds and Rothaermel, 1999). Each of them may affect innovation speed in different ways. While market-based partnerships may contribute to product development speed via providing the project with the latest market insights and innovative solutions (Ogawa and Piller, 2006; Lettl, 2007); science-based partnerships, on the other hand, provide the project team a "map in technological search" (Fleming and Sorenson, 2004) and are instrumental in solving projects' existing problems (e.g.: Cohen et al., 2002), which may help to accelerate innovation speed.

Although the notion of involving external partners into firms' innovative activities and its effect on firms' innovation performance is not new in the innovation literature (Hagedoorn, 1993; Powell et al., 1996), the effect of external partnerships on firms' operational performance (e.g.: speed) is rather under-explored. External partnerships have been claimed to "accelerate the product development process" (Chesbrough, 2003), However, so far, few

[20] If not particularly specified, "R&D partnerships" are used as the proxy of open innovation.

studies have empirically and systematically examined the effect of external partnerships on innovation speed, with the majority of studies focusing on one particular type of partnerships. A handful of studies examine customer or supplier involvement as one of the many factors that may influence product innovation speed, which have generated inconclusive findings. For instance, analyses based on a sample of 244 new product development projects show that a firm's market orientation can accelerate innovation speed of early entrants (Rodriguez-Pinto et al., 2011); findings from 233 European manufacturing firms suggest that supplier and lead user involvement accelerate speed of product development (Langerak and Hultink, 2008); results of analysis of covariance of 79 assembly firms indicate that working with a supplier that has strong technical capabilities reduces supplier-related delays (Hartley, Zirger and Kamath, 1997); surveying 31 companies in five hi-tech industries in the west coast of US, Karagozoglu and Brown (1993) found that the use of customer involvement in the innovation process ranked as high as the use of multifunctional teams as a means to compress the NPD throughput time. However, other studies give different results. Contrary to expectations, there were no significant differences found between partnerships and in-house projects in their innovation speed on any metric used (Campbell and Cooper, 1999); alliances with other firms do not significantly affect innovation speed, and collaborations with universities are associated with even longer development times (Heirman and Clarysse, 2007); in a similar vein, results from a study of 188 new product development projects in small manufacturing companies indicate that use of market-related assistance lengthens product development cycle time (LaBahn, Ali, and Krapfel, 1996); based on 75 NPD projects from ten large US-based firms in several industries, Kessler et al.(2000) find external sourcing is associated with lower competitive success or slower innovation speed. Therefore, the authors conclude that internal development is more beneficial for the firm. Not only these findings are inconclusive, but also the effect of science-based partnerships on the speed of product development is very rarely studied in the NPD literature. Hence, a systematic analysis of the effect of projects' external partnerships on their innovation speed is greatly needed.

4.2.3 Innovation Speed and Project Performance

A faster innovation speed is generally considered as desirable for innovative firms, and it is regarded as beneficial for achieving better project returns (Kessler and Chakrabarti, 1996). A study from McKinsey & Company of high-tech products found that new products that come to market six months late, but on-budget, earn 33% less profit than if they were on time, while new products which come to market on-time, but 50% over budget, earn only 4% less profit than if they were on budget (McKinsey & Co., 1983). A more recent study based on financial modelling shows that 12 months, 9 months, and 6 months reduction in time to market increases internal rate of return (IRR) by approximately 92%, 63%, and 39%, respectively, and these relationships are, for the most part, unaffected by changes in other variables including product life or product profitability (Douglass, 2011). With regard to market share, speed can help establish early segments and customer loyalty, gain first-mover advantage, as well as enjoy a wider range of strategic choices compared to slower innovators (Griffin, 1993; Kessler and Chakrabarti, 1996; Zirger and Hartley, 1994), moreover, fast product development is usually more productive and lower cost because lengthy time in product development tends to waste resources on peripheral activities and mistakes (Tabrizi, 2005). However, recent studies have also cast doubts on a (overly) speedy innovation process (Swink et al., 2003), as there may be potential tradeoffs between respective pairs of NPD performance outcomes: speed-quality (Calantone and Di

Benedetto, 2000; Harter et al., 2000); time–cost (Graves, 1989; Mansfield, 1988); and time-quality (Karlsson and Ahlstrom, 1999). As such, it is questionable whether speed is “too much of a good thing” (Chen et al., 2008), and some previous studies reveal that speedy development is not universally welcome (Kessler and Chakrabarti, 1996). For instance, Crawford (1992) and Von Braun (1990) discussed several "hidden costs" or downsides of speed, such as more mistakes, heavy usage of resources, and disruptions in workflow. Some researchers also have pointed out the general disadvantages of innovating too quickly (Langerak and Hultink, 1996) and pioneering new technologies (e.g., Golder and Tellis, 1993; Lieberman and Montgomery, 1988). As it may need longer time to innovate “the next big thing”, a pure focus on a fast innovation process may mislead the project team in incrementally improving its existing products (as it is more predictable and less risky), or impair product quality by an overly fast cycle of product development. In line with the above-mentioned aspects, it is argued that speed is not universally appropriate in each industrial context. Firms must carefully determine the need for speed for different innovations within different task and regulatory environments before blindly pursuing faster development (Kessler and Chakrabarti, 1996). Speed leads to success primarily in more predictable contexts, which suggests that a fast-paced innovation strategy is best when “you know where you’re going” (Kessler and Bierly, 2002).

Empirical studies on this topic have so far generated mixed results. While Goktan and Miles (2011) found a significant positive relationship between radical product innovation development and innovation speed, Chen et al. (2010), Langerak and Hultink (1996) both found a curvilinear effect of speed on product performance, contingent on environmental certainty and product innovativeness. In a general remark, it is suggested that “more contingencies should be explored” (Kessler and Chakrabarti, 1996). In particular, the effect of speed with external partnerships on project financial returns has not been well understood.

4.3 Hypotheses

4.3.1 Open Innovation and Project Innovation Speed

Innovation speed is one of the most important aspects of research project performance (Page, 1993 Griffin, 1997; Barczak et al., 2009)[21]. I argue that speed can be accelerated when a project team collaborates with external partners. First, partnerships allow the project to partition tasks among partners and benefit from a "division of labour". Research on the modularity of products (Brusoni and Prencipe, 2001) and architectural innovations (Henderson and Clark, 1990) suggest that innovations often can be disentangled into multiple components. Working in parallel on different components can reduce project development time. However, constrained by resource limitation of the firm (Griffin, 1997; PDMA, 2008; Baczark, 2009), it may be difficult for the project to obtain all the resources within the firm to work on all the components simultaneously. In contrast, when collaborating with partners, a project team can leverage the resources of its partners. This, in turn, may shorten innovation time by pooling resources together and dividing project tasks among partners. Moreover, R&D partnerships also help to leverage partners' expertise in particular technology fields. As products get increasingly complex and usually involve technologies from multiple disciplines (Rycroft and Kash, 1999; Brusoni and Prencipe, 2000), it is difficult for a firm to develop all the required expertise in-house. The "division of labor" concept suggests that work can be

[21] There are also some contradictory arguments against fast NPD process, such as "first mover disadvantage" (Lieberman & Montgomery, 1988), "power of imitation" (Bolton, 1993), or "fast follower advantage", despite these arguments, here I stick to the main stream that it is beneficial to develop a *good* product *faster*.

done faster if it is split in different pieces, which are handled by specialists in each particular (technical) field, preferably in a parallel manner.

Furthermore, working together with external partners speeds up the innovation process by gaining and leveraging ready-to-use knowledge and technology. Slow innovators “reinvent the wheel” (Deschamps and Nayak, 1992) instead of actively building on knowledge that already exists (Tao and Magnotta, 2006; Chesbrough, 2003). Faster project teams know how to build on existing knowledge and concentrate their efforts only on the crucial and not yet developed parts of their product. This enables them to save considerable amount of time in innovation.

Last but not the least, R&D collaboration with external partners also helps to reduce the possibilities of rework and potential mistakes that may occur along the project process. As it is pointed out, a large portion of delays in product development stems from mistakes and rework (PDMA, 2005). Since new product development is probing into the unknown, timely feedbacks are necessary because they point out ways for improvement and adjustment before substantial reworks take place. When the project is exclusively composed of team members internal to the firm, the project team may concentrate on its own way of working without being aware of the mistakes it has made, or the potential risks it may encounter. On the contrary, if external partners are involved in the process, the project is exposed to external scrutiny and different perceptions, therefore timely solutions as well as feedbacks can be (more easily) obtained, which, in turn, reduce chances of rework and shortens innovation time. Therefore, I hypothesize:

H 4: R&D Partnerships accelerate the innovation speed of research projects.

Despite the potential benefits that R&D partnerships in open innovation networks may bring in terms of project speed, it is well-known that collaboration with external partners is not an easy task. The complex nature of collaborations, such as goal diversity among partners (Lorange and Roos, 1992), different working habits (Bstieler and Hemmert, 2010), distinct organizational culture and thought worlds (Dougherty, 1992), as well as considerable coordination and communication complexities along the collaboration process (Gulati, 1999; Rothaermel and Deeds, 2006), may all offset the potential benefits of external partnerships on project speed, or even make the development time longer. These factors, however, are likely to differ according to the type of partners that are involved in the partnership. Science-based partners are claimed to put their strength in long-term explorative-oriented research which is not readily transferred into new, commercial applications (Mowery, 1998; Harryson et al., 2008). Moreover, bureaucratic hierarchy, schedule inflexibility, as well as different rewarding systems of science-based partners (Mowery, 1998) may all hinder the efficiency of R&D partnerships. Frictions may arise resulting from different organization cultures and perceptions (Bstieler and Hemmert, 2010). Compared to science-based collaborations, the goal between the project team and its market-based partners are easier to get aligned because market-based partners represent market needs, and the objective of the project is to come up with innovative ideas to meet these needs. Moreover, searching for the right target market, monitoring customer behaviour, as well as catering to up-to-date market preferences, all take considerable time if the project team is working on its own without a clear view what customers exactly wants. When partnering with market-based partners, the project team is equipped with up-to-date market information and customer preferences, which enable it to better target the market needs, more quickly detecting and responding to market trends, while adjusting its product strategy along each development phase. Therefore, I hypothesize:

H5: Partnerships with market-based partners accelerate the innovation speed of research projects rather than partnerships with science-based partners.

Further, I consider the effect of R&D partnerships on project innovation speed is not as given, but is contingent on the technical strength of the project. In order to gain efficiency in product development via R&D partnerships, the project team needs to have a certain level of technical capability in place to understand the underlying "knowledge architecture" of the innovation that it's going to develop. Only then the project team is able to appropriately divide the project into different parts, partition work among its partners and coordinate their progress if needed. The technical strength of the project team also enables its (smooth) integration of different parts of the envisaged innovation in a timely fashion, and it can be leveraged if some partners fail to perform as expected. In contrast, when the project team has a relatively weak technology capability, it may not have a thorough understanding of the "knowledge architecture" of the innovation it's going to develop, nor with an overarching reference in mind, it is possible that the project team will be simply running between different parts of the innovation, each is handled by a different partner. In such case, there may be a big chance of delay instead of speeding up the innovation process.

Moreover, the problems of aligning different "thought worlds" (Leonard-Barton, 1992) and communicating between the project team and its external partners may be more pronounced if the technical capability of the project team is not well in line with the type of partners it collaborates with. Projects that have a relatively strong technical strength may have developed a higher level of absorptive capacity (Cohen and Levinthall, 1990) which enables them to better interact with their science-based partners and thus quicken the innovation process. In sum, I hypothesize:

H6: Projects that are with a higher level of technical strength innovate faster when partnering with science-based partners, while slower when with market-based partners.

4.3.2 Project Innovation Speed and Project Performance

The ultimate goal of innovative companies is to generate financial returns. In this process, project speed may play an indispensable role to increase (or decrease) such returns. There are a number of reasons to believe that a fast product innovation speed will benefit the project (and eventually the firm) financially. First, a major goal of product innovation is to detect and satisfy customer needs in a timely manner. Firms which are quick in responding to such needs may serve the market earlier than their competitors, establish product visibility, company brand and image, gain customer royalty, and benefit from "network effects". Therefore, they may be able to enjoy first-mover advantages in the marketplace (Lieberman and Montgomery, 1988). Second, a fast product development may also help to reduce opportunity costs of product development. Because of the velocity of market needs and customer preferences (Eisenhardt and Martin, 2000), what the market wants today may no longer be the same tomorrow, particularly if market trends switch or competitors come up with some new and better product offerings to address market needs. Therefore, firms which serve the market in a timely and efficient manner will be able to minimize their opportunity costs if the market trend changes during the innovation process of a new product. Last but not the least, a fast product innovation speed also helps quicken the pace of "metabolism" within the firm and release resources for better usage. The efficient usage of resources may reduce unnecessary product development costs, which may, in turn, increase potential revenues of the project.

However, an overly speedy product innovation process may be harmful to project financial returns. Prior studies point out that there are trade-offs in pairs of product performance dimensions (Swink et al., 2005). High speed in product development may imply that a project team skips (or combines) some intermediate development steps resulting in a product which has not a strong functionality or quality, and, therefore, is negatively influencing customer purchasing decisions (Cooper, 1979; Cooper and Kleinschmidt, 1987). Moreover, an overemphasis on speed may promote adoption of the standardized and formalized product development techniques (Harry and Schroder, 2000; Hackman and Wageman, 1995) such as adhering to documented systems and procedures, eliminating variations in processes and outputs, as well as standardization and generalizability across projects. As a result, it may rule out the possibilities of generating truly novel innovations, which in many cases have to experience several trails, errors, and drawbacks before they are ready, and require a much longer time to complete than those normal, routinized products.

Therefore, combining the aforementioned arguments, I hypothesize:

H7: There is an inverted U-shaped curve relationship between project speed and the financial results of research projects.

4.4 Data and Sample

To test my hypotheses, I use a unique longitudinal dataset on the research projects that are conducted by a large multi-national multi-divisional European-based manufacturing company. The research laboratories conduct research projects and transfer the results of the research projects to business units for further development and commercialization. This can be done either in the existing business lines of the firm, or be licensed or transacted to a third party, and the same project can be associated with multiple transfers if it is perceived as commercially attractive by multiple business units (or the same business unit but for different usages). The exact starting date and transfer date were carefully recorded for each project. Furthermore, there is information on project characteristics and on project collaboration practices (annually). For more detailed information, please refer to Chapter 2.

4.4.1 Dependent Variables

Project Innovation Speed. Following the definition of speed as the rate at which a product is transformed from an idea to a *marketable* entity (Stalk and Hout, 1990; Kessler and Chakrabarti, 1996), I use the elapsed time from the start of the research project to it transfer as my measure of innovation speed. As mentioned before, along the research phase, a project may generate multiple transfers; therefore, one project can be linked to different innovation speeds. Consequently, I use two types of innovation speed in this study: the elapsed time from project start to its first transfer, and the multiple elapsed time to project's different transfers (each transfer is considered as an event in the regression model. More details will follow in the methodology session). I will discuss the technique in more details in the methodology section.

Project Financial Performance: I use the financial revenue that is captured after transfer of the project results to the business as project financial performance. Moreover, I take into account of revenues from both internal and external paths to market (e.g.: existing BGs, licensing, IP transaction, etc.). Of the 508 projects, in total there are 41 projects (8.1%) generated financial revenues.

4.4.2 R&D Collaboration Variables

I make a distinction between different types of research projects by categorizing them into three categories based on the type of external partners they collaborate with: science-based partnership projects, market-based partnership projects, and closed projects. Closed innovation projects are those that do not collaborate with any partner in the research project. I assume that once the collaboration takes place, the effect remains for the following years. Therefore, collaboration with science-based and / or market-based partners is captured by cumulative variables. More specifically, a collaboration variable gets a value of 1 if collaboration (with the particular type of partner) took place in at least one of the previous years.

Science-based Partnerships. Following prior studies, I define science-based partners as partners that are science-oriented such as universities and research institutions (Faems et al., 2005; Danneels, 2002; Deeds and Rothaermel, 2006). This is a 0/1 variable that takes a value "1" when during a research project the company collaborates with science-based partners in one of the previous years or in the current year.

Market-based Partnerships. Market-based partnerships denote the other type of external partnership which is more market-oriented. A market-based partnership implies that the project team collaborates with market-based partners such as customers, users, communities, or suppliers[22] during its

[22] The "horizontal" type of partners, such as competitors are labeled as either market-based collaboration or technology-based collaboration according to the

lifetime. In line with the science-based collaboration variable, this is a dummy variable with value "1" if the project team collaborates with market-based partners in the current year or in any of the previous years, and "0" otherwise.

4.4.3 Control Variables

I use a range of control variables for the possible counfounding effect. The control variables I used are: project resources (measured as full time equivalent researchers working on the project), project technology fields, project technical strength (firm's previous 5 years patent stock in the technological field of the project), project monitoring, corporate research, as well as project initiating years. Note, project technical strength is also served as a moderating variable in the speed analyses. For a detailed description of those above-mentioned variables, please refer to Chapter 2, Data and Sample.

A possible influential factor for innovation speed is the technology risks embodied in the project. Strong technical teams are used to tackle more challenging projects. As a consequence, they may be associated with slower time to transfer. As such, strong technical teams may be mistakenly considered as slower, but in fact is just that they were tackling tougher projects. To address this potential bias, I use double controls. First is the IPC class of the technology that the project is developing, Second is the stage of the Technology Life Cycle (TLC) each particular technology is in. Typically, a technology evloves gradually from the *Emergent Phase*, to *Growth Phase*, to *Maturity* Phase, and finally comes to the *Decline Phase* (Haupt et al., 2007). In each different phase, the technology faces different challenges. For instance, in the *Emergent Phase*, as little knowledge has developed in this field. As there is no exisiting routine to follow, nor experience to learn from, many trials and errors are possible As

type of knowledge they provide in the innovation process. However, this type of collaboration is seldom adopted by research projects in my sample.

such, it is the most risky and might be particularly more difficult for the project team to develop a certain innovation. In the *Growth Phase*, more experience has been accumulated, although not complete and exhaustive, risk of innovation is lower, innovation speed can be faster, but still in a probing stage. While when it comes to the *Maturity Phase*, the technology development becomes stable and (most of) it have been standardized, resulting in lower risks and an easier development curve. The development risk is the lowest in the *Decline Phase*, although the desire of development is lower as well.

Following this reasoning, I calculated the yearly patent applications of each IPC-4digit class (worldwide patent applications at EPO) and listed them across all the years from 1978 to 2010. The IPC-4digit class is calculated in a fractional manner, which means, if one patent application covers multiple (e.g.: "N") IPC-4digit class, then each of these covered IPC-4digit class is assigned with a weight (e.g.: "1/N") for that patent application. I then sum up all these weighted IPC-4digit class in each year, the figures then enabled me to have a visual judgement of in which stage of the technology life cycle the technology is[23] (Lecocq and Van Looy, 2009; Haupt et al., 2007).

For the sample projects (558) in this chapter, in total 17 of them are in the *Emergent Phase*, 90 of them are in the Growth Phase, 308 of them are in the Maturity Phase, 29 of them are in the Decline Phase. Moreover, 111 of them were in the Growth Phase and later on moved to the Maturity Phase, and still 3

[23] Usually the emergent phase of TLC is characterized by the number of patent applications starting at a moderate level and having a steady, linear increase, while in the growth phase there is an exponential growth in the number of patent applications. In the maturity phase the growth rate is reduced and the number of patent applications remains more or less constant in that period. Finally, in the decline phase, the number of patent applications decreases over the years (Lecocq and Van Looy, 2009; Haupt et al., 2007).

of them were innitialy in the Maturity Phase and then moved to the Decline Phase (Table 9).

Table 9 Number of Projects in Each Phase of Technology Life Cycle (2002- 2008)

Phases of Technology Life Cycle	Number of Projects
Emergent Phase	17
Growth Phase	90
Maturity Phase	308
Decline Phase	29
(first) Growth Phase (and then) Maturity Phase	111
(first) Maturity Phase (and then) Decline Phase	3
Total	558

Figure 12- Figure 17 give visual inspection of the IPC-4digit classes (of my sample projects) that are in different phases of their respective technology life cycle. All the graphed technologies are associated with my sample projects. All the investigated years are from 2002 to 2008. If not being specificed, all the the scale of y axis (total number of yearly patent application of the particular IPC-4digit technology class) ranges from 0 to 6000. Technologies that are in the *Emergent Phase* of TLC (Year 2002- Year 2008, 17 projects):

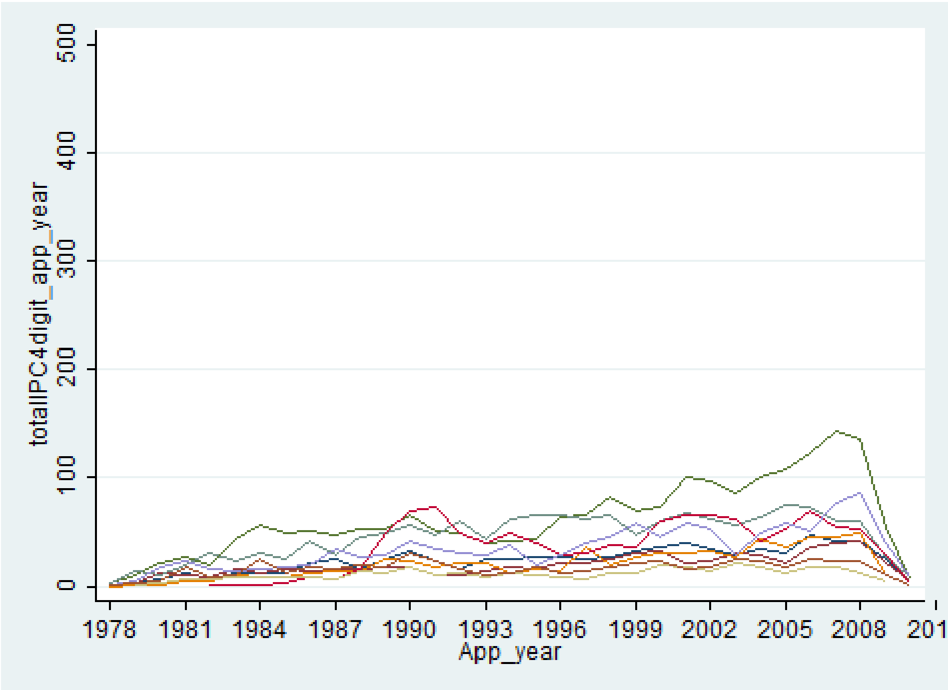


Figure 12 Technologies in the Emergent Phase of their Technology Life Cycle

Note: the scale of y axis (total number of yearly patent application of the particular IPC-4digit technology class) ranges from 0 to 500.

Technologies that are in the *Growth Phase* of TLC (Year 2002- Year 2008, 90 projects):

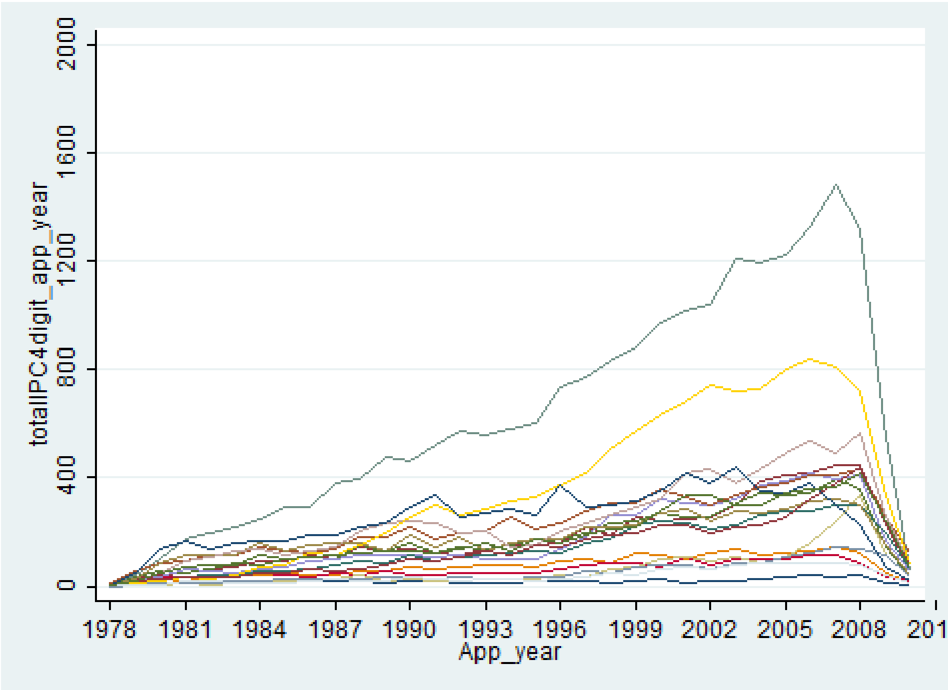


Figure 13 Technologies in the Growth Phase of their Technology Life Cycle

Note: the scale of y axis (total number of yearly patent application of the particular IPC-4digit technology class) ranges from 0 to 2000.

Technologies that are in the *Maturity Phase* of TLC (2002- 2008, 308 projects):

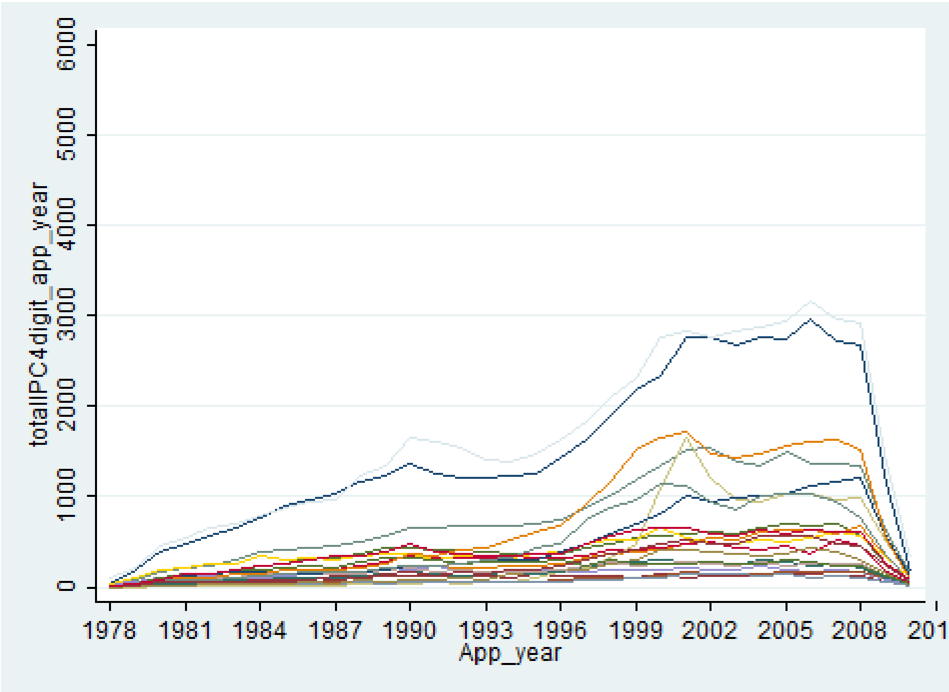


Figure 14 Technologies in the Maturity Phase of their Technology Life Cycle

Technologies that are in the Decline Phase of TLC (Year 2002- Year 2008, 29 projects):

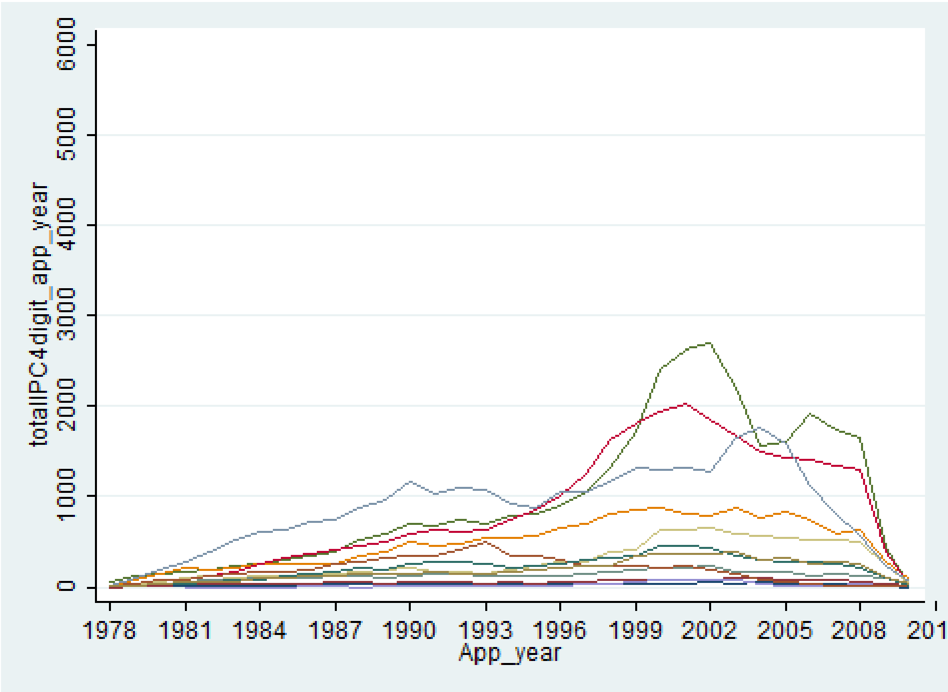


Figure 15 Technologies in the Decline Phase of their Technology Life Cycle

Technologies that are in the *Growth Phase* and then moved into the *Maturity Phase* of TLC (Year 2002- Year 2008, 111 projects):

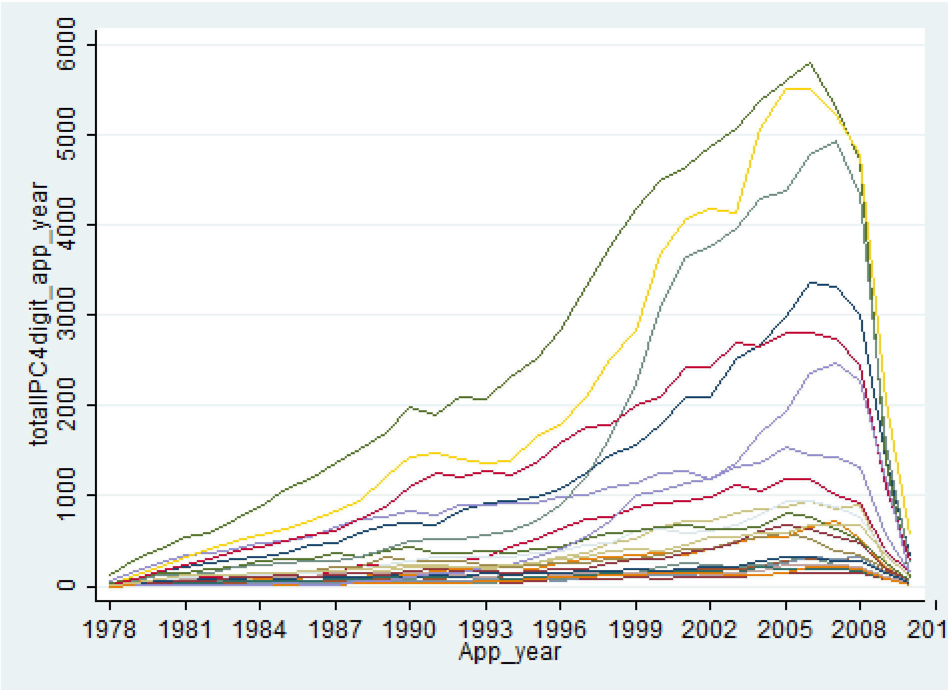


Figure 16 Technologies Evolved from the Growth Phase to the Maturity Phase of their Technology Life Cycle

Technologies that are in the Maturity Phase and then moved into the Decline Phase of TLC (Year 2002- Year 2008, 3 projects):

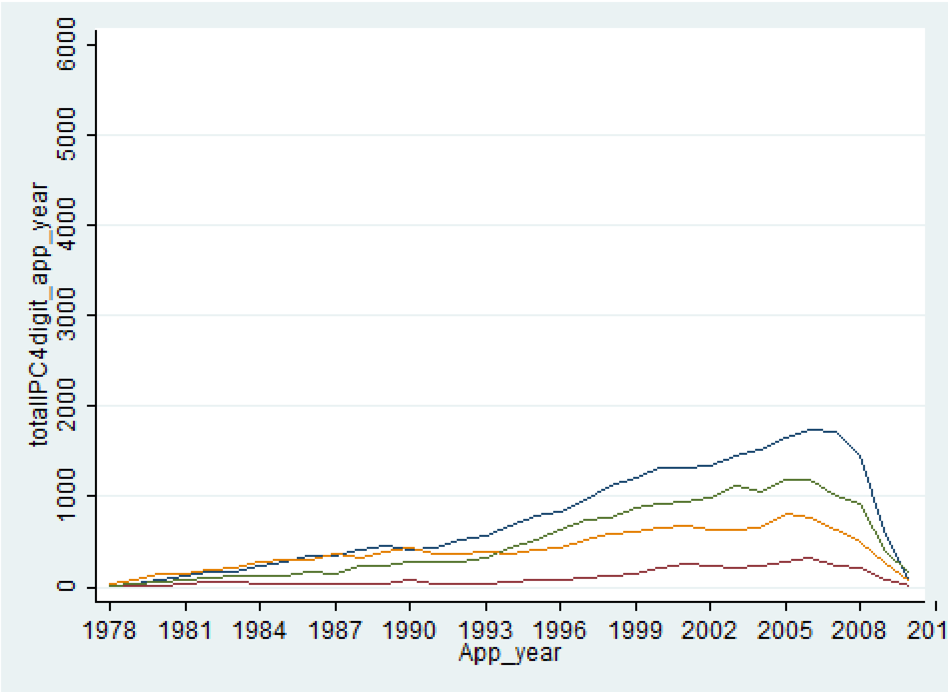


Figure 17 Technologies Evolved from the Maturity Phase to the Decline Phase of their Technology Life Cycle

Note: In total there are 4 IPC-4digit classes are involved in my sample projects, which are then corresponding to 3 different projects (one project ends before its technology class move from the *Maturity Phase* to the *Decline Phase,* therefore, it stays in the *Maturity Phase* for its whole life time. Nevertheless, I mapped the evolution of number of patent application of this IPC-4digit class as well).

4.4.4 Methodology

Event History Analysis. I use event history analysis (also known as survival analysis) to investigate the innovation speed of research projects. My research time window is 2002~2009, some projects may enter this time window earlier (left-hand truncation), some may end later (right-hand censoring), each at a different development pace. Event history analysis is known for its ability in dealing with left-hand truncation and right-hand censoring problems of time-related data (Blossfeld et al., 2007). Therefore, event history analysis techniques are chosen for this study. Further, because one project can generate several transfers to business units, I measure project innovation speed in two different ways: First, I look at how quickly a project is able to deliver its first transfer ("Time to first transfer"), regardless of whether it may deliver more transfers in a later stage. Thus, I measure innovation speed as the elapsed time from project start to its first transfer, once the first transfer is delivered, the project is considered as has reached its goal and exit my dataset; Second, I take into account of all the transfer(s) a project generates ("Time to multiple transfers"), each transfer of the same project is regarded as an individual event, but altogether they are calculated as been spawn from the same project (more details see the description on "shared frailty" below). Thus, I also measure the elapsed time from project start to its multiple transfers. Compared to parametric models in survival analysis, the semi-parametric Cox model does not assume a specific shape of the survival curve. It thus allows for sufficient flexibility in the survival function, which has been mostly adopted by prior studies. Therefore, I adopt a Cox model as my main model in this analysis. Moreover, because each record of the same project shares a commonly unobservable random frailty, thus I add a shared frailty term (follows gamma distribution) to my analyses (Blossfeld et al., 2007). I also specify the exit time of those projects that have stopped before the end of my observation window, thus only the on-going projects and their transfers are calculated. In general, my 558 projects correspond to 1913 project-year observations. Finally, for the development time of each project in my sample, I split it to monthly-recorded data. Because the same project may deliver several transfers in the same year, therefore using *year* as the basic observation unit may lose many valid "events" if they are all transferred in the same year (to model multiple events in survival analysis, each time point can only be corresponding to one event). To cope with this issue, I detail my observations at the month level instead of at the year level. In this way, project's multiple transfers which took place in the same year are able to be preserved, and it also allows me to maximally preserve time-varying information along the project development process. I apply the Cox model with shared frailty among transfers that are generated from the same project. This then leads to 19531 project-month observations in my dataset.

Tobit Regressions. "Project financial impact" is a continuous variable truncated at 0. The Tobit model is chosen in preference to the more common least square regression because the dependent variable has a censored distribution (the lower threshold is 0 for the projects that do not generate any financial impact). Finally, because I operationalize on yearly data, I adopt the Tobit techniques on the yearly dataset.

4.5 Empirical Results

4.5.1 Descriptive Statistics

Table 10 gives an overview of the most important descriptive statistics. In general, the degree of openness of the firm is relatively high, with a mean of 0.8479, which corresponds to 482 projects (of the total 558 projects) in my sample. The degree of openness with respect to market-based partnerships is 0,669, while for science-based partnerships is a bit higher (0,706). The means of a firm's 5 year patent stock (log transformed) is 5,851, and each year there are on average 1,032 full time equivalent researchers working on the project. Project management proficiency is high, with an average score around 4 (out of 5) both for project monitoring. Corporate research initiates 45% of the project transfers. It takes a project on average 2 years to get results transferred and there is 2,538 million euro per project year delivered on average. However the deviation is rather high, as much as 36 million euros which shows the heterogeneous performance among the projects. The correlation among the independent variables is low. Moreover, based on the analysis results from variance inflation factor (Gujariti, 1995), the VIF scores are relatively low (mostly are around 1.5), therefore we do not have problems with multi-collinearity among the independent variables.

Table 10 Descriptive Statistics and Correlations

	mean	s.d.	1	2	3	4	5	6	7	8	9	10	11
1. OpenInnovation	0,848	0,359	1,000										
2. Market-based Partners	0,669	0,471	0,575	1,000									
3. Science-based Partners	0,706	0,456	0,629	0,218	1,000								
4. (log)Project Patent Stock	5,851	2,028	-0,035	0,041	-0,001	1,000							
5. (log)Project Resources	1,032	0,603	-0,003	-0,022	0,052	0,010	1,000						
6. ProjectPlanning	3,989	0,878	0,082	0,160	0,027	0,063	0,027	1,000					
7. ProjectMonitoring&Review	4,041	0,747	0,079	0,181	0,012	0,030	0,030	0,645	1,000				
8. Corporate Reserach	0,449	0,498	-0,010	-0,160	0,053	-0,055	0,083	-0,194	-0,214	1,000			
9. Technical Performance	0,538	1,722	0,048	0,074	-0,004	0,107	0,136	0,073	0,103	-0,125	1,000		
10. Innovation Speed	1,978	1,571	0,220	0,247	0,233	0,030	0,673	0,098	0,083	-0,103	-0,069	1,000	
11. Financial Impact	2,538	36,001	0,029	0,037	0,022	0,023	0,019	0,004	0,018	-0,052	0,068	0,002	1,000

(Number of obs= 1913 Project-Year)

The analysis results are shown in Table 11, Table 12, Table 13, Table 14 and Table 15. Table 11 presents the impact of R&D partnerships on projects' innovation speed, Table 12 and Table 13 is the robustness check considering different phases of technology life cycle the technology is in. Table 14 shows the analysis result of project technical strength and its innovation speed with different types of partners. Finally, Table 15 shows the effect of project innovation speed on the financial revenues generated by research projects.

4.5.2 R&D Partnerships and Project Innovation Speed

Table 11 Cox Shared Frailty Regressions on Project Innovation Speed

	Cox Shared frailty Model on Time to First Transfer			Cox Shared frailty Model on Time to Multiple Transfers		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Open Innovation		0.524***			0.557***	
		(0.166)			(0.182)	
OI with Market-Partners			0.432***			0.458***
			(0.125)			(0.144)
OI with Science-Partners			0.135			0.103
			(0.146)			(0.143)
Project Resources	0.0502***	0.0548***	0.0506***	0.0521***	0.0509***	0.0470***
	(0.019)	(0.0135)	(0.0135)	(0.0134)	(0.0134)	(0.0135)
Patent Stock	0.119*	0.117*	0.114*	0.128**	0.125**	0.123*
	(0.0614)	(0.0617)	(0.0624)	(0.0628)	(0.0631)	(0.0636)
Project Monitoring	1.565***	0.550***	0.541***	3.099***	2.998***	2.875***
	(0.604)	(0.133)	(0.133)	(0.590)	(0.594)	(0.596)
# of Projects under Mngt.	0.809***	0.733***	0.721***	0.607***	0.598***	0.593***
	(0.185)	(0.184)	(0.186)	(0.105)	(0.106)	(0.105)
Corporate Research	-0.531***	-0.380***	-0.370***	-0.405***	-0.400***	-0.390***
	(0.173)	(0.133)	(0.133)	(0.132)	(0.133)	(0.133)
Technology Fields	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
Business Groups	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
Initiating Years	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
Observations	17,804	17804	17804	19,531	19,531	19,531
Number of Projects	558	558	558	558	558	558
Log Likelihood	-3038	-3033	-3032	-3192	-3187	-3186
lrtest		11.40***	12.70***		9.80***	11.70***

Remark: Cox Proportional Hazard Models with shared frailty.
*** p<0.01, ** p<0.05, * p<0.1

Table 11 shows the relation between R&D partnerships and the speed of research projects. Closed innovation is the baseline model. Models 1-3 are Cox shared frailty analyses on the rate of time elapsed between the start of the project and its first transfer. Models 4-6 are Cox shared frailty analyses based on the rate of time elapsed between the start of the project and the different transfers (in case there is more than 1 transfer). All these models control for unobserved heterogeneity at the project level by adding a shared frailty term for each project. Endogeneity concerns are alleviated by shared frailty techniques and the set of time-varying control variables. Model 1 is the base model and only includes the control variables for project innovation speed to its first transfer. Positive and significant effects are found for project resources, project patent stock, as well as for project monitoring (Model 1). This shows that projects that have more internal resources and large patent stocks generate a first transfer quicker than the other projects. Also, projects that are managed with regularly monitoring and review are generating transfers faster, while the opposite effect is found for projects initiated by corporate research department (Model 1). Model 2 introduces the open innovation variable. Collaborating with R&D partners has a positive effect; collaboration helps to accelerate project innovation speed (time to first transfer) by 68.9% (=exp(0.524)-1) compared to projects where the company was not collaborating with partners. A similar effect is found for project's innovation speed to multiple transfers (Model 5), where implementing an open innovation strategy accelerates the project innovation speed (time to multiple transfers) even more with 74.5% (=exp(0.557)-1). Both findings confirm Hypothesis 4, i.e. that partnerships help to speed up project development process. Model 3 further differentiates between the two types of collaboration partners. A positive and significant coefficient is found for collaborating with market-based partners, which shows a speeding-up effect of the project by 54.0% (=exp(0.432)-1). There is no effect for collaboration with science-based partners. A similar result is found in Model 6, where innovation speed to multiple transfers is examined. This confirms Hypothesis 5, which states that it is R&D collaboration with market-based partners, rather than collaboration with science-based partners, that helps to speed up the execution of research projects.

As a robustness check of whether different phases of technology life cycle affect the effect of open innovation on innovation speed, I then include 4 dummy variables to the shared frailty model to indicate the 4 phases of technology life cycle (Emergent, Growth, Maturity, Decline). However, the model is unable to converge as there are too many controls but insufficient sample size. An alternative way I used is to group the sample projects into "Growth Phase" and "Other Phases". As the former are still under-development while the latter are already stable and mature, therefore the former group should embody more risks than the latter group. I perform the same techniques on the split sample of the two groups, and compare results between them. Time to Multiple transfers is investigated in this set of regressions. The results are shown in the following Table 12 and Table 13.

In Table 12, only the Growth phase of TLC is investigated, while in Table 13, both the Emergent and the Growth Phase are grouped together, in comparison to the combined group of Maturity and Decline Phases.

Table 12 Cox Shared Frailty Model on Innovation Speed in Split Sample (Technology Growth Phase vs. Others)

VARIABLES	Model 1 _t	Model 2 _t	Model 3 _t	Model 4 _t	Model 5 _t	Model 6 _t
		Technology Growth Phase			Other Phases	
Open Innovation		0.356			0.732**	
		(0.528)			(0.323)	
OI with Market-Partners			1.370***			0.487*
			(0.486)			(0.254)
OI with Science-Partners			-0.262			0.170
			(0.468)			(0.252)
Project Resources	0.057***	0.0123	0.0152	0.042**	0.0896***	0.0860***
	(0.0209)	(0.0514)	(0.0544)	(0.0167)	(0.0258)	(0.0262)
Patent Stock	0.285	0.267	0.366	0.106	0.210**	0.218**
	(0.194)	(0.274)	(0.305)	(0.076)	(0.0963)	(0.0966)
Project Monitoring	2.572***	3.118*	3.096*	4.051***	1.619**	1.452*
	(0.895)	(1.642)	(1.723)	(0.778)	(0.746)	(0.759)
# of Projects under Mngt.	0.314	0.990**	0.994**	0.743***	1.014***	1.010***
	(0.199)	(0.394)	(0.413)	(0.130)	(0.254)	(0.255)
Corporate Research	-0.250	-0.617	-0.625	-0.553***	-0.584***	-0.563**
	(0.218)	(0.379)	(0.399)	(0.167)	(0.224)	(0.225)
Technology Fields	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
Business Groups	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
Initiating Years	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
Observations	4,841	3,889	3,889	14,690	8,917	8,917
Number of groups	199	199	199	453	356	356
Log Likelihood	-828.2	-290.1	-286.2	-1965.39	-494.5	-494.8

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

Table 13 Cox Shared Frailty Model on Innovation Speed in Split Sample (Technology Emergent & Growth Phase vs. Others)

VARIABLES	Model 1 _t	Model 2 _t	Model 3 _t	Model 4 _t	Model 5 _t	Model 6 _t
	Technology Emergent & Growth Phase			Technology Maturity & Decline Phase		
Open Innovation		0.593**			0.526**	
		(0.276)			(0.259)	
OI with Market-Partners			0.447**			0.343*
			(0.226)			(0.200)
OI with Science-Partners			0.129			0.0648
			(0.233)			(0.196)
Project Resources	0.0574***	0.0526**	0.0500**	0.0372**	0.0362**	0.0338**
	(0.0205)	(0.0206)	(0.0204)	(0.0169)	(0.0170)	(0.0172)
Patent Stock	0.249*	0.244*	0.265**	0.0869	0.0815	0.0789
	(0.130)	(0.130)	(0.129)	(0.0860)	(0.0862)	(0.0867)
Project Monitoring	2.712***	2.549***	2.478***	4.053***	3.982***	3.837***
	(0.884)	(0.900)	(0.884)	(0.787)	(0.790)	(0.795)
# of Projects under Mngt.	0.309	0.276	0.276	0.784***	0.784***	0.774***
	(0.192)	(0.196)	(0.194)	(0.133)	(0.134)	(0.134)
Corporate Research	-0.361*	-0.382*	-0.354*	-0.525***	-0.510***	-0.515***
	(0.204)	(0.207)	(0.206)	(0.172)	(0.173)	(0.172)
Technology Fields	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
Business Groups	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
Initiating Years	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
Observations	5,544	5,544	5,544	13,987	13,987	13,987
Number of groups	216	216	216	436	436	436
Log Likelihood	-926.9	-924.5	-924.4	-1853	-1851	-1851

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

The basic models in Table 12 and Table 13 both reveal that projects that are equipped with more resources and are monitored strictly enjoy a faster innovation speed (Model 1, Model 3). When only looking at the Growth Phase of technology life cycle, Table 12 shows that open innovation in general does not seem to help much in speeding up the innovation in the Growth Phase (Model 2). However, collaboration with market-based partners is beneficial in accelerating innovation process. Such effect is not found in science-based partners (Model 3). Open innovation starts to play a more positive role in innovation speed when it comes to other phases (Model 5), the positive effect of market-based partners stays (Model 6), albeit to a lesser extent. Noticeably, in both split samples, science-based partners do not seem to affect innovation speed. When combining both Emergent Phase and Growth Phase of technology life cycle, Table 13 shows that open innovation helps in both cases (higher risks—emergent/ growth phase; lower risks—maturity/ decline phase). As compared to the results in Table 12, it seems open innovation helps particularly if the technology is in its emergent phase. Again, the results show that it is market-based partners, instead of science-based partners, that help to speed up the innovation process.

I then look at the possible contingency effect of project technical strength (measured by the previous 5-year patent stock of the mother firm in the project's technology field) on project innovation speed. Table 14 shows the result. As expected, projects that have a high level of technical strength speed up their innovation process when collaborating with science-based partners (Model 3, Model 4), while such technically-strong projects are prone to delay if collaborating with market-based partners (Model 2, Model 4). The finding also suggests that the positive effect of science-based partnerships on project innovation speed may be uncovered when the project team has already strong technical capability in place. While when such capability is missing or less developed, working with science-based partners may delay project innovation, instead of accelerating it.

Contradictory to my expectation, projects that are with high technical capabilities do not seem to be more efficient in their innovation process from their collaborations with partners (do not distinguish between the type of partners, Model 1), instead, R&D partnerships seem to slow down project innovations in its technologically advanced fields. Possible explanation may be if the project is already technically advanced, it can perform the task quicker with internals within the firm, instead of reaching out for external support. After all, partner-searching, communication, coordination among partners all take considerable time, and thus may slow down the innovation process. Moreover, attention paid on knowledge protection against their partners in the technically more advanced projects can be counter-productive to innovation speed as well.

Table 14 R&D Partnerships, Project Technical Strength, and Innovation Speed

VARIABLES	Model 1	Model 2	Model 3	Model 4
Open Innovation	1.981***			
	(0.757)			
OI with Market-Partners		0.971**		1.140**
		(0.463)		(0.467)
OI with Science-Partners			-0.962**	-1.076***
			(0.400)	(0.410)
Patent Stock	0.315***	0.184**	0.0305	0.110
	(0.116)	(0.0813)	(0.0691)	(0.0844)
OI_PatentStock	-0.215**			
	(0.108)			
Market.Par _PatentStock		-0.0787		-0.111*
		(0.0688)		(0.0597)
Science.Par._PatentStock			0.183***	0.192***
			(0.0612)	(0.0625)
Project Resources	0.0503***	0.0483***	0.0479***	0.0450***
	(0.0134)	(0.0133)	(0.0133)	(0.0132)
Project Monitoring	3.037***	2.869***	2.900***	2.696***
	(0.595)	(0.594)	(0.584)	(0.587)
# of Projects under Mngt.	0.597***	0.594***	0.612***	0.600***
	(0.105)	(0.105)	(0.105)	(0.105)
Corporate Research	-0.374***	-0.369***	-0.405***	-0.384***
	(0.131)	(0.130)	(0.130)	(0.130)
Technology Fields	*Included*	*Included*	*Included*	*Included*
Business Groups	*Included*	*Included*	*Included*	*Included*
Initiating Years	*Included*	*Included*	*Included*	*Included*
Observations	19,531	19,531	19,531	19,531
Number of groups	558	558	558	558
Log Likelihood	-3185	-3186	-3187	-3181

Standard errors in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

4.5.3 Project Innovation Speed and Project Financial Impact

Finally I look at the impact of R&D partnerships on the financial revenues of research projects. Table 15 shows the result on this dimension. Note that because the dependent variable in Table 15 (project financial performance) represents the final financial performance of projects and thus is different from the dependent variable in Table 11~13 (innovation speed in the research phase which measures only the research phase), here I add a set of additional control variables for the possible confounding effect on project financials: "Project Patent Applications" is a dummy variable measuring whether the project applied for patent or not (partly signals project's technical superiority); "Sponsoring Units" is also a set of dummy variables denoting the sponsoring unit of the project (in total there are 11 broad sponsoring units); "Business Department" measures which business group receives the transferred project. Finally, because only those successfully transferred projects are able to reach the final market and therefore generate financial revenues, "Project Transfers" is added as a dummy variable measuring whether the project has generated any transfers. For a detailed description of these control variables, please refer to Chapter 2, Data and Sample. In Table 15, Model 1 is probit regression on projects' probability of generating transfers, Model 2 and Model 3 are Tobit regressions operationalized on cross-sectional data with corrections for sample selection. Because only those projects that are successfully transferred are able to have a innovation speed, and to generating financials in the marketplace, I need to correct for the sample selection problem allowing for those untransfered projects (at the same time also do not have an "innovation speed") to be included into the analysis. In doing so, in the first stage, the transfer equation is estimated. In a probit model, I regress whether the project is transferred on the following independent variables: project management, number of projects under management, project patent applications, project resources, firm patent stock, corporate research, sponsoring units, technology fields, and initiating years. From the resulting estimation, I construct the Heckman correction term (λ) to be included in the financial regression. From the first step equation (Model 1), it is clear that a higher level of project monitoring, more project resources, and corporate research projects have higher possibility to transfer results to business departments. In the cross-sectional model, I calculated the relation between project innovation speed and project financial performance (Model 3 and Model 4). Model 2 is the baseline model with only control variables. More project transfers, more project patent applications, greater project patent stock, are important factors that lead to better financial returns at the project level, however, it seems that regular project monitoring, number of projects under management, corporate research have a negative effect to monetary returns (Model 2). The negative effect of corporate research on project financial impact, may capture the fact that most long-term research projects are conducted in corporate labs, with the result that there is a high attrition rate and only few projects make it. Also, corporate research is not always intending to develop new product launches, the corporate research projects may be ordered to test whether a particular technology road works or not; to explore new technical areas without specific applications in mind; as well as to piggyback on technologies others developed to explore that area and build defensive IP walls. During the long time to get the product developed and launched also implies that alternative technologies may pop up in the meantime, competitors are earlier on the market which makes the initial market opportunity unattractive. Model 3 confirms the hypothesis that there is an inverted U-shaped curve relation between project speed and their financial performance (Model 3). Therefore, Hypothesis 7 is supported, that project innovations should neither be too fast nor too slow to realize the highest financial outcome.

Table 15 Tobit Regressions on Project Innovation Speed and Project Financial Performance

VARIABLES	Model 1 Selection	Model 2 Performance	Model 3
MultiSpeed			34.17***
			(9.571)
MultiSpeed2			-15.85***
			(1.015)
Project Resources	0.508***	3.562	-116.6***
	(0.111)	(9.75)	(9.643)
Patent Stock	0.0343	11.98***	18.77***
	(0.0503)	(3.61)	(3.504)
Project Monitoring	0.284***	-43.99***	-133.6***
	(0.0904)	(5.77)	(5.737)
Corporate Research	1.749***	-37.14**	-725.7***
	(0.423)	(18.77)	(18.99)
# Projects Under Management	0.0261	-96.60***	-124.4***
	(0.103)	(8.36)	(8.372)
Project Patent Applications	0.146	120.22***	36.45*
	(0.154)	(21.14)	(20.86)
Project Transfers		122.95***	99.57***
		(11.11)	(10.95)
invmills		-330.37***	-986.1***
		(31.08)	(32.39)
Sigma		277.1***	264.8***
		(8.293)	(8.429)
Constant	-5.746***	-63.54***	2,587***
	(0.763)	(24.51)	(24.41)
Total Observations	536	487	487
Uncencored Observations		41	41
Log Likelihood	-276.7	-332.3	-325.8
Pseudo. R-squared	0.238	0.142	0.159

Note: Dummies of Sponsoring Units, Busness Departments, Technology Fields and Initiating Years are all included.
Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

4.6 Discussion and Implications

This chapter focuses on the research phase of innovation. It investigates whether collaboration with external R&D partners accelerates innovation speed, and what the relationship is between project speed and financial performance. To my knowledge, this chapter is among the first empirical studies that systematically examine the effect of partnerships in open innovation networks on the speed of research projects. I compare "open" projects - those projects in which R&D teams collaborate with external partners - with "closed" projects - those projects in which R&D teams do not collaborate with external partners. Within those "open" projects, I compare between projects with market-based partnerships and projects with science-based partnerships. I examine their respective effect on project innovation speed taking into account of contingencies of project technical strength, and I further examine the effect of project innovation speed on project financial success.

This study contributes to the literature in different ways. Open innovation as a burgeoning field of research, has attracted considerable scholarly attention in recent years. The majority of studies explored the number of patent applications/grants (e.g.: Sampson, 2007) and/or financial revenues generated in the marketplace (e.g.: Faems et al., 2005; Belderbos et al., 2010). Our understanding on the time side, namely, the impact of OI on speed of innovation has been lagging. Although it is argued that open innovation helps to speed up product development (Chesbrough, 2003), so far there is little hard evidence systematically showing that collaborations with external parties indeed shorten (or lengthen) product development time.

I found that open innovation can be beneficial for the innovation speed of large companies and their research projects support and enrich the existing open innovation framework. I test the effect of open innovation based on a reliable, longitudinal dataset, therefore I am able to rely on accurate data about the formal and informal partnerships of each research project, as well as the exact starting and ending date of each research project in my sample. Thus, instead of relying the subjective, retrospective evaluation of project managers, which is usually inevitably error-prone, this study gives me objective information based on the real timing of each research project. Moreover, I make a distinction between science-based partners and market-based partners. This study suggests that product development speed may depend on different types of partners that are involved in research projects.

My results show that, for project efficiency, being open generally pays off, even when considering the different phases of technology life cycle the project is dealing with: collaboration with external partners is instrumental in accelerating innovation speed. However, despite general benefits, open innovation should not be considered as a panacea for improving innovation efficiency under all circumstances. Collaborations with partners deserve careful consideration and implementation in practice. This study explores such contingency effects from the type of partners that are involved in research projects: while partnerships with market-based partners help to accelerate the speed of research projects, collaborations with science-based partners have no speeding-up effect. However, the positive effect of science-based partners on innovation speed will be revealed if collaborating with projects that have already had a strong technical capability, while for market-based partners, the opposite holds true. As external partners have different effects on innovation speed, managers should consider and compare the benefits and costs before establishing relations with external partners.

My results also suggest that there is an inverted U-shaped curved relation between innovation speed and its financial performance. Therefore, neither too speedy nor too slow an innovation process in the project R&D phase is beneficial for product development. Hence, project managers should control a healthy rhythm of project execution, and not overly emphasize a faster project innovation speed.

Future research may explore more into details the moderating role of possible omitted variables (such as technology risks) on the effect of open innovation on innovation speed. In this chapter, I use a relatively rough measure of different phases of technology life cycle, and split the sample into different parts. Future research may work on more finely grained indicators of technology life cycle (e.g.: Haupt et al., 2007) and study into details how do such factors influence the effectiveness of open innovation.

In sum, this study sheds light on the open innovation literature by providing a better understanding of how collaboration in research projects affects the speed of research projects. My results support that outside-in open innovation (in particular collaboration with market-based partners) can accelerate research projects considerably.

Chapter 5

Does Timing of R&D Collaborations Explain the Heterogeneity of Their Outcomes?

5.1 Introduction

Nowadays, firms' success hinges on their ability to create and share knowledge effectively and efficiently (Kogut and Zander, 1992). Due to resource limitations and fast-paced technology development, increasingly firms team up with partners in their R&D activities to improve innovation performance (Chiaroni et al., 2011; Hagedoorn et al., 2000). A number of scholars enumerate the benefits of R&D collaboration, as it helps firms to access complementary resources, to share risks and costs, to create synergetic effects, and to respond quickly to a dynamic environment (e.g.: Shan et al., 1994; Powell et al., 1996; Gulati, 1995; Hagedoorn and Schakenraad, 1994). Yet despite these benefits, it is commonly observed that many firms face serious challenges in achieving success in their R&D collaboration activities (Lokshin et al., 2011). Considerable heterogeneity exists among firms with respect to their collaboration outcomes (Hopkins et al., 2011) — some firms are quite successful in their collaboration activities (Huston and Sakkab, 2007;

Kirschbaum, 2005; Van der Meer, 2007), while others suffer from striking failures (Sivadas and Dwyer, 2000).

This heterogeneity in the effectiveness of firms' R&D collaboration activities has been explained in different ways, mainly focusing on the capabilities of the firm and its partners. For instance, some authors emphasized the type of partners, the composition of overall collaboration portfolios, and the partner selection process, play decisive roles in R&D collaboration outcomes (Carayol, 2003; Laursen and Salter, 2006; Hopkins et al., 2010; Baum et al., 2000; Faems et al., 2005; Bianchi et al., 2011); other scholars investigated the relation between the focal firm and its partners, pointing out that the way how the firm establishes and optimizes its relational links affects collaboration outcomes (Sofka and Grimpe, 2010; Caloghirou et al., 2004; Lorange and Roos, 1991; Das and Teng, 1998); still some scholars explored the characteristics of the focal firm itself, arguing that the size, industry, experience, corporate strategy, capability, or innovation policy of the firm (e.g.: Van de Vrande, 2008; Tsai, 2009; Bargegil, 2011; Asakawa et al., 2010) are important factors leading to success or failure in R&D collaboration activities. Although our understanding on the factors that affect R&D collaborations has been greatly advanced during the past decades, the success rate of R&D collaborations has been stagnated over the years (Lhuillery and Pfister, 2009).

Three reasons may contribute to the ambiguous understanding on R&D collaboration success. First, the majority of the extant studies have been mainly analyzing R&D collaboration at the firm, not at the project level. However R&D collaborations are essentially initiated and conducted in research projects (Pisano, 1990; Cassiman et al., 2009). The peculiarities of research projects (such as their resource endowments, needs, and project management approaches) are likely to vary from one project to another, and to affect collaboration outcome, which are not well controlled for in the existing firm-level studies; Second, collaboration is essentially a dynamic process and the (un-)collaboration status may vary at each point of time during a project's life cycle. To better understand the heterogeneity in R&D collaborations outcomes, research that traces partnership evolution at different points of time is needed; Third, collaboration per se is a broad concept, the currently adopted terms and research perspectives on collaborations (e.g.: collaboration portfolio, collaboration breadth and depth, etc.) are mainly static and do not clearly capture the different ways of organizing collaborations (e.g.: long and short collaborations, continuous or interrupted collaborations).

This chapter aims to explore the heterogeneity of R&D collaboration outcomes at the project level. While there are many potential sources which may contribute to the diversity of R&D collaboration outcomes (e.g.: personnel, budget, etc.), this study focuses particularly on the timing of organizing R&D collaboration activities. More specifically, in this chapter I study *when and how* to conduct R&D collaborations for better innovation performance. I suppose timing plays a vital role in the success of R&D collaboration activities. On a simple ground, time itself is a type of rare and valuable resource which promises high economic value; on a complex ground, even if both are equipped with exactly the same resources, arranging these resources based on their optimal timing, may distinguish winners from followers in their R&D collaboration activities. To understand "time" as a construct for successful R&D collaborations, I look at the following four elements in the timing of R&D collaborations: (1) collaboration duration, (2) collaboration continuity, (3) collaboration simultaneity, and (4) collaboration pattern. I empirically test their effects on innovation performance.

To examine the effect of timing on R&D collaborations, I employ a unique dataset (2002-2010) that has annual information on the R&D collaboration practices and innovation performance of 230 research projects from a leading multi-divisional, multi-national Global 100 manufacturing company with an annual R&D budget of more than 1.5 billion euros. I distinguish between two types of R&D collaboration partners— market-based partners (suppliers and customers) and science-based partners (universities and knowledge institutes)— as each of them provides a particular type of knowledge in the collaboration process (e.g.: Deeds and Rothaermel, 1999; Faems et al., 2005). The results show that firms can improve performance of research projects by optimizing the timing of their R&D collaboration activities. I find that there is an optimal level of *collaboration duration* in R&D collaboration activities: in general, collaboration needs some time to be effective, but it also cannot last too long. Next, I find that *collaboration continuity*, denoting that collaborations are carried out continuously instead of in a piecewise manner, increases the success of research projects for market-based partners, but hampers performance with science-based partners; *collaboration simultaneity*, as represented by simultaneous collaborations with different types of partners all at the same time, increases collaboration success (marginally). As for *collaboration pattern*, research projects may be better off if collaboration with science-based partners in the early phase in their life cycle, while with market-based partners in the later phase of their life cycle. In sum, the timing of collaboration activities in research projects plays an important role in explaining the heterogeneity of their performance.

The remainder of the paper is organized as follows: I first provide the conceptual background of this chapter. Next, I introduce my hypotheses about the different ways in which the timing of R&D collaboration activities impacts on project performance. The third section describes the data and presents the empirical findings. Finally, I discuss my results and provide suggestions for future research.

5.2 Conceptual Background and Hypotheses Development

Different theoretical lenses can be adopted to understand the heterogeneity of R&D collaboration outcomes from a timing perspective. The resource-based view proposes that organizations can achieve a competitive advantage by building up portfolios of valuable resources, which are rare, imperfectly tradable and hard to imitate. Firms have a mixture of resources available, and the performance differences across organizations result from variances in resource portfolios and how those resources are used and arranged (Penrose, 1959; Wernerfelt, 1984; Barney, 1991; Peteraf, 1993). Through R&D collaborations, firms get access to resources of their R&D partners. As a consequence, competitive edges of organizations do not only result from the possession of own resources, but also increasingly from the way how the organizations interact with, and use resources from, their partners in R&D activities. Even when two companies may have access to the same external resources, differences in the way how they manage and arrange these resources can lead to substantial differences in their innovation performance.

In R&D collaboration activities, interactions take place between the research team of the focal firm and its partners. The research team members interact with each other during the collaboration process, resulting in resource (in particular knowledge) transfers and accumulations (Hagedoorn, 1993; Powell et al., 1996). In R&D collaborations, resource management is an important capability. How a firm organizes and manages the exchange of resources in R&D collaborations can be a difficult to imitate capability, and therefore, a source of its competitive advantage (Zahay et al., 2004). The resource-based theory of the firm suggests that management capabilities relating to resource adoption and use are important drivers of firm success (Verona, 1999). Interestingly, while this concept is accepted for resources and their use in general, it is not known how firms organize for resource exchanges with partners at the micro-level (i.e. research projects).

Consider, for instance, two similar projects both have the same length of lifetime, they both collaborate with the same type of partners (Faems et al., 2005; Baum et al., 2000), and both share the same "depth" and "breadth" of openness (Laursen and Salter, 2006) in their collaborations. If taking a static "snapshot" of their collaboration activities, these two projects may look identical. However, if following a certain timeline, continuing taking multiple of such static "snapshots" and linking them together, things can be rather different: First, the amount of time each project spends in R&D collaborations may vary dramatically: one project may have a long time period engaging into collaborations, while the other project may have a rather limited amount of time spent in collaborations; Second, even if both projects have exactly the same amount of time engaging in collaborations, the distribution of their collaboration periods along the project's lifetime can still be very different: one project may continuously conduct its collaborations, while the other project may divide its collaboration periods in several different time slots; Third, even both projects are involved in collaboration activities for exactly the same amount of time and organize these collaborations in a continuous (or piecewise) manner, one project may allocate its collaboration periods in its beginning (earlier phase), while the other project may organize its collaboration periods towards the end of its completion (later phase); Fourth, the above mentioned situations are further complicated if different types of partners are involved into the collaboration periods, either simultaneously, or sequentially. For conceptual graphs, please refer to Table 11.

R&D collaboration is an interaction process among partners. During this interaction process, the focal firm (and its research projects therein) both commits resources to, and receives resources from, its partners (Dyer and Singh, 1998; Madhok and Tallman, 1998). In order to establish and develop relationships in R&D collaborations, each partner has to commit a certain level of resources — such as personnel (Dodgson, 1993) budget (Todeva and Knoke, 2005), and managerial attention (Cyert and March, 1963) — along the collaboration process. However, research projects are at the same time constrained by the resources they can marshal, as they have a defined deadline, limited budget and personnel (Cleland & Kerzner, 1985; Pinto and Prescott, 1988). Consequently, resource commitment has to be well planned. Successful R&D collaborations are the ones which manage to access complementary resources in need (Hagedoorn, 1993), while still keep the costs and risks of opening up and interacting with others at a minimum level (Madhok and Tallman, 1998). Sustaining a long-time interaction in R&D collaboration activities may enable the project team to access a greater number of resources, however, it may at the same time also bring unwanted commitment of own resources. Adjusting the length of time spent in R&D collaborations to its optimal level may bring better collaboration results. In other words, *collaboration duration* may affect project collaboration outcome.

Given the same amount of collaboration time, how it is distributed along a project's life cycle can still make a difference. Theories of relational capital state it is important to keep interactions intensive and on-going to facilitate knowledge transfer and effective sharing (Kale, Singh, and Perlmutter, 2000). It is stressed that, in order to effectively realize the synergies between partners in collaboration, intensive and on-going interaction between partners is necessary (Doz, 1996; Faems, Janssens & Van Looy, 2007). Learning theories, on the other hand, contend that learning is not necessarily a constant process, but can be divided into several intervals, which, in turn, improves knowledge absorption and digestion (Duncan, 1949; Brown, 2008). In the context of R&D collaboration, discontinuous interactions may also provide flexibilities in both learning as well as selecting the most desirable partner to work with. In general, the choice between whether to organize the interactions in R&D collaborations in a continuous or a piecewise manner, may affect the research project performance. In this sense, *(dis)continuity of interactions* in R&D collaboration may be an important element in the timing of collaborations explaining the heterogeneous R&D collaboration outcomes.

In the interaction process, multiple types of partners may be involved into collaborations. *Simultaneous interactions* among different knowledge sources may create synergetic effects, as different resources are allowed to possibly interact with each other, therefore increases the chance of novel knowledge re-combinations (Fleming, 2004; Fleming and Singh, 2010). However, different types of resources may not be readily compatible, and the managerial complexities may increase exponentially if they are all linked up at the same time. It is a matter of questioning whether the arrangement of timing in accessing these resources affects collaboration outcomes.

Last but not the least, so far little is known when to include different types of partners into research projects. Some studies advocate early integration of external partners into the project. For example, Zahay and colleagues (2011) find that the use of several types of information early in the project is associated with increased success, “Thus, teams should perhaps be encouraged to make more information-gathering forays outside the confines of the firm in this early project stage” (Zahay et al., 2011, p.500). Other scholars argue that it is important to keep collaboration ongoing during the whole process of project development. It is suggested that customers may be involved in the whole process of co-developing the products (Lettl, 2006) and the integration of suppliers can occur at any point of time during the NPD process (Ragatz et al., 1997). Based on the SAPPHO research project, Rothwell and colleagues found that market-related information should be updated constantly during the course of research projects (Rothwell et al., 1974). Despite these findings, there is currently little empirical evidence on the *optimal pattern* of external partner involvement in research projects.

The purpose of this chapter is to improve our understanding of how the organization of R&D collaborations at the project level has an impact on the success of research projects and the overall performance of the firm. More specifically, I focus on the following four elements of the timing of R&D collaborations in a research project: collaboration duration, collaboration continuity, collaboration simultaneity, and collaboration pattern.

5.2.1 Collaboration Duration

Successful R&D collaboration needs time. First, successful R&D collaboration requires trust among partners. Trust-building (more specifically, trust-building in the research team) is a time-consuming process. Prior studies show that higher levels of trust are associated with lower transaction costs and opportunistic behavior (Das and Teng, 1998; Gulati, 1995), which smoothens collaboration barriers (Hagedoorn et al., 2000), increases the efficiency of inter-organizational relationships (McEvily, Perrone, and Zaheer, 2003), and facilitates tacit knowledge transfers (Das and Teng, 1998). In the context of research projects, trust is not only inter-organizational, but also inter-personal (Abrams et al., 2003). As it is stated "… interpersonal trust is a central characteristic of relationships that promote effective knowledge creation and sharing in networks" (Abrams, Lesser and Levin, 2003, p.65). However, trust is not a commodity which can be obtained through market transactions, nor can it be developed overnight (Gulati, 1995). Instead, it calls for considerable time and resources to build up and maintained among partners (Ireland et al., 2002; Dyer and Singh, 1998) and the team members therein (Abrams et al., 2003). Thus, successful R&D collaboration needs some time to ensure trust building among partners. Second, it can be time-consuming to create relational rents in R&D collaborations. Adopting the resource-based view, specific investments in a partnership relation create "relational advantage" (Dyer and Singh, 1998) and "social capital" (Coleman, 1988), which help the project team create relational rents that are rare and difficult to imitate (Penrose, 1959; Dyer and Singh, 1998). As partners become familiar with each other, they may invest additional resources in strengthening and developing their collaboration ties in the research project. Relational rents require firms to invest in idiosyncratic assets, which take time and is a gradual process influenced by mutual trust (Dyer and Singh, 1998). Hence, R&D collaboration can be a time-consuming process. A third aspect of the time-consuming face of R&D collaboration relates to "time compression diseconomies", which suggests that the quicker an organization develops new resources, the less effective it might be (Dierickx and Cool, 1989). Maintaining R&D activity over a particular time interval produces a larger increment to the stock of R&D know-how than maintaining twice this rate of R&D activity over half of the time interval. For example, MBA students may not accumulate the same stock of knowledge in a one-year "crash" program as in a two-year program, even if all inputs other than time are doubled (Dierickx and Cool, 1989). In terms of R&D collaboration, firms may have to wait to reap the full benefits from the collaboration (Garcia-Canal et al., 2002), and may not realize the benefits of collaboration within a limited period of time.

Despite the aforementioned benefits, however, it may also not pay off to collaborate for too long: the marginal gains of extending the collaboration period may diminish after some point of time, while the possible disadvantages of long collaborations (such as unintended knowledge spillovers and managerial complexities) may increase during too long interactions with partners. The relationship between collaboration and new product development might be characterized by diminishing marginal returns (Deeds and Hill, 1996). Early collaboration experience allows for significant learning, which may, however, diminish in further collaboration (Hoang and Rothaermel, 2005). Empirical research has documented that learning does indeed taper off, and in fact, does so fairly rapidly (Lieberman, 1984; Darr, Argote, and Epple, 1995). Besides the diminishing marginal returns in R&D collaborations, projects may also suffer, at a certain point, limitations in capacities to further absorb external knowledge. Constrained by cognitive limitations (Katz and Kahn, 1978) , the research project team can only efficiently deal with a certain amount of resources (Schilling and Hill, 1998) in its life cycle. Therefore, the additional information which is accumulated over the collaboration period may cause an information overload problem (Eppler and Mengis, 2004) or bring “noise” which may negatively influence its decisions and main innovative activities (Grabher, 2002). As Argyris (1976) pointed out, collaboration needs some specialization and could be hampered by an excess of information. Therefore, it may not be desirable to stay in collaboration throughout the project’s whole life time. Instead, the project may need a certain closed period to keep focused and to better digest the knowledge it absorbed. Furthermore, as the environment is continuously changing, the goals and interests of partners may also evolve over time. It can bring particular challenges for the project team to align different goals and interests of partners along the collaboration phase, failing in doing so may make the partnership vulnerable (Gulati, 1995). Additionally, the communication and coordination costs among partners can be tremendous (Malone, 1987; Becker and Murphy, 1992), bringing much complexity in managing relationships with external partners. As it is pointed out, in a fast changing environment, environmental evolution may force firms to reap the potential benefits of collaboration from day one by accelerating collaboration development (Garcia-Canal et al., 2002).

Considering both the time-consuming and the time-efficiency face of R&D collaboration, the optimal collaboration time period should be long enough for tapping into the required external resources in need, but not too long in order to maximize the learning effect and reduce managerial complexities. Therefore, I hypothesize:

H 8: There is an inverted U-shaped relation between collaboration duration and the innovation performance of research projects.

5.2.2 Collaboration Continuity

The benefits of resources do not only depend on resource transfers, but also, and perhaps more importantly, on the absorption and learning capabilities of the focal organization (Cohen and Levinthal, 1990). Organization theories point out that, to ensure smooth knowledge transfers and absorption, a certain level of acquaintance among team members is needed (Katz and Allen, 1982; Brown and Eisenhardt, 1995). To create acquaintance among R&D collaboration partners, it is important to sustain a certain level of R&D interactions ongoing and strive for continuity in R&D interactions, since loose contacts may negatively influence knowledge exchange, particularly the transfer of tacit knowledge.

The unique characteristics of different types of partners (market-based or science-based) may ask for different approaches in the continuity of collaborations. There are several reasons to believe that projects would benefit from a continuous collaboration with market-based partners. First of all, it is costly to frequently renew or resume collaboration relationships in a research project. R&D collaboration is a complex process starting from partner-searching, partner engagement, relationship development, and finally collaboration completion. Each activity requires a certain level of resource investment. In the partner-searching phase, due to information asymmetries (Aboody and Lev, 2000), it may take a considerable amount of time and resources to look for the right market-based partner and to convince him/ her to establish a collaboration relation. Once the market-based partner is selected and the collaboration starts, it again takes time for the project team members to get acquainted with each other before meaningful conversations take place (Katz and Allen, 1982; Brown and Eisenhardt, 1995). Even with the same partner, the collaboration needs to be resumed again, if without, or with little contact in a previous phase (Abrams et al., 2003). Thus, compared to continuous collaboration, it may be costly to renew, or resume, collaborations if there are several interruptions in the collaboration activities.

Second, it may be beneficial to have a consistent strategy for project development, thus switching frequently between an open and closed innovation status in the research project may not pay off. Organizations develop routines over time routines to execute certain operations effectively (Kelly and Amburgey, 1991), which are stored as procedural memory (Cohen and Bacdayan, 1994). Adjusting routines is a time-consuming process, and applying old routines in new context can be counter-productive (Kelly and Amburgey, 1991). In the context of research projects, closed (inward-looking) and open (outward-looking) innovation activities require different organizational routines to be effective (Chiesa and Manzini, 1998). Managerial approaches that are better suitable for closed R&D activities may be detrimental for open R&D activities (Herzog and Leker, 2010). Consequently, routines and approaches that are applied successfully during the closed development period of a project may hamper innovation success if the research project switches to a collaborative mode (or vice versa). The situation may be aggravated if there are frequent switches between a closed and open innovation status, as the project may be slow in appropriately addressing and adapting routines to the changing situations. Therefore, I hypothesize:

H 9a: Collaboration Continuity has positive effect for the performance of research projects when collaborating with market-based partners.

Despite the possible advantages of continuous collaboration in the research project, different types of partners may ask for different approaches in (dis)continuity of collaboration. While staying in continuous collaboration with market-based partners may help the focal project to constantly update market-related information and therefore be particularly beneficial for innovation performance, when it comes to collaboration with science-based partners, it may be beneficial to organize R&D collaborations in a piecewise way. First, when collaborating with science-based partners, R&D collaboration is a learning process (Grant and Baden-Fuller, 2004) and breaks in the collaboration process may improve learning and knowledge absorption. Just as students have breaks and holidays during a school year, having some intervals in the learning process may allow the research project sufficient time to digest knowledge absorbed from partners, which, in turn, improves its learning effect (Duncan, 1949; Brown, 2008). Second, when collaborating with science-based partners, discontinuous collaboration may reduce the chance of unwanted knowledge spillovers. Being continuously open in research projects also implies that there are continuous knowledge in- and out-flows in the research project during its collaboration period. The science-based partners may be better able to tap into the knowledge base of the research project team when R&D collaborations and knowledge exchanges are organized continuously. In contrast, discontinuous collaborations, in which the collaboration period is cut into pieces which are not necessarily connected with each other, may prevent the research project from unwanted knowledge outflows. Therefore, I hypothesize:

H 9b: Collaboration Continuity has a negative effect on the performance of research projects, particularly when collaborating with science-based partners.

5.2.3 Collaboration Simultaneity

Some research projects collaborate with multiple types of partners. R&D collaboration is also a synergetic process mixing and recombining multiple types of resources (Cassiman and Veugelers, 2006). As different types of partners bringing diverse resources into the collaboration process (Ahuja, 2000; Baum et al., 2000), collaboration portfolios help to improve innovation performance (Faems et al., 2005). Market-based and/or technology-based partners are the most frequently involved types of partners in R&D collaborations (Deeds and Rothaermel, 1999; Faems et al., 2005), as successful innovation activities are grounded from the intertwinement of both market and technology knowledge (Tidd et al., 2000; Dougherty, 1992; Garcia and Calantone, 2002).

In organizing the timing of collaborations in a collaboration portfolio, the research project can choose to simultaneously collaborate with different types of partners during (most of) its collaboration period or it can organize the collaboration activities sequentially, thus mainly focusing on one type of partner at one time. Hence, *collaboration simultaneity* may be the third dimension to look at when organizing timing in R&D collaboration activities.

Because innovation activities are path-dependent and follow an evolutionary trajectory (Nelson and Winter, 1982), the next step in the development process is always built on, and to a great extent influenced by, its previous steps. Adopting a "knowledge architecture" perspective[24] (Ulrich, 1995) in the collaboration process of research projects, knowledge architecture is built up gradually and knowledge is added piece by piece. When collaborations are sequential, the chance of revising the previous parts is small as the collaboration with the prior partner is already finished, and the newly added part can only be built on the existing knowledge architecture. The flexibility of new combinations is constrained if the cost of switching trajectories is prohibitively high. Moreover, sequential collaboration also implies that the R&D team is well aware of the knowledge architecture of the new product it is going to develop, and it can plan the optimal sequence of R&D collaborations in advance. This is however unlikely if the project aims to achieve novel innovations. In fact, several scholars found that structured modularity in product development improves efficiencies but may be at the cost of hampering innovativeness (Sanchez and Mahoney, 1996; Lau et al., 2011). A number of well-known examples such as the "GlobalStar" project which was jointly developed by Loral Corporation and Qualcomm, and the "Iridium Satellite" project by Motorola, are noticeable examples in which a firm inappropriately engaged with different types of partners in sequence (see Business Week, 2000).

Compared to sequential collaboration, simultaneous collaboration improves communication and knowledge interaction not only between the partners and the focal firm, but also among the different types of partners themselves. As

[24] Knowledge architecture is the arrangement of functional elements under the specification of the interfaces among interacting components (Ulrich, 1995, p. 420).

such, it enhances the possibility of coming up with something novel if different knowledge streams are simultaneously present and recombined (Fleming, 2001; Singh and Fleming, 2009). Simultaneous collaboration with different types of partners involves open generation and sharing of new ideas, resolution of problems and disagreements by means of non-routine methods and different reference frames, and enables responsive and timely feedbacks to innovations in novel and meaningful ways (Griffin and Hauser 1996; Van de Ven 1986). Drawing from each partner's unique background and iterations through joint problem solving (Song and Parry 1997; Van de Ven 1986), the research team that acquires and disseminates divergent ideas and information through simultaneous collaborations is more likely to generate creative ideas and better innovations. Furthermore, as successful innovations are usually grounded in insights from both market and technology knowledge (Tidd et al., 2000 Dougherty, 1992), it can be beneficial to involve different types of partners simultaneously into the collaboration process to enable the full interaction among them. Thus, I hypothesize:

H 10: Collaboration Simultaneity has a positive effect on the innovation performance of research projects.

5.2.4 Collaboration Pattern

From a theoretical perspective, it is reasonable to conduct R&D collaboration in the early phase of project life cycle. R&D collaboration is about knowledge accumulation (Kale and Singh, 1999; Grant and Baden-Fuller, 2004). The externally-sourced knowledge has to be synthesized with the internally-generated knowledge (Kogut and Zander, 1992; Cassiman and Veugelers, 2006). Knowledge integration is neither an automatic nor an instant process (Grant, 1996), it only takes place when the ingredients— the pieces of knowledge that have to be combined— are readily available. Therefore, it is reasonable to keep the collaboration period in the early phase of the project to broadly prospect external knowledge, while allowing time for knowledge integration in the later phase of the project to fully synthesize all the knowledge pieces that the project has gained from both internal and external sources.

Moreover, adopting a risk reduction perspective, the risk of innovation is the highest when the uncertainty is the greatest. As the unknown resolves and the relevant knowledge architecture of the innovation emerges during the process of project development, the risk gets reduced accordingly. Therefore, innovation risk is the greatest when the project starts, and it declines as the project unfolds (Cooper et al., 2004). During the innovation process, firms collaborate with partners to collect different types of external resources, which, in turn, reduce innovation risks. Therefore, the need of collaboration is more pronounced during the earlier period of the project where the risk is the highest. Therefore, it might be beneficial to conduct R&D collaborations in the earlier period of the project.

Furthermore, there are also concerns on appropriability of the innovation resulted from collaborative partnerships. In R&D collaborations, partners share costs and risks, but they also share the outcome of their joint work. Collaborating early on in a project thus leaves room for differentiation between partners by closing down at the end of the project. In sum, I hypothesize:

H 11a: The optimal pattern to collaborate with external partners in research projects is early on in the project.

However, the optimal collaboration pattern is also likely to be contingent on the type of partners involved in R&D collaboration activities. I suppose that the optimal collaboration time period with science-based partners is earlier than with market-based partners, for at least two reasons: First, the concerns of appropriability at the end of the project may be particularly pronounced when it comes to collaboration with science-based partners. As science-based partners possess the most relevant and fundamental knowledge that may directly contribute to the final innovation, science-based partnerships may carry the most risks in successfully separating the resulting innovation and attributing it to the matched contributor. This division of resulting innovation may hamper collaboration relationship and the innovation development if both of the partners aim to claim for the rights of the innovation. Moreover, collaboration with science-based partners in the early phase of the project life time also allows for sufficient time for differentiation of innovations in their later stages of development, resolving (at least partly) appropability issues. In contrast, collaboration with market-based partners brings (mostly) practical knowledge on how the innovation is to be used in different contexts and conditions, therefore, in a later phase of innovation development (after the underlying innovation is clear), collaboration with market-based partners allows for possibilities in exploring multiple innovations based on different applications in different scenarios, and may boost both the scientific and economic value of the innovation; Second, science-based partners are in many cases able to conceptualize the possible resources in need beforehand and to articulate the underlying tacit knowledge in a relatively early phase (Katila and Mang, 2003), thus enable collaboration activities to take place in an early phase of the project lifetime. In contrast, users' ideas are usually less feasible in the beginning, and may need continuous probing and guidance in the innovation process (Poetz and Schreiner, 2012). Hence, it is more likely that the collaborations with science-based partners are carried on in an earlier stage of the project life time. Thus, I hypothesize:

H 11b: The optimal pattern to collaborate with science-based partners in research projects is earlier than with market-based partners in the project.

5.3 Data and Sample

5.3.1 Sample

In this chapter, I focus on the projects that are complete to study the timing of collaborations in their full lifetime. In my dataset, there are in total 867 research projects which are originated in/after year 2003 that have been completed. I focus on finalized projects because they give me full information on the timing of R&D collaboration activities. Since some projects can be very short lived (e.g.: for one year) and it becomes ambiguous to analyze some dimensions of the constructs in this chapter (e.g.: collaboration continuity, collaboration pattern)[25], I restrict my sample to projects with equal to, and more than, 2 years project life time and discard projects that are with missing collaboration indicators, this then leaves me with 433 projects in my sample. 230 projects entered into my final regressions as they have all information I need with no-missing data on the regressors[26]. I have dichotomous annual information on the collaboration activities of research projects with different types of partners (market-based or science-based), the indicators take value "1" if there is collaboration going on with a certain type of partners (science-based or market-based), while value "0" if otherwise. Further, this dataset includes basic information of projects such as project title, abstract; and yearly information on the practices of each project, such as number of full time

[25] In my data, I have collaboration variables at the year level. For those projects that last for only one year, if studying their collaboration continuity and pattern, it turns to be hard to judge whether the project is in collaboration in its "beginning" or at the "end". Nevertheless, in a robustness check, I still bring in those one-year projects (continuity is "1", pattern is "1" for early phase and "1" for later phase) and results are mostly unchanged. If there are more finely grained data available (e.g.: detailed at day or month level), then those concepts can be nicely adopted.

[26] Robustness checks based on sample of 433 projects (with released control variables) give similar results as if on the sample of the 230 projects.

equivalent researchers ("FTE"), project management proficiency (PMM), project leader who manages the project, the sponsoring department which initiates and sponsors the research project, the business unit(s)[27] which receive and further commercialize the resulting innovation(s) of the project, the starting year of each project, and the number of transfers that are generated from each project. A detailed description of the above mentioned information can be found in Table 16. For my analysis, I use cross-sectional information on each project.

[27] A project can generate multiple transfers to business unit(s) in its lifetime. In some cases the deliverables of a project are transferred to more than one business unit. In my sample, the finished result of 1 project (0.43%) is transferred to 3 business units, the finished result of 19 projects (8.26%) are transferred to 2 business units, the finished result of 93 projects (40.43%) are transferred to 1 business unit, and the remaining 117 projects (50.87%) generate no transfer.

Table 16 Variable Definition and Explanation

Variables	Information	Description	Note
Dept. Var.	Total Number of Transfer(s) generated by each Project	A "Transfer" is the final deliverable of a research project (to business unit(s)). It signals the final outcome of the research project as well as the intermediate financial return of an innovation (only those projects that successfully delivered a transfer to business units are able to generate financials in the marketplace)	
Indep. Var.	Market-based Partnerships	Whether or not the project is in collaboration with market-based partners (suppliers or customers) in the year	"1" if there are collaborations going on in the given year and "0" if not
	Science-based Partnerships	Whether or not the project is in collaboration with science-based partners (suppliers or customers) in the year	
Control Vars.	Patent(s) applied by the project	Patent number and destination patent office of each project if the project has applied for any patent(s)	The technology fields the innovation covers are identified by the applicant firm or revised/added by the patent examiners in the patent application file. I use this information to identify the technology fields of the project (at IPC-4 digit level) in my sample. As my sample firm is based in Europe and heavily file for patents at European Patent Office (EPO) (or jointly at EPO and at other patent offices, e.g.: USPTO, JPO and/or SIPO), I use its EPO patent information as the basic patent information for this chapter. When such information is unavailable (the project does not file for patent at EPO but at other patent offices, which is only 5% of all cases), I then use information from World Patent Office a substitution.

Project Title	Title of the project	In the absence of patent information, project title and abstract are used for manual search/ match in the World Intellectual Property Organization (WIPO) website to extract the technology fields (IPC-4 digit level) of the project
Project Abstract	Abstract of the project	
Project Management	Annual evaluation of project management proficiency by the project upper management team. Scored from 0 to 5, with a lower score indicating a looser way of project management and a higher score indicating a stricter way of project management, scores are according to the stage-gate model (Cooper et al., 1990 & 2002)	
Project Leader	Name of the manager who is leading the project	
Project Initiating Year and Ending Year	Year in which the project is initiated and ended	Jointly being used to calculate the length of the project
Project Sponsoring Unit	The department which initiates and sponsors the research project	48.04% of the projects are initiated and sponsored by "Corporate Research", while the other projects (51.96%) are initiated and sponsored by business units.
Business Unit(s) which receive the transfers	After the research project is finished, its results are transferred to one (or few) of the business units of the firm for further commercialization	There are in total 10 different business units of the firm, covering 7 broad industries and 3 external businesses (e.g.: IP, licensing, new business development and incubator). Project sponsors (sponsoring units) and project recipients (business units which receive the transfers) are not necessarily the same units for two reasons: First, among those 433 sponsored projects, 243 of them (56.12%) generate no transfers; Second, among the rest 190 projects which are transferred, 92 of them (48.42%) are transferred to a different unit other than its sponsoring unit. It is frequently the case that the research project is initiated by one unit of the firm but is finally transferred to another unit(s), if the result fits the needs of the other unit(s) better. Such situation is the most prominent when the sponsoring unit is Corporate Research while the project recipient is one of the business units (in my sample,

		96.30% of Corporate Research sponsored projects are transferred to business units).
Project Resources (FTE)	Number of full-time equivalent researchers working on the project	This variable signals project size and resource investments. I take the average full time equivalent of the project during its lifetime as project resources.
Project Patent Stock	All the patents applied by the firm at the EPO are extracted from EPO. Based on this information, I calculated previous 5-year patent stock of the firm in the technology fields of the research project	Signals the technological strength of the firm in the technology field of the research project
Year dummies	Year of project initiation	Signal macro-economic environment

Note:

- Project leader is not used in my regression because it is highly correlated with project sponsoring units and project technology fields.
- The independent variables in my paper (Collaboration Duration, Collaboration Continuity, Collaboration Simultaneity, and Collaboration Pattern) are based on the combination of the two basic collaboration variables (yearly information on collaboration with science-based or market-based partners).

5.3.2 Dependent Variable

Project Performance[28]: In this chapter I measure project performance as the number of "transfers" that a research project delivers to its business recipients. In total there are 10 broad business recipients (business units) of the firm, receiving the resulting innovation of the research project and further commercialize them in their own business. The recipients of transfers include the existing business lines within the firm, the IP and licensing department, the new business development department, as well as corporate incubators. A transfer takes place when knowledge is purposefully disclosed to a customer (business unit) of the research project, who recognizes the value of this knowledge and has agreed to apply this knowledge in his/her business for developing new products, processes or services. Technologies developed in

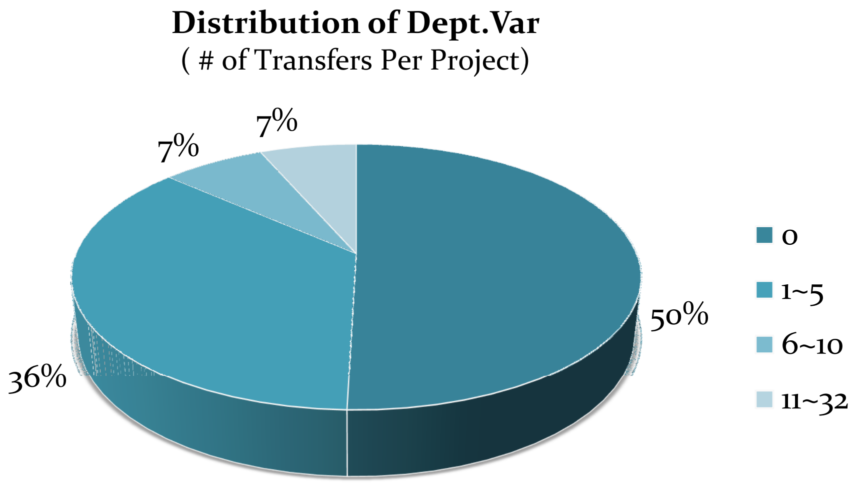
[28] Prior literature uses patent applications as a popular indicator of technical performance. Despite its popularity, there has been great concern about the reliability of patents as an output indicator (see, e.g. Basberg, 1987; Griliches, 1990). This concern stems from at least four considerations: the technological level and the economic value of patents are highly heterogeneous; the tendency to bundle claims together in one or more patents varies widely among countries; not all innovations are patented; not all patents become innovations (Griliches, 1990). Patent application only measures the innovativeness of the invention, while gives little, if any, indication on the overall real value of the underlying innovation. A considerable amount of patents are "lying on the shelf" (Chesbrough, 2003) which do not make any contribution to a firm's performance. Also, patenting can carry significant strategic considerations of the firm. For instance, firms may conduct aggressive patenting, defensive patenting, or use patents as a means for market entrance. Therefore patenting indicators may lose their representativeness, as patents are a rather noisy measurement of firms' innovative activities. Nevertheless, I used patent applications of each project as robustness check for this study. Replacing transfers by patent applications gives a similar but indeed noisier result compared to project transfers.

Another reason to use the number of transfers as dependent variable in this chapter is because I have multiple dimensions to measure but only limited projects (5% of all the projects in the sample) managed to generate financials in the marketplace, the variance in financials isn't big enough to discern and disentangle these 4 dimensions.

research projects are transferred as long as there are some parties (no matter within or outside of the firm) who value this technology and are willing to invest in it and to further develop and commercialize the technology. Transfers are the final deliverables of research projects, and serve as reliable indicator of project performance particularly for its research phase (only those wanted and promising research results are transferred to a business unit, and are able to be carried further into marketplace). In this study, I adopt the number of transfers of the project as the indicator of project performance. For a distribution of the number of transfers, please refer to Table 17.

Table 17 Distribution of Dept. Variable (Number of Transfers)

# of Transfers per Project	Frequency	Percentage
0	116	50.43 %
1~5	83	36.09 %
6~10	16	6.96 %
11~32	15	6.52 %



5.3.3 Independent Variables

Collaboration Duration. Collaboration duration is measured as the total amount of time the research project spent in collaborating with external partners, divided by the length of the project life time. This variable is further calculated as "general collaboration duration" (regardless of the type of partner involved), and as "specific collaboration duration" (collaboration activities with a certain type of partners), respectively. General collaboration duration indicates how much percent of time a project spent in R&D collaboration during its life cycle, no matter which type of partner it collaborated with. Specific collaboration duration measures collaboration duration with a specific type of partner, distinguishing between science-based partners and market-based partners.

Collaboration Continuity. Collaboration continuity is a dummy variable: "0" denotes that during the project life cycle, the collaboration activities are discontinuously organized in a piecewise manner. In the other case, when the project stays continuously in collaboration and without any breaks in the collaboration process, it takes value "1". In line with the collaboration duration measure, I created separate variables for "general collaboration continuity", regardless of the type of partners the project engages with, and "specific collaboration continuity" takes into account of collaboration continuity with a certain type of partners.

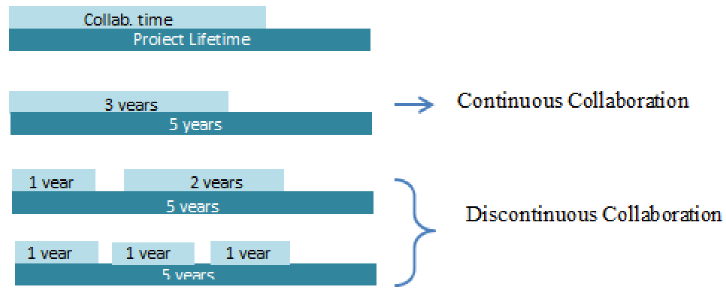
Collaboration Simultaneity. Collaboration simultaneity measures to what extent both types of partners are involved into the collaboration process at the same time. It is measured as the amount of overlapping collaboration time with both types of partners, divided by the number of collaboration years of the research project. In a significant number of cases (35.05 percent), the research projects in my sample collaborated with both market-based and science-based partners in the course of the project's lifetime.

Collaboration Pattern. Collaboration pattern refers to the stage of the project life cycle in which R&D collaboration activities take place. I distinguish between two phases of the project: collaboration in the earlier phase of the project, and/ or collaboration in the later phase of the project, where I use the mid-term of the project's life time as the cutting point.

A description table of the independent variables in this chapter is shown in Table 18.

For a detailed summary of the variables, please refer to Table 19.

Table 18 Explanation of Independent Variables (Four Dimensions of Collaboration Timing)

Variables	Description	Example	Graphical Explanation
Collaboration Duration	Percentage of years the project spent in collaboration with partners of its full life time	A 5-year project collaborates with partners for 3 years, then this variable takes a value of 0.6	
Collaboration Continuity	Whether the project is in continuous collaboration with external partners during its collaboration period, or the collaboration is interrupted in some ways	(Following the above-mentioned example), if the 3-year collaboration is continuously conducted, then this variable takes a value of "1", otherwise, it takes a value of "0".	

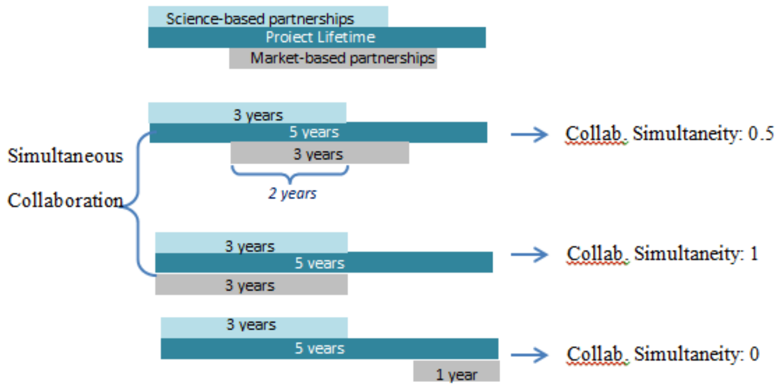
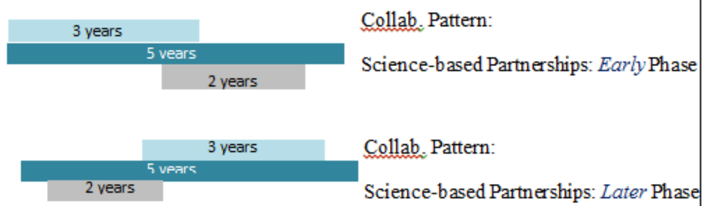
Collaboration Simultaneity	The percentage of time the project spends in simultaneous collaboration with different types of partners (Market-based and Science-based)	(Following the above-mentioned example), during the 3-year collaboration period with market-based partners, the project also collaborates with science-based partners for 2 years. Then this variable takes a value of 0.4.	
Collaboration Pattern	In which project development phase the project is in collaboration with external partners	(Following the above-mentioned example), the 3-year collaboration period with market-based partners takes place in the first 3 years of the project life time, while the collaboration period with science-based partners takes place in the last 2 years of the project's life time. Then this variable takes a value of "1" for market-based partnerships in the early phase of project (while value "0" for science-based	

Table 19 Summary of Independent Variables (Four Dimensions of Collaboration Timing)

Dimension	Type	Criteria	Frequency	Percentage
Collaboration Duration	Market-based Partnerships	<= Half of the Project's Lifetime	72	31.30%
		> Half of the Project's Lifetime	103	44.78%
	Non Market-based Partnerships		55	23.92%
	Science-based Partnerships	<= Half of the Project's Lifetime	60	26.09%
		> Half of the Project's Lifetime	110	47.83%
	Non Science-based Partnerships		60	26.09%
Collaboration Continuity	Market-based Partnerships	Continuous Partnerships	101	43.91%
		Dis-Continuous Partnerships	74	32.17%
	Non Market-based Partnerships		55	23.92%
	Science-based Partnerships	Continuous Partnership	112	48.70%
		Dis-Continuous Partnership	58	25.22%
	Non-Science-based Partnerships		60	26.09%
Collaboration Simultaneity	Both Science- & Market- based Partnerships	Simultaneous Collaboration (at least one year overlapping)	128	55.65%
		Sequential Collaboration	13	5.65%
	Either One Type of Partnership (Science- or	Only Market-based Partnerships	34	14.78%

	Market- based)	Only Science-based Partnerships	29	12.61%
	Non-Partnerships		26	11.30%
Collaboration Pattern	Market-based Partnerships	*Early* Phase of Project Lifetime	37	14.78%
		Later Phase of Project Lifetime	45	15.24%
		Equally Distributed in *Both Phases*	93	36.95%
	Non-Market-based Partnerships		55	33.03%
	Science-based Partnerships	*Early* Phase of Project Lifetime	37	16.09%
		Later Phase of Project Lifetime	39	16.96%
		Equally Distributed in *Both Phases*	94	40.87%
	Non-Science-based Partnerships		60	26.09%

- Based on calculation of whole population—230 projects;
- Collaboration Continuity is set to "0" if there is only one period of collaboration in the project's lifetime.

5.3.4 Control Variables

I control for a range of other factors that may affect the innovation performance of research projects. The control variables I employ in this chapter are: *Project Resources: 1) Project Staffing*(FTE), 2) *Project Prior Technological Capabilities* (based on 4-digit IPC code); *Project Technology Fields; Corporate Research; Development Departments; Project Management; Length of the Project; and Project Initiating Year.* For a detailed description of the variables mentioned above, please refer to Chapter 2, Data and Sample.

5.3.5 Method

Poisson quasi maximum likelihood regression techniques are used in this study. Poisson type of regression is a form of generalized linear model which is mostly suitable for analyzing count models. As my dependent variable (number of transfers per project) is random and with non-negative integer values, Poisson type of regressions are used in the analyses. The basic form, Poisson regression, is widely adopted in count models but also with limitations as it assumes a particular parametric conditional mean for the dependent variable to be its standard deviation. Negative binomial regression partly releases the limitation and allows for over-dispersion of the dependent variables with the variance being a quadratic function of the mean. Poisson quasi regression techniques also releases the constraint of the basic Poisson regressions on the distribution of the dependent variable given the independent variable to be of a particular form, with the variance being a linear function of the mean (Wooldridge, 1997). As my dependent variable is over-dispersed, I did both negative binomial regression analysis and poisson quasi maximum likelihood analysis. The hausman test suggests that poisson quasi maximum likelihood analysis is the better and more reliable approach to carry forward. Therefore in this chapter, poisson quasi maximum likelihood regressions are taken as my analysis approach.

5.4 Empirical Results

The descriptive statistics of the explanatory variables are shown in Table 20. On average, there are 2.5 transfers delivered per project, large percentage of project lifetime (71%) is involved in some sort of collaborations, with 53% openness for market-based partnerships and for science-based partnerships. 44% projects engaged into continuous collaborations with market-based partners and 49% projects engage into continuous collaborations with science-based partners. For the whole collaboration period, 43% is spent in joint collaboration with both science-based and market-based partners. For those projects that collaborate with market-based partners, 57% of them conduct market-based partnerships in an early stage, while 61% of them are open in a later stage; similarly, for those projects that collaborate with science-based partners, 56% of them are open in an early stage, while 57% of them are open in a late stage of the project development (in several cases, there is overlapping of collaborations in both early and late stages, meaning that there is collaboration going-on in both phases of the project and it is hard to determine a dominant phase for collaboration). Finally, the average project lifetime is 2.89 years, roughly half of the projects are sponsored by corporate research unit, the average project resources (total FTE) amounts to 3.46, and the average previous 5 years patent stock of the firm in the same technology fields is 5.54.

Table 20 Correlation Table

	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. # of Transfers	2,50	4,95	1,00															
2. Duration Collab.	0,71	0,34	0,01	1,00														
3. Duration Collab.MP	0,53	0,37	0,13	0,66	1,00													
4. Duration Collab.SP	0,53	0,39	-0,08	0,69	0,26	1,00												
5. Continuous Collab. MP	0,44	0,50	0,07	0,50	0,80	0,20	1,00											
6. Continuous Collab. SP	0,49	0,50	-0,10	0,58	0,23	0,85	0,31	1,00										
7. Collab. Simultaneity	0,43	0,43	0,07	0,31	0,58	0,59	0,42	0,46	1,00									
8. Collab.MP intheEarlyPeriod	0,57	0,50	0,08	0,43	0,74	0,15	0,48	0,08	0,48	1,00								
9. Collab.MP intheLaterPeriod	0,61	0,49	0,12	0,47	0,71	0,20	0,54	0,18	0,45	0,27	1,00							
10. Collab.SP intheEarlyPeriod	0,56	0,50	-0,04	0,48	0,16	0,78	0,10	0,58	0,52	0,20	0,09	1,00						
11. Collab.SP intheLaterPeriod	0,57	0,50	-0,04	0,50	0,17	0,72	0,11	0,56	0,45	0,09	0,23	0,34	1,00					
12. Project Length	2,89	1,05	0,25	0,14	0,08	0,06	0,17	0,20	0,04	0,01	0,18	-0,04	0,11	1,00				
13. Corporate Research	0,50	0,50	-0,11	0,09	-0,08	0,11	-0,05	0,03	-0,04	-0,09	-0,08	0,09	0,11	0,02	1,00			
14. Project Resources	3,46	1,69	0,13	0,08	0,11	0,19	0,08	0,12	0,23	0,14	0,00	0,21	0,10	-0,04	-0,01	1,00		
15. Project Management	3,80	0,65	0,19	0,17	0,31	0,11	0,25	0,12	0,25	0,18	0,33	0,11	0,10	0,23	-0,10	0,08	1,00	
16. (log)Patent Stock	5,54	1,82	0,01	-0,10	-0,05	-0,01	-0,03	-0,04	0,05	-0,02	-0,12	-0,02	-0,01	-0,04	-0,07	0,02	0,03	1,00

The models analyzing the effects of collaboration duration on the innovation performance of research projects are in Table 21. Model 1 only includes the control variables. Positive and significant effect is found for project resources, while being sponsored by corporate research is negative for the number of transfers generated by a research project. The IPC and year variables are each jointly significant (variables omitted in the result table). Models 2 to 5 add the collaboration duration variables. There is a curvilinear relation between the overall duration of R&D collaborations and the performance of research projects (Model 2). When looking into each type of collaboration partners, I find strong evidence of a curvilinear relation between the duration of R&D collaboration with market-based partner and the performance of research projects (Model 3). While no such relation has been found for science-based partners and project performance (Model 4). Hypothesis 8 is thus only partially supported for collaboration with market-based partners. More specifically, I find that the project will achieve its best performance when the general openness of the project is 45.79%, and with market-based partners is 45.61%.

Table 21 Poisson Quasi Maximum Likelihood Regressions on Collaboration Duration and R&D Project Performance

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Duration Collab.		3.209**			
		(1.513)			
Duration Collab.^{2}		-3.504***			
		(1.133)			
Duration Collab. MP			2.533**		2.688**
			(1.056)		(1.095)
Duration Collab. MP^2			-2.777***		-2.765***
			(0.923)		(0.991)
Duration Collab. SP				-1.082	-1.558*
				(0.851)	(0.869)
Duration Collab. SP^2				0.275	0.913
				(0.823)	(0.858)
Project Length	0.114	0.0202	0.0323	0.0833	0.0354
	(0.121)	(0.110)	(0.105)	(0.144)	(0.119)
Corporate Research	-0.588**	-0.466*	-0.621**	-0.511**	-0.560**
	(0.256)	(0.268)	(0.243)	(0.247)	(0.238)
Project Resources	0.152**	0.170***	0.168***	0.196***	0.202***
	(0.0691)	(0.0602)	(0.0601)	(0.0719)	(0.0613)
Project Management	1.247	2.346***	1.873**	1.726	1.979**
	(0.932)	(0.842)	(0.860)	(1.108)	(0.968)
(log)Patent Stock	-0.0995	-0.0937	-0.0774	-0.0109	-0.00780
	(0.0709)	(0.0791)	(0.0751)	(0.0785)	(0.0776)
Constant	-0.0349	-1.428	-0.718	-0.584	-0.925
	(0.893)	(0.943)	(0.869)	(0.982)	(0.914)
Observations	230	230	230	230	230
Log Likelihood	-403.3	-371.8	-382.3	-388.1	-371.6
Pseudo. R-squared	0.534	0.571	0.558	0.552	0.571

- *Note: Dummies of Technology Fields, Business Groups, and Initiating Years are all included.*
  Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

The results of my models analyzing the effects of collaboration continuity' and collaboration simultaneity on the innovation performance of research projects are shown as in Table 22. I look at two other dimensions of timing when the project is in collaboration with a certain partner, and I add these two dimensions to the baseline models that I tested before. The first models (Models 1, 2, 3) focus on collaboration continuity with different types of partners. Model 1 and Model 2 tested the continuity variable with market-based partners and with science-based partners, respectively. In Model 3, where information is aggregated, the effect of continuity is tested on both types of partners. Models 1 provides (marginal) evidence that staying in collaboration in a continuous way with market-based partners pays off, while Model 2 provides strong evidence that engaging in continuous collaboration with science-based partners does not (Model 2). In a more complete Model 3 where both types of partners are present, a continuous way of collaboration with market-based partners and a discontinuous way with science-based partners emerge to be optimal. Therefore, Hypothesis 9a and 9b are both supported, that collaborations in research projects with market-based partners should be conducted continuously, while with science-based partners may be better if conducted in a piecewise way.

Model 4 adds the collaboration simultaneity variable to the set of control variables. The variable "Collab. Simultaneity" in Model 4 measures in how much percentage of a project's collaboration time, there is simultaneous collaboration with both types of partners. I find that staying in collaboration simultaneously with different types of partners may be beneficial to the performance of a research project. The coefficient for this variable is positive, confirming Hypothesis 10: simultaneous collaboration improves innovation performance. Therefore, it is desirable to simultaneously collaborate with different types of R&D partners, instead of adopting a sequential manner of collaborations.

Table 22 Poisson Quasi Maximum Likelihood Regressions on Collaboration Continuity, Simultaneity and R&D Project Performance

VARIABLES	Model 1	Model 2	Model 3	Model 4
Duration Collab.MP	2.503**		1.573	2.271*
	(1.034)		(1.003)	(1.190)
Duration Collab.MP^2	-3.214***		-2.716***	-2.554**
	(0.959)		(0.851)	(1.035)
Continuous Collab. MP	0.392		1.043***	
	(0.301)		(0.314)	
Duration Collab.SP		-0.0624	-0.264	-2.293**
		(0.843)	(0.818)	(1.059)
Duration Collab.SP^2		0.536	0.833	1.350
		(0.785)	(0.771)	(0.954)
Continuous Collab. SP		-1.195***	-1.376***	
		(0.368)	(0.348)	
Collab. Simultaneity				0.454$^+$
				(0.327)
Project Length	0.0112	0.0905	-0.00876	0.0574
	(0.110)	(0.0951)	(0.0935)	(0.119)
Corporate Research	-0.611**	-0.712***	-0.710***	-0.514**
	(0.239)	(0.228)	(0.206)	(0.242)
Project Resources	0.165***	0.191***	0.184***	0.194***
	(0.0597)	(0.0581)	(0.0455)	(0.0624)
Project Management	2.055**	1.874**	2.583***	2.055**
	(0.905)	(0.877)	(0.919)	(0.943)
(log)Patent Stock	-0.0810	-0.0414	-0.0299	-0.0182
	(0.0770)	(0.0793)	(0.0804)	(0.0793)
Constant	-0.723	-1.394	-1.938**	-1.028
	(0.888)	(0.891)	(0.967)	(0.900)
Observations	230	230	230	230
Log Likelihood	-379.7	-365.4	-344.7	-369.3
Pseudo. R-squared	0.561	0.578	0.602	0.574

- *Note: Dummies of Technology Fields, Business Groups and Initiating Years are all included.*
  Robust standard errors in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Finally, the regression results of the relationship between the R&D collaboration pattern and the innovation performance of research projects is shown in Table 23. Here, two pairs of variables are used to indicate the collaboration patterns with different types of partners of research projects: collaboration with market-based partners in the earlier/ later period of the project (Model 1), and collaboration with science-based partners in the earlier/ later period of the project (Model 2), I also show a model in which all these 4 variables are included simultaneously (Model 4). Since the variable "Collab. MP in the Later Period" has a negative effect on innovation performance, it shows that it may not be optimal to collaborate with market-based partners in the early phases of research projects (Model 1), but in a later phase instead.

As for collaboration pattern with science-based partners (Model 2), my results show a different pattern compared to collaboration with market-based partners. I find that it is beneficial if collaborating with science-based partners in the early phase the project. In sum, Hypothesis 11a is rejected for market-based partners, while Hypothesis 11b is supported for collaborating with science-based partners. In a final model, Model 5, all the dimensions are brought into one regression. Again, the above mentioned findings are confirmed in this set of final regression.

Table 23 Poisson Quasi Maximum Likelihood Regressions on Collaboration Pattern and R&D Project Performance

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Duration Collab.MP	3.652***				2.628**
	(1.289)				(1.288)
Duration Collab.MP²	-3.006***				-2.349***
	(0.914)				(0.863)
Duration Collab.SP		-3.793**			-2.423*
		(1.569)			(1.418)
Duration Collab.SP²		0.956			1.136
		(0.960)			(0.852)
Collab.MP intheEarlyPeriod	-0.556*		-0.418*	-0.594***	-0.658*
	(0.318)		(0.249)	(0.209)	(0.369)
Collab. MP intheLaterPeriod	-0.359		0.116	-0.263	-0.508
	(0.353)		(0.268)	(0.230)	(0.324)
Collab.SP intheEarlyPeriod		1.493***	-0.0186	0.465*	0.956**
		(0.561)	(0.231)	(0.248)	(0.472)
Collab.SP intheLaterPeriod		0.459	-0.480**	-0.147	0.304
		(0.329)	(0.215)	(0.221)	(0.338)
Continuous Collab. MP				0.540**	0.668*
				(0.258)	(0.354)
Continuous Collab. SP				-1.415***	-1.074***
				(0.270)	(0.405)
Collab. Simultaneity				0.380^{+}	0.334^{+}
				(0.289)	(0.265)
Project Length	0.0463	0.140	0.131	0.112	0.0602
	(0.106)	(0.127)	(0.122)	(0.0887)	(0.100)
Corporate_Research	-0.637***	-0.491**	-0.527**	-0.636***	-0.599***
	(0.227)	(0.230)	(0.225)	(0.216)	(0.213)
Project Resources	0.168***	0.171***	0.182***	0.165***	0.163***
	(0.0590)	(0.0619)	(0.0702)	(0.0540)	(0.0462)
Project Management	1.944**	1.812*	1.825*	2.433***	2.702***
	(0.947)	(0.929)	(1.043)	(0.882)	(0.906)
(log)Patent Stock	-0.112	0.000960	-0.0742	-0.0875	-0.0594
	(0.0819)	(0.0828)	(0.0832)	(0.0834)	(0.0847)
Constant	-0.513	-1.434	-0.450	-1.901*	-2.188**
	(0.900)	(0.926)	(0.971)	(0.980)	(1.010)
Observations	230	230	230	230	230
Log Likelihood	-378.5	-371.7	-387.5	-348.1	-337.2
Pseudo. R-squared	0.560	0.568	0.550	0.596	0.608

- *Note: Dummies of Technology Fields, Business Groups and Initiating Year are all included.*
  Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

5.5 Robustness Checks

1) Logit regressions on whether or not a research project generates transfers.

Besides using count variables for my dependent variable "project transfers", I also used dummy variable to denote dichotomously whether the research project delivers transfers or not. Correspondingly, logit techniques are used for this set of regressions. For some variables, the significance level is slightly affected (may due to a reduction of information in the dependent variable), but the signs and directions of the coefficients remain.

2) Tobit regressions on the financials that each project has generated in the marketplace.

Besides using transfers as the dependent variable, I also tried to use financial data of each research project as another dependent variable in my robustness check. As financials are continuous values which are truncated at 0, Tobit techniques are used in this set of analyses. This set of analyses also gives me similar results as I find before, mainly being the same signs and direction of the coefficients. However, as only rather limited number of projects generated financials in the marketplace, it does not introduce sufficient differential power in discerning all 4 dimensions of collaboration timing.

3) Poisson Quasi Maximum Likelihood regressions on the number of patents a research project generated.

Besides transfers and financials, I also tried to use the number of patents a research project has applied for in public patent offices. I further distinguish between number of patent families[29] a project applied for in all public patent

---

[29] A patent family counts the first filing of the same innovation filed at different public patent offices

offices, and number of patent families a project applied for in Triad patent offices[30]. While results are basically similar as obtained via using number of transfers as dependent variable, I find that transfers in general give better and more stable results (patent is a noisy variable which may not perfectly reflect the real value of an innovation, see previous footnote).

4) Increase sample size.

As one of my control variables (Project Management) has many missing data, bringing in this variable drops half of the sample size (from 433 to 230). Therefore, I tried to exclude this variable and increase sample size. Results are mostly unchanged, but the general model fit compromises. Therefore, also following the previous literature that project management matters for project performance (Cooper, 1990; Cooper et al., 2004), I decide to include this variable in my final regressions.

5) Adding more controls to the regressions.

As technologies that are in their different technology life cycle may affect collaboration timing choices, also projects that are initiated in different research labs[31] may have different "routines" of collaboration, in this set of regressions, I include all the 11 lab dummies, as well as all the 4 technology life cycle indicators (Emergent, Growth, Maturity, Decline) into the regression. As supposed, the "technology fields" dummies already pick up much of the explanatory power of the 4 technology life cycle indicators, and the various control such as technology fields, number of project under management, business units may have picked up the explanatory power of the 11 lab dummies. Thus in this set of robustness checks, both the two sets of newly

[30] Triad Patent offices are United State Patent Trade Office (USPTO), European Patent Office (EPO), and Japan Patent Office (JPO).

[31] In my data, the name of different research labs correspond to different geographical locations they are located.

added controls do not work significantly, the results remain, with the effect of "collaboration simultaneity" improves to be significant at 5% level.

5.6 Discussion and Conclusion

In this study, I explore how firms organize their inter-organizational collaboration activities in research projects and the performance of these projects. More specifically, I focus on the role of timing in R&D collaborations. Based on 230 research projects of a Global-100 manufacturing company, I find empirical support for the assumption that the success of R&D collaborations in research projects hinges on the timing of R&D collaborations with external partners.

This study contributes to the existing literature in several ways. First, it adds a new level of analysis to the extant research on R&D collaboration and innovation performance. I start from the observation that in large companies most R&D collaboration activities are conducted in relation to specific research projects where researchers from partnering organizations work together in a particular project. Prior studies on R&D collaboration (mainly) take the firm as the unit of analysis, therefore, how firms organize their R&D collaborations during research projects is oftentimes neglected. On the contrary, I investigate different collaboration activities during the research projects, taking into account the fact that projects develop over time and that collaboration needs to be managed dynamically, instead of statically. I examine how the four dimensions of timing of R&D collaborations at the research project level have an impact on projects' innovation performance: the duration of the collaboration, the continuity of the collaboration, the simultaneous collaboration between science-based partners and market-based partners, and the pattern of the collaboration during the entire lifetime of the project. I find that these characteristics of collaboration activities are important to explain research projects' innovation performance which has been neglected in prior research. Second, the empirical evidence of this study allows me to put the current debate about the pros and cons of "open innovation" (in particular R&D collaboration activities therein) in a different light. I argue that more R&D collaboration will not necessarily improve the innovation performance of research projects and companies. In contrast, it is the organization and timing of R&D collaboration activities that may help to generate better innovation performance. My results indicate that collaboration with external partners can indeed improve innovation performance, however, the success of R&D collaboration hinges on when and how R&D collaboration activities are organized during research projects life cycle. In other words, although R&D collaboration can improve the innovation performance of research projects (or firms with multiple research projects), merely conducting R&D collaboration without considering its timing is no guarantee for success. Third, besides success factors that have been identified in prior research, I introduce four dimensions of organizing R&D collaborations during research projects: collaboration duration, collaboration continuity, collaboration simultaneity, and collaboration pattern. These dimensions enrich the literature on R&D collaboration.

Furthermore, I can draw a number of managerial implications from this study. First, timing of R&D collaboration activities is crucial for the performance of research projects. Thus, managers should pay careful attention to when and how long they should collaborate with partners. When one makes no distinction between different partners I find that there is a curvilinear relation between the duration of project openness and its performance. When I make a distinction between two types of partners (market- and science-based), I find that a firm should not collaborate with all partners all the time. Optimal results are obtained when research projects collaborate a limited period of their lifetime with market-based partners, while there is no significant duration of collaboration has been found for collaborating with science-based partners. Second, with respect to collaboration continuity, research projects benefit from continuous collaboration activities with market-based partners, while the opposite effect is found for collaborating with science-based partners. Thus, when conducting collaborations with market-based partners, is suggested to do it continuously without interruptions in the process, while it may be more beneficial if collaborating with science-based partners in a piecewise manner. Third, as for collaboration simultaneity, I find that the benefits of knowledge recombination from different sources outweighs the actual managerial complexities and coordination costs, thus, the project that conducts simultaneous collaborations with multiple types of partners may outperform the projects which do it in sequence. Finally, projects are performing better when collaborations with market-based partners takes place at the end of the project, while with science-based partners at the beginning of a project. Relating to the current debates over Intellectual Property (IP) issues of collaborations, my findings suggest that the research project may need to have some closed period at the end of the project life cycle if it collaborates with science-based partners, in order to allow sufficient time for differentiation of collaborative efforts and prevent opportunistic behavior of the partner in patent filing.

Despite the contributions and implications of this study, it has also several limitations. First, the data I rely on only describes the situation of one Global 100 manufacturing company. Although it is a large multinational company covering a wide range of technologies and industries, my findings may reflect firm-specific situations and ways how management is organizing research projects. It should therefore be tested whether the findings can be generalized using project-level data of projects from a larger sample of different firms. I am currently conducting research in this direction. Second, I test whether different approaches of organizing the timing of R&D collaboration activities are contingent on the type of partners that are involved into the collaboration process. However, this might be a relatively simple approach since I did not differentiate between different types of research projects. Research projects serve different purposes, thus the optimal way to organize for R&D collaborations may also vary with the type of projects. For instance, projects that are more explorative in nature perhaps require longer collaboration and a stronger involvement of technology-based partners, compared to projects that are more exploitative in nature. Such improvements can be made if I can control for the technology complexity and novelty of the projects. Third, I have only indications whether or not a firm is collaborating with a particular type of partners at a particular point in time. I have no indication of how many partners are involved, and how intense the collaboration is in terms of the time and resources that different partners invest into the collaboration. Moreover, as I have no information about the identity of the partners, I cannot investigate the moderating role of the market reputation or technological capabilities of partners on project performance. Thus, I call for more qualitative studies analyzing the drivers behind the data, on duration, simultaneity, continuity, and pattern. In order to understand the data better, in-depth case studies are needed in the future.

Chapter 6

The Up- and Downside of Collaboration in Core and Non-Core Technologies

6.1 Introduction

Survival and growth have been two major themes in firms' development. While firms compete in the marketplace on their *core* competencies (Prahalad and Hamel, 1990) which help them to sustain profit engines (Christensen, 1997), at the same time firms also possess and develop technological fields which they are less strong at, either as background knowledge supporting their core technology activities (Patel and Pavitt, 1997), or as new technology opportunities which may help them respond to frequent changes in a dynamic environment (Teece et al., 1997).

Because of the aggravating risks, costs, and complexity of innovation, firms increasingly collaborate with external parties in their innovation activities to access and leverage outside resources and expertise (Powell et al., 1996; Hagedoorn, 2002). Recent practices show that many firms open up their boundaries and engage into R&D collaboration activities in their core (Caloghirou et al., 2004) or non-core (Chesbrough and Schwartz, 2007) technological fields. As firms develop idiosyncratic technology development trajectories over time (Nelson and Winter, 1982), certain technological fields may have accumulated more resources, established better technologies, developed higher levels of absorptive capacity, and are strategically more important for the firm than the others. Gradually, they evolve into core technological fields of the firm. During this evolution process, some related technologies— although non-core to the firm— emerge in the surroundings of firm's core technological fields (Helfat, 1994), while some other non-core technological fields remain at distance to them. As collaboration activities essentially reflect the strengths and weaknesses of the technologies of the firm (Keupp and Gassmann, 2009), there are discrepancies in terms of resource allocation, decision making, activities and outcomes among these different types of technological fields. Hence, the propensity and consequences of firms' collaboration behavior in these technological fields are also likely to vary accordingly. Against this backdrop, in the context of R&D collaboration, some conceptual contributions suggest that firms should distinguish and develop different strategies when collaborating in their core or non-core technological fields (Chesbrough and Schwartz, 2007). However, so far, there is no empirical study investigating firms' collaboration strategies and consequences based on different types of technological fields involved in collaboration. This chapter aims to address these issues by examining the propensity and outcome of firms' collaboration activities in their core and non-core technological fields.

As R&D collaboration is essentially a knowledge exchange process which is featured with inbound, outbound, and coupled (both inbound and outbound) knowledge flows (Enkel et al., 2009) between the firm and its partners, the outcome of firms' R&D collaboration activities is likely to be dependent on the characteristics of knowledge from both sides of the partnership. However, prior writings on firms collaboration activities have been greatly focusing on the *external* knowledge, such as the characteristics and nature of external partners (Danneels, 2002; Rothaermel and Deeds, 2002), the partnership portfolio

(Faems et al., 2005), and partnership breadth and depth (Laursen and Salter, 2006). The characteristics of the *internal* knowledge of the firm that is involved into collaborations, however, are not yet well understood [32]. As firms' collaboration activities are essentially set up around certain technological fields, knowledge embedded in these different technological fields (core or non-core) serves as the source that the firm relies on to feed into the knowledge exchange process with its external partners, and may actively contribute to, or impair, collaboration outcome. Consequently, studying collaboration activities in firms' different technological fields extends our understanding on the heterogeneity of firms' collaboration activities from *external* knowledge sources (such as the type, breadth, depth of partnerships) to *internal* knowledge sources and organizational activities of the firm, such as the type and characteristics of knowledge brought into collaboration, the decision and organization of activities the firm adopts to guide and support its partnerships. The propensity and outcome of involving core and non-core technological fields into the firm's collaboration activities is one of these *internal* aspects which may improve our understanding on firms' collaboration behavior and outcome.

To understand these issues, I rely on an extensive dataset of projects from a large multinational firm between the year 2003 and 2010. I identified the technological fields of its research projects and classified them as core or non-core technological fields based on the strength of specialization of firms in the field (Patel and Pavitt, 1997). In my data, technological fields of each project are carefully assessed and denoted by the 4-digit IPC code of the technological fields the project covers. Following Patel and Pavitt (1997), I calculate the

[32] Few studies analyze the internal factors of the firm, in most cases being the overall absorptive capacity of the firm as a whole (e.g.: Tsai, 2009; Escribano et al., 2009).

Patent Share and *Revealed Technology Advantage*[33] of each technological field the firm covers and identified 25 core technological fields of the firm in the 9-year time (at IPC 4-digit level). Projects that are with both high patent share and high revealed technology advantage are classified as core technologies, while the rest are non-technologies (for more details please refer to methodology section). Within these non-core technologies, I further distinguish between related non-core technological fields and distant non-core technological fields of the firm, based on technology relatedness of the non-core technologies to the firm's core technological fields (Leten et al., 2007). Those technological fields that are highly related to firm's core technologies are considered as related non-core technologies, while the ones that are with a low relatedness to firm's core technologies are considered as distant non-core technologies (for a graphical explanation, please refer to *Figure 18: Technological Fields of the Firm*).

[33] For a more detailed description of the calculation procedure, please refer to the methodology session of the paper.

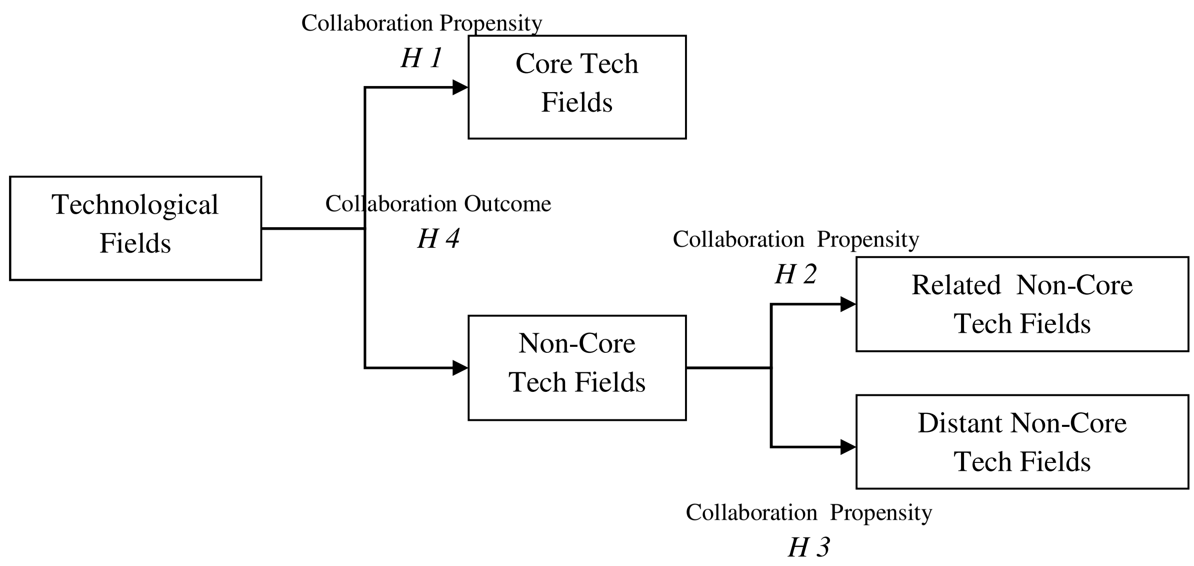


Figure 18 Technological Fields of the Firm
(Hypotheses and Conceptual Framework)

I study both the firm's collaboration propensity and collaboration outcome (measured as financial returns each research project generated in the marketplace) in involving core and non-core technological fields. The empirical results suggest that although there is a higher propensity to collaborate in firm's core technological fields, it is collaboration in firm's non-core technological fields that brings the firm the most benefits. However, collaborations in firm's non-core technological fields are not easy, as there appears to be a "technology threshold" of firm's technology capability to start up R&D partnerships. When comparing collaboration propensities between related non-core technological or unrelated non-core technological fields, I find that the propensity to establish partnerships in related non-core technological fields is higher than in distant non-core technological fields. Collaboration activities conducted in firms' related non-core technological fields show the largest benefits to the firm. In sum, my findings show first empirical evidence that firms should make clear decision in choosing which technological field to engage into external partnerships before they start R&D collaboration activities.

This chapter is organized as follows: I first provide a brief literature review on R&D collaborations in firms' core and non-core technological fields. Next, I develop hypotheses on: 1) the propensity to collaborate in firms' core, related non-core and distant non-core technological fields; 2) the outcome of collaborations in these different technological fields. The fourth section details the empirical findings. Conclusions and discussion are presented at the end of the paper.

6.2 Theoretical Background

Prahalad and Hamel brought the notion of core competencies into the innovation literature. In their 1990 paper, they describe the diversified corporation as a large tree: “The trunk and major limbs are core products” and “the root system that provides nourishment, sustenance, and stability is the core competence” (p 5). In a later paper by Hamel (1994), the author tries to provide a working definition for core competencies. He clarifies core competencies as a bundle of knowledge and skills. “Competencies are skills and technologies, providing superior customer value, deployable in multiple markets and rare among competitors”. There are different types of core competencies a firm may possess, such as technological competencies which relate to technology development and R&D, or commercial competencies which relate to market development and production (Hamel, 1994; Ahuja, 2000). This chapter focuses on the former— firms’ core competencies in technologies.

The past decades witnessed a strong trend in firms’ development to refocus on their *core* technological fields (Patel and Vega, 1999; von Zedtwitz and Gassmann, 2002). This trend can be explained by two major reasons: First, there are resource and capability limitations of firms in scattering their resources in multiple fields, particularly in those which are technologically less related. Many firms have suffered from the negative effects of over-diversification in the late 1980s (Hoskisson and Hitt, 1994). As over-diversification scatters precious firm resources into different fields, it dilutes managers’ attention and time, engenders intra-firm competition for internal resource allocation (Bruton et al., 1994), and thus impairs firms’ core competencies. Therefore firms have been divesting units that are unrelated to their core competencies to strategically refocus or "down scope" and concentrate on their core products and technological fields (Hoskisson and Hitt, 1994). Second, there is also a strategic need for firms to establish visibility and competitive advantage via concentrating resources in developing a few expertise fields. The driver of the development of core technological fields is the need to establish and maintain competitive advantages in different businesses. It is found that a specific set of idiosyncratic technological core capabilities is needed to generate performance differentials with competitors. Technological specialization, for instance through a focused patent position, appears more important than technological performance as such (Duysters and Hagedoorn, 2000). The great need to address a specific market niche and profit therein brings increasing specialization among firms (Carroll, 1985). As no firm is able to simultaneously pursue leaderships in multiple (unrelated) technological fields (Hagedoorn, 1995), being specialized in a particular or limited number of technological fields helps the firm to optimize the use of its resources, to establish its position in a certain market, to better appropriate and protect its technology value, and to build up competitive advantage based on its specification and expertise. Core competences are therefore also defined as "technological capabilities and specialization" by a number of scholars (e.g. Duysters and Hagedoorn, 2000).

As such, core technologies enable firms to achieve innovations which may lead to a competitive advantage. It is argued that, other things being equal, firms' existing technology strengths enable them to deliver more successful products (Tushman and Romanelli, 1985; Zirger and Maidique, 1990). However, being solely concentrated on the existing core technological fields may be dangers to the firm: as it may "miss the next big wave" (Bower and Christensen, 1995) and be vulnerable in face of competence-destroying technological discontinuities (Gavetti, Henderson and Giorgi, 2004; Tushman and Anderson, 1986). Therefore, at the same time, firms are suggested to diversify their technology portfolio and develop competences in new, non-core technological fields. Those *non-core* technologies enable the firm to explore new areas which may predict a potential technology direction (Granstrand, Patel and Pavitt, 1997), to sustain the long-term thrive (Teece et al., 1997), to build up a wider range of capacities and better monitor technology developments (Brusoni and Prencipe, 2001), to be responsive and adaptive to a highly dynamic environment (Eisenhardt and Martin, 2000), and still, to provide "background knowledge" which support the development of their existing core technologies (Pavitt and Patel, 1997). Hence, non-core technologies also play an important role in firms' innovation strategies (e.g.: Galunic and Rodan, 1998; Brusoni and Prencipe, 2001).

It should be noticed that here the distinction between core and non-core technologies is static. In reality, firms' technology capabilities are not static, but evolve over time (Teece, 1997; Lei, Hitt and Bettis, 1996). Consider, for instance, the Finnish firm Nokia who changed its technology base from wood-pulp mills to electricity production and mobile telephone, and the highly specialized Dutch chemical firm DSM was originally a coal mining company – as still reflected in its name "Dutch State Mining (DSM)". Therefore, firms' technology competences are dynamic (Lei, Hitt and Bettis, 1996), technological fields that were previously non-core to the firm may gradually evolve into its core technological fields, and vice versa. As technology development is an idiosyncratic and cumulative process during which firms gradually add *related* competencies to their existing knowledge stock (Helfat, 1994), therefore, although both are "non-core" technological fields of the firm, some technological fields may be closely *related* to the firm's existing core technological fields, while some others may be at distance (or even *unrelated)* to its existing core technological fields. Consequently, a technological field is considered as "related" when it shares a similar underlying knowledge base with at least one of the core technologies of the firm (Leten et al., 2007).

The existing literature sheds some light on the necessity of involving external partners in firms' core and/or non-core technological fields. Unique and idiosyncratic resources and knowledge possessed by the firm constitute firms' core competencies (Penrose, 1959) and such competencies evolve over time (Teece et al., 1997). Therefore firms have to dynamically upgrade their existing core capabilities and also probe into those fields that are "non-core" to them. In this process, knowledge acquisition and transfer from external sources may help to strengthen firms' existing knowledge base (Grant, 1996), providing opportunities to explore new technological fields (Duysters and de Man, 2003), and build up firms' competitive advantages (Grant and Baden-Fuller, 2003). Two frequently highlighted benefits of R&D collaboration are the potential to leverage partner's complementary resources (Teece, 1998; Das and Teng, 2001), and to facilitate organizational learning from partnerships (Kale and Singh, 2007; Grant and Baden-Fuller, 2003). To benefit from R&D collaborations, a certain level of absorptive capacity of the firm is needed (Tsai, 2009; Escribano et al., 2009) as it will be very hard for the firm to absorb the knowledge in need and learn from its collaborating partners if without a basic level of understanding of that knowledge (Cohen and Levinthal, 1990). Prior research has established that the more experience and knowledge stock a firm has in a certain technological field, the stronger absorptive capacity it develops in that field (Cohen and Levinthal, 1990; Zahra and George, 2002), which may, in turn, facilitate learning in a R&D partnership. Taken together, the above-mentioned factors may affect the decision making and development outcome of core/non-core technological fields of the firm.

Despite the benefits, there are, however, a number of potential obstacles in R&D collaborations as well. A main concern is competition with partners in cooperative research relationships. A firm may enter alliances primarily to learn its partner's knowhow (Hamel, 1991) and hence the partner that is slow in the learning race may find itself at a great disadvantage in gaining benefits from the collaboration (Ireland et al., 2002). Also, considerable risks of knowledge dissipation and leakage in a research partnership may exist as there may be unwanted knowledge spillovers from the technologically stronger partner to its less advanced partners (Ahuja, 2000; Belderbos et al., 2004), which may, be particularly pronounced in firms' core technological fields. Therefore, R&D partnerships are not unambiguously welcome, and their effects are likely to differ according to different technological fields that are involved into collaborations.

Given their benefits and drawbacks, firms may strategically choose to engage into research partnerships and be selectively open in different technological fields in order to better leverage the benefits of R&D collaborations. However, it is unclear in which technological fields the firm tends to collaborate with external partners, and what the outcome will follow the different choices. The existing studies on the relation between collaboration and firms' different technological fields are rather scant. Among the limited number of studies, most of them are centered on the tendency of firms' collaboration decisions. As collaboration involves considerable investments in the process of partner-searching, information-gathering, and relationship-nurturing (Fisher and White, 2000), some studies suggest that whether collaboration is conducted in the core technological fields of the firm reveals "whether the investment is well connected with a cohesive technology strategy and does not represent a random action" (Caloghirou et al., 2004, pp 74-75), thus the authors advocate conducting collaboration activities in technological fields that are core to the firm. A higher level of absorptive capacity may be another factor that favors firms' decision in collaborating in their technology core fields, as they are able to learn better and faster in the collaboration partnership. For instance, Vega-Jurado and colleagues (2008) show that the stronger the firm's technological competences, the higher the level of cooperation with external partners. Therefore, in-house R&D activities not only act as the powerhouse to generate new knowledge for the firm, but also promote its usage of external knowledge from outside sources. Some other studies, however, suggest that to sustain co-development relationships and to avoid knowledge leakage, firms should mainly collaborate in their non-critical technological fields, while leaving the core fields (to a great extent) to internal development (Chesbrough and Schwartz, 2007). As the distinction between firms' core and non-core technological fields is dynamic, the attractiveness of firms' related or distant non-core technological fields may also vary. Via their linkages with the core technological fields of the firm, related non-core technologies may act as bridges or structural holes for partners to access focal firms' technology strong fields through indirect ties (Vanhaverbeke et al., 2008), which may affect their collaboration propensity and outcome over the distant non-core technologies of the firm.

Considering all the foregoing discussion, I can illustrate the main points by the following graph (Figure 19). I classify firms' technologies in three groups (core technological fields, related non-core technological fields, and distant non-core technological fields). I will compare firms' propensities to collaborate and the performance effects of collaboration in those three groups of technologies. The boundary of firms becomes increasingly porous in the context of open innovation, as represented by the dashed oval in the following graph. The dark-colored circles represent core technological fields of the firm, and the light-colored circles are the non-core technologies. The size of the circles denotes the knowledge coverage in a particular technological field, and the distance between circles represents the technological distance between them. Hence, the circles that are close to the firms' (at least one of the) core technological fields denote the firm's related non-core technologies, while the circle that is remote to the firm's core technological fields represents the firm's distant non-core technologies.

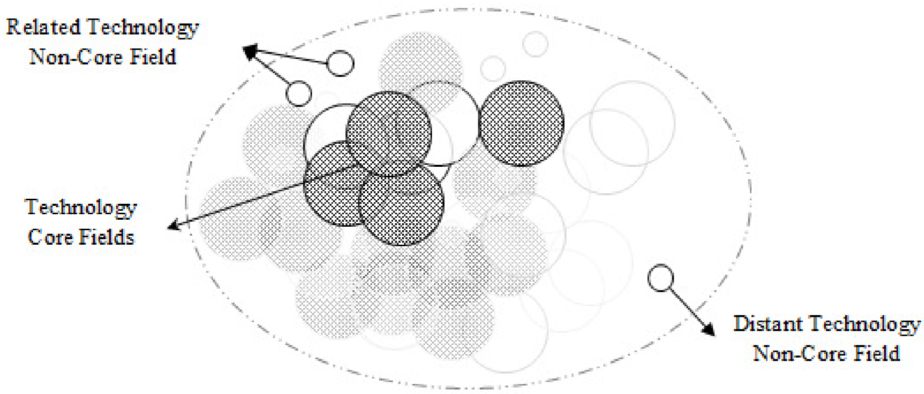


Figure 19 Technological Fields of the Firm (Cont.)

6.3 Hypotheses

In this section, I will first discuss firms' collaboration propensities in their core/ non-core technological fields, and then in a second step, I will discuss firms' collaboration outcomes.

6.3.1 Collaboration Propensity in Core and Non-Core Technologies

I suppose the firm will have little incentive to be open to external parties in their core technological fields. Although collaboration is a realistic strategy, there may be less incentive to collaborate when the firm is highly professional in a particular field (Daft, 1978). Moreover, from a pure economic point of view, the considerable time and efforts the firm may spend in searching for the right partners and establish relationships with them (Fisher and White, 2000) to jointly exploit its own core competencies is not desirable as well. First, the benefits of collaboration in a core technological field of the firm may be limited. As the building-up of core competencies is a long term endeavor, it may be difficult to improve firms' core technologies through the relatively short term of collaboration process. It is both the complex character of modern technology and the difficulties associated with the transfer of technological knowledge (Mowery, 1988) that seem to favor internal development instead of external competence appropriation through R&D partnerships (Duysters and Hagedoorn, 2000). Further, firms that have developed core capabilities in a particular technological field likely have also established trajectories that negatively affect its receptivity to externally generated knowledge (Song et al., 2003). Because of the "Not-Invented-Here" syndrome (Katz and Allen, 1982), when a firm has developed strong capabilities in a particular technological field, it also developed certain routines which improve operations in that field, but makes it less receptive to changes and external knowledge. For instance, analyzing the knowledge base of the hiring firm and its newly hired engineers, Song and colleagues (2003) find that core areas, in which innovative activity proceeds along well-trodden paths, are less receptive to external influence[34] offer fewer opportunities to incorporate external knowledge than less-established or peripheral technological areas. Thus, learning in firms' core technological fields may be limited.

Second, there is also fear of unwanted knowledge leakage to its external partners, which may discourage the firm from collaborating in its core technological fields. In its core technological fields, the firm attaches significant value to reducing governance-based risks (Vanhaverbeke et al., 2012) and the prevention of leakage of strategically sensitive knowledge to collaboration partners. Therefore, in the case of core technologies, firms tend to put greater emphases on possibilities of reducing the risks in a partnership, compared to profiting from its benefits (Cassiman and Veugelers, 2002). For instance, it is found that the leading American carmakers, GM, Ford, and Chrysler act independently of each other as far as their core activities are involved (Hagedoorn, 1995). A number of risks are also involved in the process of R&D collaborations. For instance, there is potential learning race among partners in an R&D collaboration (Hamel, 1991), opportunistic behavior of partners such as technology free-riding (Tripsas et al., 1995), as well as technology appropriation and intellectual property (IP) allocation issues on the resulting innovations of the R&D collaboration (Dekker, 2004). While collaborating in the firm's non-core technological fields may partly solve these problems, the collaboration outcome can be influenced as it was not built on

[34] In their case, it is the new hirer's influence to the hiring firm.

the best available expertise. Hence, taking into account both the problems of marginal learning effects and knowledge-leakage risks of conducting collaborative activities in the core technologies, I hypothesize that:

H 12: Compared to their non-core technological fields, firms have little propensity to collaborate in their core technological fields.

6.3.2 Collaboration in Related and Distant Non-Core Technologies

Knowledge that is core to a firm is developed through a long-established and well-implanted development trajectory (Nelson and Winter, 1982) which although provides the firm with competitive advantage over some period of time, may also create problems of "core rigidities" (Leonard-Barton, 1992) or "information myopia" (Rumelt, 1974; Levinthal and March, 1993) that erode its core advantages. As such, the core technological fields of the firm need to be rejuvenated over time, and knowledge transfer via collaboration is oftentimes mentioned as one possibly effective approach to address such needs (Chesbrough, 2003). However, knowledge that is core to a firm should be carefully protected and only limited shared. Knowledge transfer with external partners can "hollow out" the core competencies of the firm advantages (Reich and Mankin, 1986; Hamel, Doz, and Prahalad, 1989; Doz and Hamel, 1998). Hence, firms may be reluctant to open their core fields to external partners (Zhang and Baden-Fuller, 2008; Vanhaverbeke et al., 2008). While the fear of knowledge leakage exists when collaboration is conducted in firms' core technological fields, such concern may be less severe if firms collaborate in their non-core technological fields. Non-core technological fields are more positioned to "learn", where the firm has little or no prior knowledge to lose or leak away. As suggested by Chesbrough and Schwartz (2007), firms should collaborate in those "contextual fields" which are not in their core competencies. While from the perspective of the focal firm, it is favorable to establish partnerships in its non-core technological fields, it may face many challenges in doing so.

First, I suppose that in the non-core technological fields, the firm may suffer from unwillingness of potential partners in establishing collaborative relationships. Unlike the core technological fields, it can be particularly hard for the firm to convince external parties to collaborate with it in the non-core technological fields. As collaboration is essentially a mutual choice by both sides of collaborating partners, relation formation inherently requires that not only the firm in itself is desirous to establish a partnership, it should also be considered as attractive to its potential partners (Kogut, Shan, and Walker, 1992; Shan, Walker, and Kogut, 1994; Ahuja, 2000). In the non-core technological fields of a firm, if the technology is rather peripheral in which the firm has little knowledge to refer to, and its partner face great risks of knowledge leakage, it may be undesirable for external parties to establish collaborations with it.

Second, apart from concerns of knowledge leakage, the weaker partner may also serve as a limiting factor in collaboration activities, which in turn, bring uncertainties in the collaboration process[35]. Therefore, a weaker partner may reduce the desire of a stronger partner in establishing collaboration relationships because of a fear of uncertain (or unsuccessful) collaboration result. Hence, I suppose, compared to core technological fields, in the non-core technological fields of the firm, the observed possibility of collaboration is low.

[35] "Liebig's Law of the Minimum" states that growth is controlled not by the total amount of resources available, but by the scarcest resource (limiting factor).

However, not all non-core technologies should be treated the same, as there are differences between related and distant non-core technologies. The problems in collaborating in non-core technological fields may be alleviated if collaboration is conducted in fields which are backed-up by some pockets of background knowledge in the firm's core technological fields. Such background knowledge may help the firm better understand the content in collaboration, and can act as "indirect links" which enable the firm to be more attractive to its potential partners compared to if the collaboration field has no, or little knowledge to offer to its partner. The potential partner in the collaboration process may not directly aim to access the technology in the particular collaborating field of the focal firm, but instead, it may be interested in the related resources and expertise that surrounding it. For instance, some companies such as Cisco and IBM provide platforms (in which they themselves are not necessarily experts) for collaboration, the external partners are attracted to those platforms, contributing their expertise, and jointly developing products with them. They are attracted not because of the technological strength of Cisco or IBM in that certain fields, but the pockets of related background knowledge they may tap into during the collaboration process. Therefore, although the firm may not be strong in the focal technological field involved in the collaboration, if it has relevant background knowledge in its vicinity, the chance of collaboration may still be high. On the other hand, from the focal firm's point of view, there is also a need to engage into collaboration relationships in its related non-core technological fields. Organizational learning theory suggests that incumbent companies attempt to learn new knowledge from their alliance partners and internalize the knowledge to build up their own internal competencies (Mowery, Oxley, and Silverman, 1998; Inkpen and Tsang, 2007). They may start with local search in fields that it is more familiar with (Katila and Ahuja, 2002). Consequently, learning through alliances can complement endogenous learning to create new competences (Kogut, 1991; Auster, 1992), which can be particularly helpful for developing firms' related non-core technological fields. Because of the stock of background knowledge the focal firm has developed around a certain related non-core technological fields, it may also be easier for the focal firm to absorb knowledge (Cohen and Levinthal, 1990) and transfer it via the collaboration relationship. Hence, I hypothesize:

H 13: *Compared to other technological fields, firms have a higher propensity for adopting R&D collaborations in related non-core technological fields.*

6.3.3 Collaboration Outcome in Core and Non-Core Technological Fields

Given the collaboration propensity in different technological fields of the firm, I am also interested in the outcome of these collaborations. I suppose that the actual effects of collaborating in firms' technology non-core fields will be higher compared to collaborations in the firm's core technological fields.

First, firms may learn more and better in their non-core technological fields compared to in their core technological fields. As the firm has already developed deep pockets of competencies and well-defined routines in their core technological fields, the effect of learning from external parties may be rather limited in those fields. On the contrary, as the firm lack in-house competencies in its non-core technological fields, it may benefit more from learning from external parties. The firm may facilitate learning from interactions with their (technologically more advanced) partners, even just simply being immersed in a learning environment.

Second, to create value from collaborations, opening up and freely sharing knowledge is needed. Compared to their core technological fields, firms are more willing to open up in their non-core technological fields, which, in turn, may improve their collaboration effects. Collaborations conducted in firms' core technological fields may be hampered by the particular attention paid to knowledge protection. It is stressed that, in order to effectively realize the synergies between partners in collaboration, intensive interaction between partners is necessary (Doz, 1996; Faems, Janssens & Van Looy, 2007). Existing studies on inter-firm R&D collaboration, however, observed that the willingness of partnering firms to engage in intensive interaction is often low because of ex-ante knowledge appropriation concerns. Madhok and Tallman (1998: 332), for instance, argue that 'such interaction acts as a double-edged sword since, in order to attain the underlying purpose of transferring, absorbing, and, generally, more effectively combining complementary capabilities at the heart of the collaboration, the firm also exposes critical resources and capabilities to transmission through the alliance to the partner firm.'. This may, in turn, negatively affect the collaborative interactions in firms' core technological fields. In a similar vein, Heiman and Nickerson (2004: 401) mention that intensive and fine-grained interaction 'increases the likelihood that economically valuable knowledge [...] is expropriated.' In other words, these scholars suggest that firms' ability to come to joint value creation in collaborative projects might be restricted because of ex-ante concerns that the other partner might opportunistically appropriate the knowledge that results out of such interaction, while it is a serious concern of collaboration in firms' core technological fields, it is less a problem in their non-core technological fields. Therefore, I hypothesize:

H 14: *Compared to collaboration in their core technological fields, firms benefit more from collaboration in their non-core technological fields.*

6.3.4 Collaboration Outcomes in Related and Distant Non-Core Technologies

Besides the differences of collaboration in core and non-core technologies, within non-core technologies themselves, there may also be differences between firms' related and distant non-core technological fields. Compared to unrelated non-core technologies, when firms collaborate in related non-core technological fields, they likely have more opportunities to find the right and willing partners, and have necessary absorptive capacity to benefit from collaborations (Cohen and Levinthal, 1990). In contrast, collaboration outcome may be negatively affected if collaboration is conducted in firms' distant non-core technological fields. First, the firm may have very little absorptive capacity to enable effective learning in their unrelated non-core technological fields. It is often noted that a firm's absorptive capacity to a large extent depends on the knowledge it accumulated in a specific field (Dodgson, 1989; Cohen and Levinthal, 1990). If the firm has not yet developed a sufficient level of knowledge in a specific field, it will then turn out to be extremely difficult for the firm to absorb externally acquired knowledge into its existing technological fields. As it is observed, many mergers and acquisitions (M&As) that are conducted outside of the firm's existing main business are not successful in achieving good performance (Duysters and Hagedoorn, 2000). Similarly, compared to collaborating in those related non-core technological fields where the firm has a better understanding about the underlying knowledge and mechanisms, collaborations conducted in those unrelated non-core technological fields in which their future development is still largely uncertain, may not pay off.

Second, collaborating in firms' related non-core technological fields may also open up a range of new opportunities for innovations and knowledge (re-) combinations within the firm. Via their linkages and immediate references to the core technological fields of the firm, collaborations conducted in the firm's related non-core technological fields allow for knowledge synergies and cross-fertilization among different knowledge streams both within the firm, and between the firm and its external partners. Therefore, I hypothesize:

H 15: Compared to collaborations in their unrelated (distant) non-core technological fields, firms benefit more from collaborations conducted in their related non-core technological fields.

6.4 Data and Sample

To test my hypotheses, I use a unique dataset on research projects which are conducted by a large multi-national multi-divisional European-based manufacturing company. The company adopts a global R&D structure which is typical for large technology-based companies (von Zedtwitz and Gassmann, 2002). Research projects are conducted in central Research laboratories and are initiated by either Corporate Research– a central unit of the firm, or by one of the firm's business units. Corporate Research overviews the R&D activities of the firm as a whole, and mainly sponsors research projects that are highly explorative, have a long-term orientation and are of strategic importance to the firm. Business units, on the other hand, being restricted by the need to show (quick) returns on R&D investments and a regular evaluation of business achievements, mainly sponsor research projects that are application-oriented and have a relatively shorter time window.

The Research laboratories execute research projects and transfer the research outcomes to the business units that express their interest in taking up these outcomes for further development and commercialization. Each project is evaluated on a yearly basis from its start to termination (or to the latest year of data collection— 2010, if it is ongoing). From the beginning of a research project, there is annual information on its R&D partnerships, project practices (full-time equivalent researchers, project management, project sponsoring units and recipient business units). After excluding the observations that have missing data, I have a cross-sectional dataset that contains 876 observations (research projects). Financial performance is measured as total performance, and the explanatory variables are constructed as stock variables (e.g. partnership variables and full time equivalent researchers) or take average values over the course of research projects. More details on the construction of the different variables are provided below.

6.4.1 Dependent Variable and Empirical Method

I use two dependent variables in this analysis.

***Collaboration Propensity*.** The first dependent variable is collaboration propensity. Here I use the observed collaboration behavior of the project and test possible influential factors that lead to the (un-)adoption of collaboration behaviors. The first set of regressions is based on Logit analysis. Projects' choice of being "open" is measured as a 0/1 variable. "0" indicates that the project is closed, and "1" means the project has established collaborative partnerships during its lifetime.

***Project Financial Performance*.** Based on analyzing collaboration behavior of the project, I take financial performance as a second dependent variable. Financial performance is the most frequently used measure of the performance of research projects (see Cooper et al., 2004, for a review of project-level performance indicators). Financial performance is measured as the total revenues that are generated by the "transferred" outcomes of a research project to one or multiple business departments, being conducted either in an open or closed manner. R&D partners share development costs and risks, but they also share innovation revenues (Belderbos et al., 2010). The dependent variable is the part of financials the focal firm earns through the revenues generated via internal and external paths to markets (e.g. licensing or IP sales). Financial performance is a continuous variable that takes an average value of 10,4 million euro, and ranges between 0 and 920 million euro. The variable is truncated at a value of 0. To account for the truncation, Tobit regressions are used (McDonald and Moffit, 1980; Greene, 2000). I control for heteroskedasticity by using robust standard errors.

6.4.2 Independent Variables

R&D Collaborations. I have annual information on the R&D collaboration practices of the research projects. More specifically, I know– for all project years– whether a research project is in collaboration with partners or not. The *R&D partnership* variable gets a value of "1" if there is an R&D partnership with external partners in at least one of the project years. Out of the 876 research projects, 325 (37.1%) are "closed" projects, and 551 (62.9%) are "open" projects where the research team collaborated with external partners. Of all the projects, 119 (13.6%) projects are conducted in the firm's core technological fields, 205 (23.4%) are in the firm's related non-core technological fields, and 552 (63.0%) are in the firm's unrelated non-core technological fields. Below, I explain how I divide the research projects into those that are related to core technologies and those that are related to non-core technologies.

Technological fields of the Firm. I distinguish between three types of technological fields of the firm, namely, core technological fields, related non-core technological fields, as well as unrelated non-core technological fields. I first distinguish between core and non-core technological fields. In calculating firms' core technological fields I adopt two criteria: 1) *Patent Share*: the shares of the firm's total patenting in each of the technological fields (at IPC-4digit level), that is, a relative importance for the firm of competencies in each of the technological fields. 2) *Revealed Technology Advantage*: the shares of the firm in total patenting in each of the technological fields, divided by the firm's aggregate share in all the fields (Patel and Pavitt, 1997). In other words, these two criteria measure the absolute importance of the firm to these technological fields, as well as the relative importance of the firm to these fields of technological competence, after taking account of the firm's total volume of competencies. Following Patel and Pavitt (1997), for the first criterion, *Patent Share*, I use a 3% patent share (at the IPC-4digit level) of the firm in the technological field of all patents filed in that technological field as the cutting point of firm's high/ low patent share. A patent share that is equal to, or more than, 3% among all the patents filed in that technological field is considered as high. For the second criterion, *Revealed Technology Advantage*, I use 2.0 as the cutting point of firm's strong/ weak revealed technology advantage, that is, the firm's technological fields with a patent share (among all patents filed by all patent applicants) at least double the size of the firm's overall patent share in all technological fields, are considered as of high revealed technology advantage. Combining the two criteria together, the technological fields that are of both high patent share and high revealed technology advantage are defined as "core technological fields" of the firm (for a detailed graphical explanation, please refer to Figure 20). I did the calculation on a yearly basis, therefore, the core/ non-core technological fields of the firm are identified yearly. As a research project may last for several years, I take the classification of its technological fields (core/ non-core) at the start of the project as the classification of the research project. For robustness check, I also use 5% patent share as the cutting point of the firm's core/ non-core technological fields[36], which gives similar results.

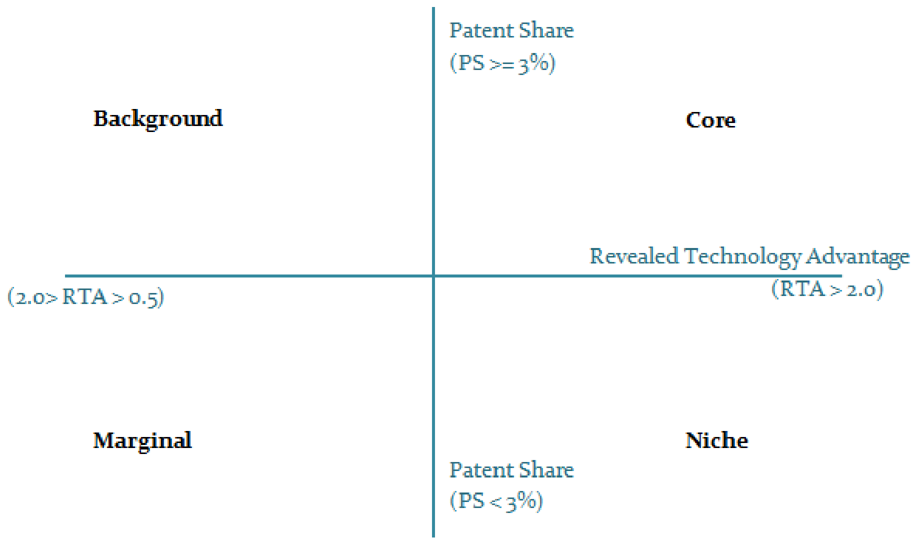


Figure 20 Classification of Firms' Technological Profiles

Source: Patel and Pavitt, 1997

[36] For the cutting point of revealed technology advantage, at least in my sample, 2.0 is quite consistent.

After classifying a project to core or non-core technological fields, I further distinguish between firm's related non-core fields and unrelated non-core fields. Based on Leten et al. (2007), I measure the technological relatedness of two technology classes via comparing the observed numbers of citations between these classes with expected numbers of citations, under the hypothesis of random occurrence of technology classes on cited patents. Let N_j be the total number of patents that are classified in technology class *j*, with $T= \sum_j N_j$. making no specific assumptions about the form of the random distribution of technology classes across cited patents, this gives the following expression for the expected number of cited patents of technology class *j* in citing patents of technology class *i* (E_{ij}): $E_{ij} = O_i * (N_j / T)$. A measure of technological relatedness is then calculated as follows: $R_{ij}= (O_{ij} + O_{ji}) / (E_{ij} + E_{ji})$. This leads to the creation of a symmetric matrix of relatedness measures for each pair of distinctive technology classes. The interpretation of R_{ij} is straightforward: if $R_{ij} >$ 1, then technologies *i* and *j* are more related than could be expected on the basis of random citation patterns (Leten et al., 2007). Citation data in European Patent Office (EPO) is used for this chapter. I calculate the pairwise patent citations of each two technology classes, which results in an indicator with a value larger than 1 (meaning more observed citations than expected citations between the two technology classes) representing high relatedness between the two technology classes, and a value smaller than 1 (meaning less observed citations than expected citations between the two technology classes) denoting low relatedness between the two technology classes. Thus, the non-core technological fields which share high levels of technology relatedness with the firms' core technological fields are considered as "related non-core technological fields", while the non-core technological fields which share low levels of technology relatedness with the firm's core technological fields are considered as "unrelated non-core technological fields". For robustness check, I also use 1.5 as the cutting point of technological relatedness in this chapter, which gives similar results.

For a distribution of different project technological fields, please refer to Table 22 (overall) and Table 23 (yearly).

6.4.3 Control Variables

There are several factors that may influence project performance. I operationalize on a number of variables to control for possible confounding effects at the project level in this chapter. The control variables that I employed in this chapter are: *Project Resources (FTE); Project Technical Strength (Firm Patent Stock)*; *Project Technological fields; Corporate Research; Project Transfer; Sponsor Units; # of Projects Under Management; Project Initiating Years (Year Dummies).* For more detailed explanations, please refer to Chapter 2, Data and Sample.

Descriptive statistics and correlations for the variables are provided in Table 24. As mentioned above, most of the research projects have open innovation partnerships (62,90%). 31.74% of the research projects generate transfers. None of the reported correlations are high. The variance inflation (VIF) score is 1.5, which is well below 10; hence multi-collinearity is not an issue in my analyses. In general, my sample projects spreading among a wide range of 25 "core" technological fields (at IPC-4 digit level, Pavitt & Patel definition), which are clustered into 15 broad technological fields (at IPC-3digit level) and 4 general technological areas (at IPC-1 digit level). For more details, please refer to Table 25 and Table 26.

Table 24 Descriptive Statistics and Correlations

	mean	s.d.	1	2	3	4	5	6	7	8	9	10
1. Project Financial Performance	4,082	36,562	1,000									
2. R&D Collaborations	0,629	0,483	0,044	1,000								
3. Core Technology Fields	0,136	0,343	0,021	0,174	1,000							
4. Related Non-Core Technology Fields	0,234	0,424	0,010	0,212	-0,219	1,000						
5. Distant Non-Core Technology Fields	0,650	0,477	-0,016	-0,307	-0,519	-0,673	1,000					
6. Corporate Research	0,495	0,500	-0,032	-0,033	-0,033	0,046	-0,004	1,000				
7. # Projects under Management	19,414	10,917	0,082	0,045	-0,013	0,004	0,056	-0,089	1,000			
8. Project Resources	4,510	4,978	0,033	0,314	0,309	0,432	-0,566	0,009	-0,067	1,000		
9. Project Transfer	0,317	0,466	0,164	0,229	0,166	0,133	-0,234	-0,180	0,040	0,291	1,000	
10. Firm Patent Stock	4,898	2,530	0,035	0,070	0,261	0,005	-0,229	-0,052	-0,072	0,125	0,181	1,000

(Number of observations = 876 Projects)

Table 25 Distribution of Core/ Related Non-Core/ Distant Non-Core Technological Fields

	Number	Category	PS> 3% Relatedness> 1	PS>5% Relatedness> 1.5
Technological fields in my sample (at IPC-4 digit level)	118	Core	25	17
		Related Non-Core	72	62
		Distant Non-Core	21	39
Projects in my sample	876	Core	342	234
		Related Non-Core	441	491
		Distant Non-Core	93	151

Table 26 Yearly Evolution of Core/ Related Non-Core/ Distant Non-Core Technological Fields (Sample Firm)

Year	PS> 3% Relatedness> 1			PS> 5% Relatedness> 1.5		
	Core	Related Non-Core	Distant Non-Core	Core	Related Non-Core	Distant Non-Core
2003	18	39	9	11	40	15
2004	15	25	3	11	23	9
2005	17	22	6	15	19	11
2006	14	36	7	10	34	13
2007	10	21	3	8	18	8
2008	6	19	3	5	15	8
2009	3	7	3	3	6	4

Note:

- Focusing of the firm's business and technological fields is ongoing in recent years. Further, business is increasing in areas where the volume of patents is less important than its quality.
- Here I only show the technological fields in my sample, which is in proportion of, but not, the whole technological population of the firm.

6.5 Empirical Results

6.5.1 Collaboration Propensity and Technological fields

The results of the regression analyses on collaboration propensity and technological fields are shown in Table 27. Collaboration activities in research projects are measured by 0/1 dummy variable, and all the five models test the propensity to collaborate of the project. The main independent variables: core technological fields, related non-core technological fields as well as unrelated non-core technological fields are mutually exclusive. Model 1 is the baseline model which includes only the control variables. Research projects that are initiated by Corporate Research and are equipped with a larger number of project resources (FTE) are more likely to adopt R&D partnerships in their innovation activities. Furthermore, the more projects sharing the same project leader (larger number of research projects under management), the more likely they adopt R&D partnerships. Controlling for different technological fields of the firm and its patent stock in the relevant technological fields does not seem to influence project's propensity to collaborate. Finally, the sets of dummy variables controlling for the sponsoring departments, technological fields and initiating years are jointly significant.

Table 27 Logit Regressions on Collaboration Propensity

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Core Technology Fields		0.508*			0.654**
		(0.305)			(0.328)
Related non-Core Technology Fields			0.156		0.351
			(0.245)		(0.269)
Distant non-Core Technology Fields				-0.572**	
				(0.253)	
Corporate Research	1.490**	1.549**	1.502**	1.631**	1.595**
	(0.629)	(0.640)	(0.634)	(0.655)	(0.651)
Project Resources	0.310***	0.292***	0.298***	0.250***	0.261***
	(0.034)	(0.035)	(0.037)	(0.0419)	(0.0412)
Firm Patent Stock	0.0090	-0.0011	0.0096	-0.00199	-0.00274
	(0.0323)	(0.0325)	(0.0323)	(0.0324)	(0.0325)
# Projects Under Management	0.044***	0.045***	0.044***	0.0453***	0.0448***
	(0.011)	(0.012)	(0.011)	(0.0117)	(0.0120)
Sponsor Units	*included*	*included*	*included*	*included*	*included*
Technology Fields	*included*	*included*	*included*	*included*	*included*
Year Dummies	*included*	*included*	*included*	*included*	*included*
Constant	-5.180***	-5.300***	-5.178***	-4.744***	-5.474***
	(1.319)	(1.351)	(1.323)	(1.361)	(1.489)
Observations	876	876	876	876	876
Log Likelihood	-484.7	-483.2	-484.46	-481.80	-482.29
Pseudo. R-squared	0.161	0.164	0.161	0.166	0.165

Robust standard errors in parentheses:
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

I now look at projects' collaboration propensity in different technological fields of the firm. The "Core Technological fields" variable is added to Model 2. The results of the other variables remain unchanged when including this variable. The coefficient of the Core Technological field variable is positive and significant. Hence, Hypothesis 12 is not supported: The likelihood to set up R&D partnerships is higher when in the firm's core technological fields. In Model 3, collaboration propensity in firms' related non-core technological fields is added into the model. I do not find a significant relation between collaboration propensity and firms' related non-core technological fields. This means, on average, firms' collaboration propensity in their related non-core technological fields is not significantly stronger (or weaker) than its other technological fields. Therefore, Hypothesis 12 is not supported. In Model 4 I test firms' collaboration propensity in their distant non-core technological fields. For this set of regression, I find a negative and significant effect of the collaboration propensity and firms' distant non-core technological fields. The negative coefficient confirms Hypothesis 13: There is less collaboration conducted in firms' distant non-core technological fields than the others. Finally, in Model 5, I test for the relative effect of firms' collaboration propensity in their technology core, and related technology non-core fields. The baseline category in this model is collaboration propensity in firms' distant technology non-core fields.

6.5.2 Collaboration Outcome and Technological fields

Table 28 and Table 29 show the financial outcome of engaging (or not) into R&D collaborations in firms' different technological fields. In Table 28, I split the sample into three mutually exclusive groups: namely, firms' core technological fields, related non-core technological fields, and distant non-core technological fields. Project financial return is the dependent variable. Since the dependent variable is a continuous and truncated at "0", Tobit techniques are used. Model 1, 3, 5 are baseline models for each different technological fields, Model 2, 4, 6 are models added with open innovation partnerships. The negative and significant coefficient in the result of technology core fields shows that open innovation partnerships in firms' technology core fields actually are not paying off. However, when looking at firms' related non-core technological fields (Model 4), open innovation partnerships then play a positive and rather significant role, which means, open innovation partnerships pay off in collaborations conducted in firms' related non-core technological fields. Finally, Model 6 shows the result of establishing open innovation partnerships in distant non-core technological fields, which also shows a positive effect, but not significant. In Table 29, I created interaction terms of R&D collaborations and different technological fields of the project and ran regressions again on the full sample. Findings in Table 28 are mostly confirmed: while firms have a high possibility to suffer from failures in innovations conducted in their related non-core technological fields, while leveraging external expertise in R&D collaborations help them to improve the performance (Model 3). Maybe due to limited absorptive capacity, or because of the "technology threshold", collaborating in firms' distant non-core technological fields does not seem to pay off (Model 4), although at an insignificant level. The above findings are consistent when are pulled into a complete regression model, where collaborations in firm's distant non-core technological fields is the baseline (Model 5). In sum, Hypothesis 14 is supported, that compared to collaboration in their core technological fields, and firms benefit more from collaboration in their non-core technological fields, in particular, related non-core technological fields.

Table 28 Tobit Regressions on Technological Fields and R&D Collaboration Outcomes

VARIABLES	Core Technology Fields		Related Non-Core Technology Fields		Distant Non-Core Technology Fields	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
R&D Collaborations		-104.3***		114.8		104.9***
		(9.689)		(91.13)		(36.44)
Corporate Research	294.9***	277.9***	150.1*	182.9*	1,568***	1,612***
	(7.755)	(8.514)	(81.64)	(101.9)	(37.99)	(38.83)
Project Resources	5.781***	7.351***	1.461	-1.019	61.15***	53.68***
	(0.487)	(0.497)	(4.424)	(5.835)	(7.844)	(8.321)
Firm Patent Stock	86.24***	102.6***	14.75	16.68	47.69***	46.17***
	(1.329)	(1.365)	(11.33)	(12.31)	(6.182)	(6.326)
# Projects Under Management	-1.112***	0.0585	18.53**	20.32**	6.296***	4.641**
	(0.163)	(0.170)	(9.011)	(9.772)	(1.925)	(1.981)
Sponsor Units	*included*	*included*	*included*	*included*	*included*	*included*
Technology Fields	*included*	*included*	*included*	*included*	*included*	*included*
Year Dummies	*included*	*included*	*included*	*included*	*included*	*included*
Sigma	70.13***	67.10***	152.0***	146.1***	422.7***	419.9***
	(3.027)	(2.940)	(57.18)	(52.11)	(17.88)	(18.07)
Constant	-781.9***	-870.7***	-1,593**	-1,848**	-4,987***	-4,967***
	(9.800)	(9.980)	(765.7)	(890.1)	(43.06)	(44.08)
Observations	123	123	216	216	549	549
Log Likelihood	-77.76	-76.52	-117.8	-116.8	-118.9	-118.6
Pseudo. R-squared	0.225	0.238	0.181	0.188	0.0900	0.0924

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 29 Tobit Regressions on Technological Fields and R&D Collaboration Outcomes (Cont.)

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
R&D Collaborations		79.74	59.25***	118.7	60.72***
		(55.79)	(15.31)	(107.2)	(15.49)
Core Technology Fields		63.33			47.67***
		(118.85)			(16.63)
Related Non-Core TF			-1,204***		-1,201***
			(21.06)		(21.62)
Distant Non-Core TF				45.26	
				(104.8)	
Collab.& Core TF		-55.48			-33.77*
		(129.90)			(17.48)
Collab. & Related Non-Core TF			1,208***		1,211***
			(21.06)		(21.62)
Collab. & Distant Non-Core TF				-57.36	
				(120.3)	
Corporate Research	51.77	52.39	37.52**	39.31	41.54***
	(101.36)	(100.03)	(15.05)	(99.76)	(15.02)
Project Resources	10.30***	8.563***	8.865***	8.444**	8.445***
	(2.939)	(2.896)	(1.036)	(3.471)	(1.077)
Firm Patent Stock	28.669***	27.07***	27.55***	27.50**	26.68***
	(10.773)	(9.984)	(2.390)	(10.70)	(2.403)
# Projects Under Management	7.076**	6.801**	6.963***	6.814**	6.968***
	(3.379)	(3.389)	(0.323)	(3.354)	(0.323)
Sponsor Units	*included*	*included*	*included*	*included*	*included*
Technology Fields	*included*	*included*	*included*	*included*	*included*
Year Dummies	*included*	*included*	*included*	*included*	*included*
Sigma	256.3***	254.9***	254.2***	254.6***	254.3***
	(66.75)	(66.30)	(68.94)	(66.32)	(69.14)
Constant	-971.8***	-996.32***	-982.6***	-1,024***	-986.6***
	(353.91)	(355.95)	(16.64)	(360.5)	(16.63)
Observations	876	876	876	876	876
Log Likelihood	-338.1	-337.0	-336.4	-337.0	-336.4
Pseudo. R-squared	0.0896	0.0924	0.0940	0.0924	0.0942

Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

6.6 Robustness Checks

I conducted various robustness checks, using different cutting points of core/non-core technologies and technological relatedness of two technology classes (for the criteria that I used, please refer to Table 30). In general, a vast majority of innovation activities of the firm are conducted in the core and related non-core technological fields. According to different combinations that I use, these two technological fields together account for between 70% ~ 90% of the firm's overall R&D activities (based on Pavitt and Patel definition of core technologies).

Table 30 Different Criteria Adopted for Robustness Checks (N= 876 projects)

	Core Technology Fields (I) (Patent Share >= 3%)	Core Technology Fields (II) (Patent Share >= 5%)	Core Technology Fields (III) (Patent Share >= 10%)
Core Technology Fields	342 *(39.04%)*	234 *(26.71%)*	16 *(1.83%)*
Related Non-Core Technologies[1] (Technology Relatedness> 1)	441 *(50.34%)*	521 *(59.47%)*	425 *(48.52%)*
Medium Related Non-Core Technologies[2] (Technology Relatedness>= 1.5)	431 *(49.20%)*	491 *(56.05%)*	389 *(44.41%)*
Fairy Related Non-Core Technologies[3] (Technology Relatedness>= 2)	415 *(47.37%)*	473 *(54.00%)*	380 *(43.38%)*
Very Related Non-Core Technologies[4] (Technology Relatedness>= 5)	266 *(30.37%)*	265 *(30.25%)*	296 *(33.79%)*

Note:

- Focusing of the firm's business and technological fields is ongoing in recent years.
- Criterion 1, 2, 3, 4 are inclusive, not mutually exclusive.

The first set of robustness checks are related to collaboration propensity. Where I first separate the general collaboration variable "open innovation" (whether or not in collaboration with any type of external partners) into more finely-grained types of collaborations, based on the type of partners that are involved in the partnership (market-based or science-based). When breaking down collaboration into different types of partnerships, it is interesting that openness in core technological fields is more relevant to market-based partners, than to science-based partnerships. It seems it is indeed the technological excellence of the firm in a certain technological fields that drives its partnership establishment with externals. In contrast to the significant finding of collaboration propensity with market-based partners, the propensity of collaboration with science-based partners seem to be less clear. As expected, (may be) driven by the learning effect, firms links up more with science in their relatively weak technological fields (distant non-core). Firms also collaborate more with science in their core technological fields, albeit to a lesser extent compared to in their distant non-core technological fields. However, unlike the strong effect as what we've found for collaborations with market-based partners, both effects with science-based partners are not that significant.

I also tried to replace the "core/ non-core" concept with more extreme cases, that is, 1) whether the technological field is completely new for the firm, and 2) whether the technological field is completely unrelated to the firm's core fields. For the former, I denote those technological fields with no prior patent applications as *New Technological fields* of the firm; and for the latter, I indicate those technological fields with technology relatedness of "0" to the firm's core technological fields as *Unrelated Non-Core Technological fields*. I run logit regressions using each of them as independent variable respectively, and I use different types of collaborations (general collaboration, with market-based partners, with science-based partners) as dependent variables. What I find is that for those new technological fields, firms tend to leverage collaborations as a means for new technology development. In more details, while the propensity with market-based partners is high, such propensity with science-based partners is although positive, but insignificant. On the contrary, for firms' unrelated non-core technological fields, collaboration propensity with all three types of partnerships are low. Hence, combining the findings, it then turns out to be that firms can leverage partnerships in developing their new technological fields (as long as it has some relatedness with its core technologies), while it is particularly hard for them to develop technologies that are completely irrelevant to their core technologies. Due to limited space, the results of other similar combinations, which all give similar results, are omitted.

Finally, following the categories as mentioned before, I did also robustness checks on the collaboration outcome in firms *New Technological fields* and *Unrelated Non-Core Technological fields*. In line with previous chapters, open innovation partnerships are positive and significant to project financial returns. I find that conducting R&D activities in new technological fields per se brings negative financials, but open innovation helps to overcome such negative effect. Interestingly, there is a positive financial effect of R&D activities conducted in unrelated non-core technological fields, where open innovation partnerships do not seem to help much.

6.7 Discussion and Implications

In this chapter I aim to examine 1) In which technological fields firms have higher propensity to collaborate with external partners; and 2) What are the collaboration outcomes of these choices. I distinguish between three types of technological fields of the firm: core technological fields, related non-core technological fields, and distant non-core technological fields, and compare firms' collaboration propensity and collaboration outcome in these different technological fields, respectively. In exploring these issues, this chapter sheds light on collaboration decisions and their outcome, particularly to the internal organizational activities of innovative firms.

The findings are thought-provoking. I find that although firms collaborate more in their core technological fields, it is collaborations conducted in their non-core technological fields (more precisely, related non-core technological fields) that benefit them the most. In terms of collaboration propensity, I find that, at least for research projects, there is a surprisingly low collaboration propensity in their non-core technological fields, which is contradictory to some existing suggestions (e.g.: Chesbrough and Schwatz, 2007). A possible explanation is that, because the establishment of R&D partnerships is essentially a process of mutual choice of both partners, therefore the focal firm needs to be considered as desirable and attractive to its potential partner as well (Ahuja, 2000). It seems a certain level of "technology threshold" exists for firms that wish to establish external R&D partnerships. Projects that are below such a threshold (e.g.: distant non-core technological fields or even unrelated non-core technological fields) seem to suffer from difficulties in establishing R&D partnerships with external partners, thus show a low collaboration rate. Another explanation may be that in non-core technological fields of the firm, strong ties (more time-consuming to establish and maintain, may need more investments of intimacy and reciprocity, thus may be fewer ties) will be preferred by the focal firm because the firm will learn more through some very dedicated ties in their distant non-core technological fields as it is so difficult to learn; While in core technological fields of the firm, loose ties (thus more and easier to establish) will be preferred by the focal firm, because loose ties with partners help the firm to explore new technological fields and potential technological opportunities. Future research may explore into details on these issues. Nevertheless, based on my research findings, it is suggested that in order to benefit from R&D collaborations, it is useful for those distant non-core technological fields to firstly develop their technology capabilities to a certain level (i.e. beyond the technology threshold) or develop familiarities with their existing core technologies (higher level of relatedness), instead of trying to rashly start R&D partnerships from scratch with low technology capabilities. In terms of collaboration outcome, this study shows that despite a high collaboration propensity in firms' core technological fields, collaborations that are conducted in firms' non-core technological fields (in particular distant non-core technological fields) that benefit them the most. Hence, the additional gains of collaboration in firms' core technological fields may not offset the potential chance of knowledge leakage and spillover in such fields.

This study contributes in different ways to the literature. Open innovation as a field of research needs hard empirical evidence to explore how project management activities and decisions may influence project outcomes. Most existing literature adopts a lens looking at external factors, while with considerable shortage of looking at the intra-firm organizational behaviors and activities. This study thus enriches this literature stream and provides new insights on organizing intra-firm activities (namely, decisions on collaborations and firms' technological fields) for better collaboration outcomes. Moreover, in the literature stream of open innovation, "openness" is considered as a simple construct (whether or not in collaborations and with whom), I propose that openness should be shaped according to the competences of the firm. The type of technology is a very important contingency factor to keep in mind when studying open innovation, its behaviors and performances.

Chapter 7

Conclusions

7.1 Discussion

In nowadays increasingly competitive technology landscape, collaboration with external partners in firms' R&D process becomes an imperative for innovating firms (Chesbrough, 2003). Despite the popularity of open innovation and its proposed benefits, real-life practices show that not every successful firm adopts open innovation strategies, and among those that do conduct open innovation, many of them fail. Open innovation was found to have a positive (Laursen and Salter, 2006) or negative (Knudsen and Mortensen, 2011; Kessler et al., 2001) on firms' innovation performance. Other scholars found it has no effect at all (Campbell and Cooper, 1999). The wide range of performance heterogeneity among firms in their open innovation practices calls for more in-depth examination of this strategy.

The existing quantitative studies on open innovation have been mostly focusing on the firm as the observation unit. Although firm-level analyses are important for understanding open innovation principles, as the vast majority of R&D activities are essentially carried out as research projects (Pisano, 1990; Cassiman et al., 2009), aggregating data at the firm level may lead to spurious conclusions on the practice of open innovation, and subsequently, its effects on innovation performance. Responding to the call of Chesbrough and colleagues (2006, p. 287), “neither the practice of, nor the research on open innovation are limited to the level of the firm”, and “the sub-firm level of analysis is particularly salient in understanding the sources of innovation” (2006, p. 287), this thesis is among the very first contributions that examine open innovation at other levels, being the research project level. Research projects are highly relevant as a sub-firm level of analysis as most collaborative innovation initiatives are executed at the research project level: A wide range of characteristics of the research projects can capture the heterogeneity of the impact of open innovation on performance when it is measured at the firm level. More specifically, in this thesis I examine the effect of (outside-in) open innovation practices on two types of innovation performance of research projects, namely, project innovation speed and financial performance. I further investigated a number of contingent effects of open innovation, from internal, external, and the process perspective of open innovation.

Based on data from a large multinational, multidivisional global firm, I tested a number of hypotheses relating to the effect and the contingencies of open innovation. The results shed lights on the existing open innovation literature. While my results bring evidence that open innovation is indeed beneficial for firms' innovation performance, I find that the effect of open innovation hardly comes on its own. Rather, it is contingent on a wide range of factors, which are internal or external to the firm. Those factors include - but are not limited to - the type of partners that are involved into collaborations, the timing of collaborations, the project management process of the collaborations, as well as the technology fields targeted in the collaborations. Inappropriate management of these factors may result in a sub-optimal, effect of open innovation strategies. Hence, despite its potential benefits, firms should adopt open innovation with caution. Given its costs and risks, firms should bear in mind the pros and cons of open innovation strategies and use it flexibly depending on the circumstances. Drawing on the findings of this thesis, I can conclude the following: 1) In terms of the effect of open innovation, market-based partners (customers and suppliers) are beneficial to speed up the innovation, but do not affect project financial returns. On the contrary, science-based partners (universities and research institutions) are instrumental for generating higher levels of financials, but do not seem to influence project speed. 2) In terms of contingency effects of open innovation, I find that to generate higher financial returns, successful open innovators strictly manage market-based partnerships but loosely monitor science-based partnerships. Moreover, they innovate at a moderate pace, neither too fast nor too slow. Additionally, they follow a certain length of collaboration time in a continuous manner, and collaborate with science-based partners prior to collaboration with market-based partners. 3) Last but not least, successful open innovators collaborate more in technological fields that are relatively distant from their core technologies, instead of collaborating in their core technological fields.

7.2 Implications and Future Research[37]

7.2.1 Managerial Implications

This thesis sheds light on a number of managerial issues of open innovation based on hard evidence. This thesis contributes to the clarification of the current debate on the effects of open innovation. Mainly due to the reliance of an aggregation of firm level data, current research on the effect of open

[37] Part of this section is forthcoming as "VANHAVERBEKE, W., DU,J., LETEN, B., & AALDERS, F. 2013. Exploring open innovation at the level of research projects. In Chesbrough, H.W., Vanhaverbeke, W., & West, J. (eds), Exploring the next wave of open innovation research, Oxford University Press"

innovation generates a variety of, sometimes even contradictory findings. By narrowing down the focus of analysis to the project level, I find that open innovation is beneficial to project performance. However, two things have to be kept in mind:

First, the effect of open innovation (more specifically, R&D collaboration) is dependent on the type of partners involved in the collaboration process as well as the performance dimension of the project that managers are focusing at. Generally speaking, while collaborating with market-based partners quickens the innovation process, partnerships with science-based partners bring the project more financial returns, but such benefit takes a relatively long time before it can be realized. Thus, when the firm (and its projects therein) is under pressure of generating *quick cash flows* or is not yet sufficiently prepared to afford the relatively long waiting time to harvest the benefits of collaborating with science-based partners (e.g.: during financial downturns), then it is suggested to focus on collaborations with market-based partners. On the contrary, if the firm (and its projects therein) is in a good financial shape and is prepared to wait for the results of collaboration with the science-based partners, then this type of collaboration can be highly rewarding. For a graphical explanation of the effect of open innovation on different performance dimensions, I refer to Figure 21.

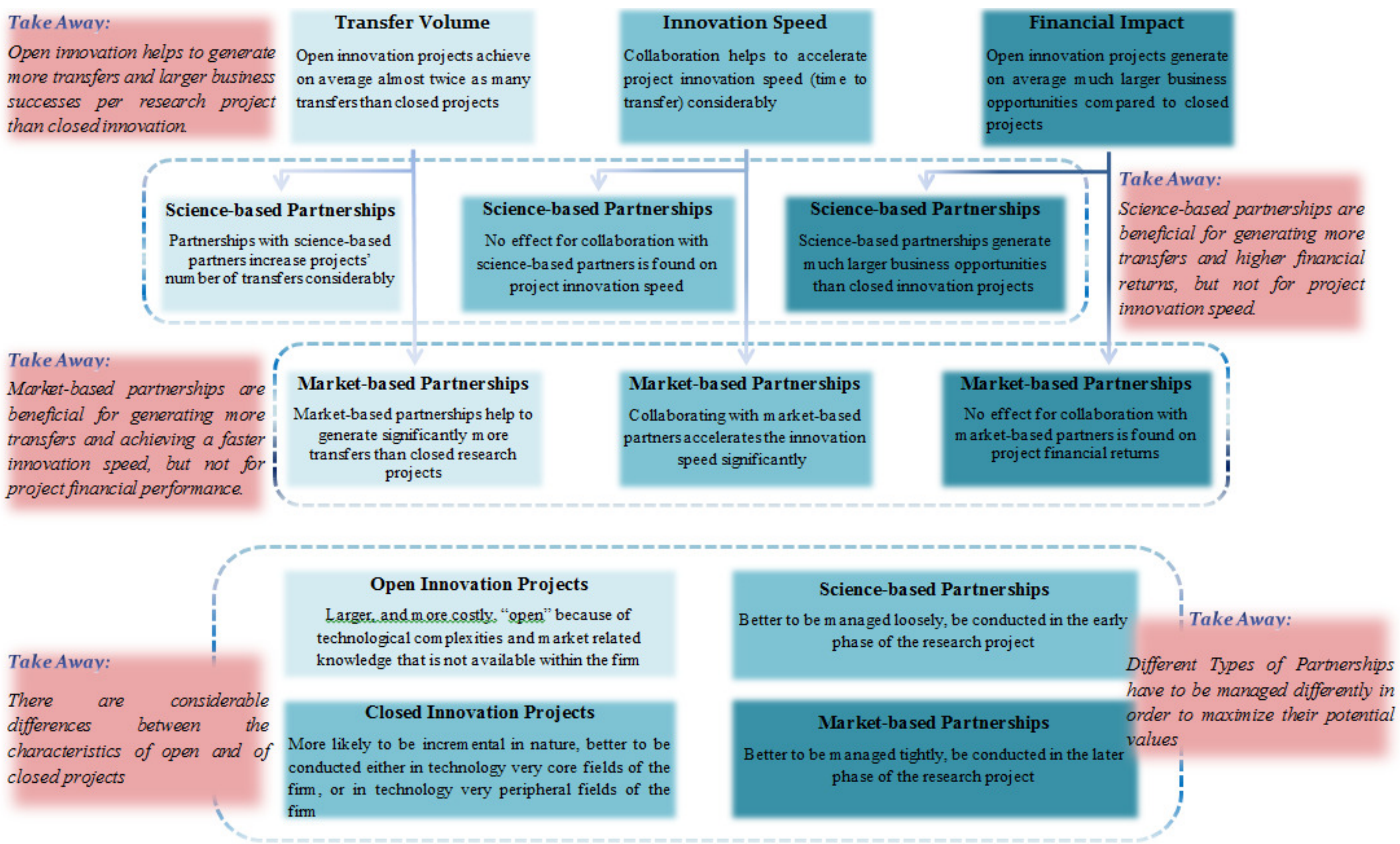


Figure 21 The Effect of Open Innovation on Different Dimensions

Second, the effect of open innovation is dependent on a number of contingent factors. First of all, the way in which the open project is managed matters for project performance. Strong financial outcome of projects with market-based partnerships is found to be associated with a strict way of project management, where the stage-gate principles are nicely applied. On the contrary, when such projects are managed in a loose way with few milestones and little project review, then their likelihood to become a failure increases rapidly. Interestingly, in contrast with collaborations with market-based partners, partnerships with science-based partners are found to be more beneficial if the project is managed in a loose way. Although strict management does not hamper the performance of projects with science-based partnerships (as compared to closed innovation projects), a loose way of project management helps to improve projects' financial returns.

Moreover, the timing of collaboration also matters for project performance in an open innovation context. In addition to the traditional question of whether or not the firm should collaborate, firms (and their research projects) should consider more thoroughly about with whom they collaborate, and for how long they should be open with external partners. All else being equal, only except for the timing of collaborations, the projects that open for only one year in their lifetime can reach a rather different outcome in their performance, than projects that are open for their whole lifetime. Consequently, firms that wish to gain from open innovation should bear in mind that wrong timing of collaborations may result in suboptimal results of collaborations. I examined in this thesis how the four dimensions of timing of R&D collaborations: collaboration duration, collaboration continuity, collaboration simultaneity, and collaboration pattern, have an impact on projects' innovation performance. I find that these characteristics of collaboration activities are important, which have however been neglected in prior research. More R&D collaboration will not necessarily improve the innovation performance of research projects and companies. In contrast, it is the organization and timing of R&D collaboration activities that may help to generate better innovation performance. In other words, although R&D collaboration can improve the innovation performance of research projects (or firms with multiple research projects), merely conducting R&D collaboration without considering its timing is no guarantee for success. When one makes no distinction between different partners I find that there is a curvilinear relation between the duration of project openness and its performance. When I make a distinction between two types of partners (market- and science-based), I find that a firm should not collaborate with all partners all the time. Optimal results are obtained when research projects collaborate a limited period of their lifetime with external partners. With respect to collaboration continuity, research projects benefit from continuous collaboration activities with market-based partners, while the opposite effect is found for collaborating with science-based partners. Thus, collaboration with market-based partners should be conducted in a continuous way without interruptions in the process. In contrast, it may be more beneficial to collaborate with science-based partners in a piecewise manner. As for collaboration simultaneity, I find that the benefits of knowledge recombination from different sources outweigh the actual managerial complexities and coordination costs. Thus, the project that conducts simultaneous collaborations with multiple types of partners may outperform the projects which do it in sequence. Finally, projects are performing better when collaborations with market-based partners take place at the end of the project, while with science-based partners at the beginning of the project. Relating to the current debates over Intellectual Property (IP) issues of collaborations, my findings suggest that if the research project collaborates with science-based partners, it may need to have some closed period at the end of the project life cycle. This may be because it needs to allow for sufficient time for differentiation of collaborative efforts and to prevent opportunistic behavior of the partner in patent filing.

Furthermore, besides project management and timing of collaborations, managers also have to keep in mind that different technological fields that are involved into collaborations may affect their innovation performance differently. While my sample firm seems to collaborate more in the core technology fields, my research findings suggest that collaborations conducted in firms' non-core technology fields lead to higher returns. However, establishing partnerships in firms' non-core technology fields is not easy, as the focal company may suffer from both a weak absorptive capacity as well as the unwillingness of potential partners in establishing links. To cope with these issues and to maximize the value of collaborations, firms may therefore first start collaborating in their related non-core technology fields (which are related to its core technologies), instead of in distant non-core technology fields (which are at large distance to its core technologies). Also, I find that projects which are with a high level of technical strength benefit from collaborating with science-based partners in terms of innovation speed, while these technically-strong projects are prone to delay if they are in collaboration with market-based partners. These findings also suggest that the positive effect of science-based partnerships on innovation speed may be realized when the project team has already strong technical capability in place. When such capability is missing or less developed, working with science-based partners may delay project innovation, instead of accelerating it.

In sum, in this thesis I provide first-hand hard evidence on the effect of open innovation on different performance dimensions at the level of research projects. It made a first attempt in exploring a variety of contingency effects of open innovation in different scenarios. Managers are encouraged to take into considerations the discussed factors in their innovation practices to improve the innovation performance of their research projects. Despite the great care I took in writing up this thesis, there are a number of limitations and room for future research. I will detail them in the following sections.

7.2.2 Linking Project Level Open Innovation to Other Levels of Research

I have shown that studying research projects is important to advance open innovation research. Lowering the level of analysis to projects does however not imply that analyses at other levels are unimportant. There are clear links between decisions that are taken at the project level and at the other levels of analysis, such as individuals, R&D units, firms, R&D networks, sectoral, national and regional innovation ecosystems. Multi-level analyses that take into account the relationships of decisions that are taken at multiple levels could increase my current understanding of open innovation strategies. In the previous sections I have shown that studying research projects is important to advance open innovation research. In fact, the role of open innovation in research projects can only be fully understood when the project level is linked to the firm and other observation levels. Examining open innovation activities in research projects can lead to great insights about the mechanisms how collaboration with different partners enhances the technological and commercial success of projects, but I should also study how decisions about open innovation at the firm level affect open innovation at the project level and vice versa. Think for instance about a firm's corporate growth strategy, where management may decide to explore growth options in a particular new technical domain. Linking up with external partners in research projects to explore new opportunities in new technological fields may have to be organized in a different way than open projects that serve ongoing innovations for the mainstream businesses. Open innovation at the research project level should thus be related to corporate strategy and the ambidexterity literature to understand why managers open up research projects and which partners they select to obtain specific strategic objectives.

Likewise, we should not look at individual projects in isolation from each other but take the portfolio of research projects into account. Research projects are embedded in the organizational context of the firm and, consequently, their value has to be derived from their position within the network of research projects in the firm. Firms not only set up a range of research projects, they also coordinate and integrate internally developed and externally sourced knowledge across projects. Each individual project develops a piece of technological knowledge but a firm should also develop mechanisms to disseminate and integrate the knowledge in its overall technology and business developments. Hence, there is an urgent need to connect the project and the firm level to each other for two major reasons: First, it is only possible to fully understand why firms engage in open innovation projects if they can be positioned within a firm's portfolio of projects and connected to the overall innovation strategy of the firm. Second, one can only understand (firm level) concepts such as technology depth, breadth, orientation or absorptive capacity if they are related to open innovation activities in research projects. An optimal level of breadth of technology search at the firm level for instance is after all the outcome of a mix of open and closed research projects. Question is how companies decide on the mix of these projects? What are the reasons behind the choice for open or closed innovation in each project, and how is this choice affected by a company's prior experience with open innovation and the open innovation culture that it had developed previously? The most interesting research in open innovation could be developed at the intersection of these different levels of analysis. We badly need a multilevel analysis of open innovation to advance research in this field.

The interaction with other (micro-) levels of analysis deserves more attention too. Success of open innovation in research projects is most likely dependent on the quality and experience of individuals and the R&D team both of the focal company as well as the individuals and the R&D team with whom they interact in the partnering organizations. Studying the role of individuals and R&D teams in open innovation is still uncharted territory, and interaction with the openness in research project level investigations is not touched upon yet.

Besides linking the project-level study to portfolio-, firm-, as well as individual-/team- level of research, it is also possible to link open innovation practices in research projects to the "macro" levels such as innovation ecosystems or R&D networks (Nambisan and Sawhney, 2011; Adner, 2012; Leten et al, 2012), national or regional innovation systems (Freeman, 1987; Lundvall, 1992; Nelson, 1993; Acs, 2000) and sectoral innovation systems (Malerba 2002, 2004). National and regional innovation systems influence the way open innovation is shaped in research projects (Chesbrough and Vanhaverbeke, 2011). At the national level, culture and institutional arrangements may play a role in the way firms (can) reach out to their innovation partners. It is, for example, frequently said that Asian countries have a relational view rather than a transactional view on open innovation and inter-firm collaboration. Therefore, it would be interesting to study how openness in research projects is organized differently in Asian companies compared to Western companies, and what the consequences are for both open innovation management and the resulting success of open research projects. Moreover, besides national innovation systems, regional innovation systems are also emerging as a hot research topic. Prior research shows that even within the same firm, subsidiaries in different regions with other innovation system characteristics may display different innovation behavior. Hence, linking the project level study to the regional innovation system can also be a promising future path for research.

Another level of analysis is innovation ecosystem. In more recent years, innovation ecosystems get more and more attention (Nambisan and Sawhney, 2011; Adner, 2012) but they have never been studied from the perspective of research projects between ecosystem partners. It is beyond doubt however that the contracts, trust and power structure in the ecosystem influence both the openness in the research projects as well as the success of the projects. Ecosystems or networks of partners also point to the roles of different partners in research projects. "As an ecosystem orchestrator, a hub firm defines the basic architecture for the core innovation and then invites network members to design and develop the different components that make up this core innovation. The hub firm integrates these different components to build the core innovation and then markets it." (Nambisan & Sawhney 2011, p. 41). Thus, an ecosystem orchestrator is envisioning the core innovation and is integrating the different contributions of partners to create the core innovation. To deliver these contributions the hub firm will set up a range of research projects with different partners and will manage them in such a way to maximize (internal) innovation coherence in the ecosystem that is the alignment of the innovation tasks, components, and interactions of the partners within the network. Lack of coherence will lead to process delays, design redundancies, technological incompatibilities, higher innovation costs, and inferior performance (Bullinger et al., 2004; Gerwin, 2004). The requirement for innovation coherence in an ecosystem implies that the hub firm will coordinate research projects as pieces of a bigger puzzle. Likewise, the implementer in the innovation ecosystem also determines innovation performance. An analysis at the research project level has to incorporate the roles of different partners in the ecosystem and the choice of partners can only be understood from the potential role they can play in the ecosystem that the hub firm envisions.

7.2.3 Extending the Research Coverage to More Companies/ Industries

Despite the richness of the data, the analysis is constrained to a single company. Therefore, a more encompassing dataset with data from different companies is beneficial to check the external validity of my conclusions. As prior research show, companies in different industries may behave differently, thus, the firm diversity is likely to influence the projects embedded within (Chesbrough and Crowther, 2007). As my research is on a high-tech manufacturing firm, future research may approach this line from 1) including more companies in manufacturing industry itself, as well as 2) including companies in other industries, such as service, low-tech, and slow-product-life-clock industries.

Second, the focus on research projects has the advantage that we get a detailed picture how companies benefit from open innovation, but I do not test how portfolios of projects and prior strength and experience in collaborating with particular partners may contribute to the firm's overall innovation performance.

Third, I use dummy variables to code whether a project is open or not. However, some scholars pointed out (e.g. Barge-Gil, 2010) that openness should be considered as a continuum. An research project is never fully open or completely closed: there is always some openness and there is always a need to fend off partners from particular parts in the project. In this way, it would be interesting to use indicators that reflect the degree of openness of research projects. Given the limitations of my data, I tried to differentiate between the different timing and technological fields involved in collaborations, but I could not look into this further in this study. However, I encourage other scholars to examine how different levels of openness may affect the performance of research projects.

Finally, openness of research projects can also be examined over time - at different stages in project activities. R&D teams not only have to figure out whether they will open up a project to partners or not, but also when and for how long. Therefore, it is interesting to examine with longitudinal datasets the effect of external collaboration on project performance in each stage of the research project.

7.2.4 Researching More Contingent Effects of Open Innovation Strategies

In this thesis, I explored a limited number of contingent effects of open innovation activities. Each of the contingent factors I chose represents a certain element from the internal conditions in the firm, the external environment of the firm, or the open innovation process itself. However, firms' open innovation practices are influenced by a wide range of factors, not only restricted to the ones that are shown in the present study. Future research may take it forward by looking at other contingent variables, but it can also take new perspectives and explore contingencies that are related to other topics. In sum, it is of particular importance to understand the effect of open innovation, combined with factors and scenarios that either enable or impair its adoption and effects.

As it is an emerging field of research and many more findings and implications are yet to come, I encourage fellow researchers to further explore into the phenomenon, practices and implications of open innovation at different levels of analysis. Research about open innovation at the research project level has proven to be an interesting future avenue in innovation research, but it is in fact a first explorative research. More research is requested to unravel the dynamics of open innovation at other research levels as well as the interactions among them. Also, more contingencies of open innovation are encouraged to be explored in future studies.

7.3 Limitations

This thesis contributes to the open innovation literature by analyzing several important but yet unexplored topics, i.e. whether collaboration with external partnerships improves the performance of research projects, and under which circumstances open innovation may/may not work. Informative as it is, this thesis also has several limitations.

First, despite the richness of the data, the analysis is constrained to a single company. Therefore, a more encompassing dataset with data from different companies will be helpful to check the external validity of my conclusions. Second, compared to studies analyzing R&D collaboration at the firm level, this study does not capture the benefits of a research project portfolio approach or any potential synergies between projects, as a research team that learned from external partners in one project may use this knowledge in other research projects. The focus on research projects has the advantage that we get a detailed picture how companies benefit from open innovation, but I do not test how portfolios of projects and prior strength in collaborating with particular partners may contribute to the firm's overall innovation performance. Third, in Chapter 3 and Chapter 4, I use dummy variables to code whether a project is open or not. However, some scholars pointed out (e.g. Barge-Gil, 2010) that openness should be considered as a continuum. A research project is never fully open or completely closed: there is always some openness and there is always a need to fend off partners from particular parts in the project. In this way, it would be interesting to use indicators that reflect the degree of openness of research projects. I encourage scholars to examine how different levels of openness may affect the performance of research projects. Next, openness of research projects can also be examined over time - at different stages of an research project. R&D teams not only have to figure out whether they will open up a project to partners or not, but also when and for how long. Therefore, it is interesting to examine with longitudinal datasets the effect of external collaboration on project performance in each stage of the research project. I made some first attempts in this direction in Chapter 5 and Chapter 6, where I tried to look into the timing and collaboration fields of collaboration activities. However, more efforts have to be made to better understand the contingencies of open innovation. Moreover, the database does not allow me to quantify the number of external partners, nor to identify the individual partners with whom the research project collaborates. These limitations of the database prevent me to come to a more finely-grained categorization of different open innovation partnerships. My data does only allow me to differentiate between two broad categories of external partners: science-based partners and market-based partners. I believe that further splitting these two types of partnerships into more finely-grained sub-categories will help me to further improve our understanding on open innovation partnerships and project management styles. Moreover, the interplay between the number of open innovation partnerships and project management style is another interesting avenue for future research. Finally, as I grouped both formal and informal collaborations and studied its overall effect, it may be possible that I cover a too broad set of institutional arrangement which may have different mechanisms in collaboration. Future research is needed to disentangle the effect of these mechanisms.

Despite these shortcomings of the current analysis, there are several areas for future research that emerge from this thesis. First, empirical findings about the impact of open innovation on firm level performance are mixed. In contrast, the results in the current study indicate that analyzing open innovation at the research project is a promising way to understand under which conditions it is useful to collaborate with partners in research projects. Project level analyses provide several opportunities to further analyze, and understand, open innovation activities: First, the impact of openness on the research project performance can be measured in different ways: I focused in this chapter on the financial performance and innovation speed of projects, but the success of research projects can also be measured in terms of successful transfers to the businesses in the company and the number of patents they generate. Second, a research project is managed by a team: team (leader) characteristics which are beneficial for closed innovation projects may be detrimental for open innovation projects. Third, projects are temporary constructs and they evolve and change over time: investigating the time aspect of open innovation opens a promising future research avenue.

The analysis at the research project level is interesting as a new approach for existing open innovation research. At the same time, introducing collaboration with different types of partners and study their contingencies is fairly new to the research project management literature. Collaboration with suppliers and customers have received attention in the past, but less attention is given to science-based partnerships, nor to the comparison of both types of partners. Further, to the best of my knowledge, prior work has not made a clear comparison of the project performance effects of different types of partners. Moreover, this study provides the first evidence that the collaboration with different types of partners has to be managed in different ways. This observation may encourage scholars to reconsider how to manage research projects when a firm is collaborating with different types of partners. The classical research project management approach has been developed for closed innovation projects and might not be useful for particular types of open innovation projects. Studies investigating these different themes on the research project level may advance both a stronger theoretical understanding of open innovation as well as managerial practice.

Appendix A: Table 31 Project Management Questionnaire and Score Guidelines

1. <u>Project Ownership</u>
   5 points

An identified project owner/gatekeeper has played an active role in the definition of the project and its aim.

2. <u>Project Start-up</u> 5
   points

A formal project start-up meeting has taken place, in which project stakeholders have discussed and agreed on their respective project roles and key decisions have been documented.

3. <u>Project Planning</u>
   5 points

An up-to-date project plan/description, agreed by the project team, with smart deliverables and milestones and/or decision points agreed with the Project owner/PD (or BU) gatekeeper, is available.

4. <u>Project Monitoring and Review</u>
   per item 5 points

Regular review of the project progress, involving management, project owner and customers (eg PD/BU gatekeepers) takes place
During project reviews, corrective actions are identified, documented and tracked through to completion.
Progress reports are available at the project level in PROJECTS, including information on transferred results.

5. <u>Project Rationale</u>
   5 points

A business rationale at Domain or project level is available.

6. <u>Project closure/termination</u>
   5 points

At project termination, all relevant project documents have been uploaded to the Project Vault and a report is made containing the most important learning points.

Scoring guidelines:

- Only consider projects of at least 2.5 man-years
- If the project is still running, and no intermediate evaluation report has been made, then no score should be assigned to question 6.
- If a condition is partly satisfied take a fraction of the total score per question:
  0 – nothing is done in this area
  1 – little is done
  2 – there is some evidence of activity in this area
  3 – there is regular activity in this area, but improvement is needed
  4 – this area is satisfied well although there is room for improvement
  5 – performance in this area is excellent
- The project score is the average of the assigned scores, not counting question 6 if no score has been given, expressed in a percentage of the total achievable score

References

ABOODY, D., & LEV, B. 2000. Information Asymmetry, R&D, and Insider Gains. *The Journal of Finance,* 55(6), 2747-2766.

ABRAMS, L. C., CROSS, R., LESSER, E., & LEVIN, D. Z. 2003. Nurturing Interpersonal Trust in Knowledge-Sharing Networks. *The Academy of Management Executive (1993-2005),* 17**,** 64-77.

ACS, Z. 2000. *Regional Innovation, Knowledge and Global Change*. Pinter, London.

ADAMS, R., BESSANT, J., & PHELPS, R. 2006. Innovation Management Measurement: A Review. *International Journal of Management Reviews,* 8**,** 21-47.

ADNER, R., 2012, *The Wide Lens: A New Strategy for Innovation*. Penguin Books Ltd, London.

APPIAH-ADU, K., & RANCHHOD, A. 1998. Market orientation and performance in the biotechnology. *Technology Analysis & Strategic Management*, 10, 197.

AGHION, P., DEWATRIPONT, M., & STEIN, J. 2008. Academic freedom, private-sector focus, and the process of innovation. *RAND Journal of Economics*, 39(3): 617-635.

AHRWEILER, P., PYKA, A., & GILBERT, N. 2011. A New Model for University-Industry Links in Knowledge-Based Economies. *Journal of Product Innovation Management,* 28, 218-235.

AHUJA, G. 2000. The Duality of Collaboration: Inducements and Opportunities in the Formation of Inter-firm Linkages. *Strategic Management Journal*, *21*(3), 317-343.

AHUJA, G. 2000. Collaboration Networks, Structural Holes, and Innovation: A Longitudinal Study. *Administrative Science Quarterly,* 45**,** 425-455.

APPIAH-ADU, K., & RANCHHOD, A. 1998. Market Orientation and Performance in the Biotechnology. *Technology Analysis & Strategic Management*, 10, 197.

ARORA, A., & CECCAGNOLI, M. 2006. Patent Protection, Complementary Assets, and Firms' Incentives for Technology Licensing. *Management Science*, 52, 293-308.

ASAKAWA, K., NAKAMURA, H., & SAWADA, N. 2010. Firms' Open Innovation Policies, Laboratories' External Collaborations, and Laboratories' R&D Performance. *R & D Management,* 40**,** 109-123.

AUSTER, E. R. 1992. The Relationship of Industry Evolution to Patterns of Technological Linkages, Joint Ventures, and Direct Investment between US and Japan. *Management Science*, *38*(6), 778-792.

BARCZAK, G., GRIFFIN, A., & KAHN, K. B. 2009. PERSPECTIVE: Trends and Drivers of Success in NPD Practices: Results of the 2003 PDMA Best Practices Study. *Journal of Product Innovation Management*, 26, 3-23.

BARGE-GIL, A. 2010. Open, Semi-Open and Closed Innovators: Towards an Explanation of Degree of Openness. *Industry and Innovation,* 17**,** 577-607.

BARNEY, J. 1991. Firm Resources and Sustained Competitive Advantage. *Journal of Management,* 17**,** 99-120.

BAUM, J. A. C., CALABRESE, T., & SILVERMAN, B. S. 2000. Don't Go it Alone: Alliance Network Composition and Startups' Performance in Canadian Biotechnology. *Strategic Management Journal,* 21**,** 267-294.

BECKER, G.S., & MURPHY, K.M. 1992. The Division of Labor, Coordination Costs, and Knowledge. *The Quarterly Journal of Economics,* 107(4), 1137-1160.

BECKER, W., & DIETZ, J., 2004, R& D Cooperation and Innovation Activities of Firms— Evidence for the German Manufacturing Industry, *Research Policy*, 33(2), 209-223.

BELDERBOS, R., CARREE, M., DIEDEREN, B., LOKSHIN, B., & VEUGELERS, R. 2004. Heterogeneity in R&D Cooperation Strategies. *International Journal of Industrial Organization,* 22**,** 1237-1263.

BELDERBOS, R., FAEMS, D., LETEN, B., & LOOY, B. V. 2010. Technological Activities and Their Impact on the Financial Performance of the Firm: Exploitation and Exploration within and between Firms. *Journal of Product Innovation Management*, *27*(6), 869-882.

BELDERBOS, R., GILSING, V., & LOKSHIN, B. 2012. Persistence of and Interrelation between Horizontal and Vertical Alliances. *Journal of Management*, 38, 6 1812-1834.

BENNER, M. J., & TUSHMAN, M. L. 2003. Exploitation, Exploration, and Process Management: The Productivity Dilemma Revisited. *Academy of Management Review,* 28**,** 238-256.

BIANCHI, M., CAVALIERE, A., CHIARONI, D., FRATTINI, F., & CHIESA, V. 2011. Organisational modes for Open Innovation in the Bio-Pharmaceutical Industry: An Exploratory Analysis. *Technovation,* 31**,** 22-33.

BIANCHI, M., CHIARONI, D., CHIESA, V., & FRATTINI, F. 2011. Organizing for External Technology Commercialization: Evidence from a Multiple Case Study in the Pharmaceutical Industry, *R&D Management*, 41(2), 120-137.

BIRKINSHAW, J., BOUQEUT, C., & BARSOUX, J.-L. 2011. The 5 Myths of Innovation. *MIT Sloan Management Review*, 52(2), 42–50.

BLOSSFELD, H.P., GOLSCH, K., & ROHWER, G. 2007. *Event History Analysis with Stata*, New Jersey: Lawrence Erlbaum Associates, Inc., Publishers.

BOUGRAIN, F., & HAUDEVILLE, B. 2002. Innovation, Collaboration and SMEs Internal Research Capacities, *Research Policy*, 31(5), 735-747.

BOWER, J. L., & CHRISTENSEN, C. M. 1995. Disruptive Technologies: Catching the Wave. *Harvard Business Review*, Jan-Feb, 43-53.

BRADY, T., & DAVIES, A. 2004. Building Project Capabilities: From Exploratory to Exploitative Learning. *Organization Studies*, 25, 1601-1621.

BROCKHOFF, K. 2003. Customers' perspectives of involvement in new product development, *International Journal of Technology Management*, 26(5-6), 464-481.

BROWN, S. L., & EISENHARDT, K. M. 1995. Product Development: Past Research, Present Findings, and Future Directions. *The Academy of Management Review,* 20**,** 343-378.

BRUSONI, S., & PRENCIPE, A. 2001. Unpacking the Black Box of Modularity: Technologies, Products and Organizations. *Industrial and Corporate Change*, *10*(1), 179-205.

BRUSONI, S., PRENCIPE, A., & PAVITT, K. 2001. Knowledge Specialization, Organizational Coupling, and the Boundaries of the Firm: Why Do Firms Know More than They Make? *Administrative Science Quarterly*, December 46: 597-621.

BRUTON, G.D., OVIATT, B.M., & WHITE, M.A. 1994. Performance of Acquisitions of Distressed Firms. *Academy of Management Journal*, 37: 972-989.

BSTIELER, L., & HEMMERT, M. 2010. Increasing Learning and Time Efficiency in Interorganizational New Product Development Teams. *Journal of Product Innovation Management,* 27**,** 485-499.

BULLINGER, H. J., AUERNHAMMER, K., & GOMERINGER, A. 2004. Managing Innovation Networks in the Knowledge-driven Economy. *International Journal of Production Research*, 42(17), 3337–3353.

Business Week. 2006. The World's Most Innovative Companies. http://www.businessweek.com/stories/2006-04-23/the-worlds-most-innovative-companies

Business Week. 2008. A Ripe Time for Open Innovation (by Jeneanne Rae).

http://www.businessweek.com/stories/2008-03-19/a-ripe-time-for-open-innovationbusinessweek-business-news-stock-market-and-financial-advice

CALANTONE, R.J., & DI BENEDETTO, C.A. 2000. Performance and Time to Market: Accelerating Cycle Time with Overlapping Stages. *IEEE Transactions on Engineering Management*, 47(2), 232-244.

CALOGHIROU, Y., KASTELLI, I., & TSAKANIKAS, A. 2004. Internal capabilities and external knowledge sources: complements or substitutes for innovative performance? *Technovation,* 24**,** 29-39.

Cambridge IfM Report (by Mortara, L., I. Slacik, J.J. Napp, T. H. W. Minshall). 2009. *How to Implement Open Innovation. Lessons from Multinational Companies*. Report ISBN: 978-1-902546-75-9.

CAMPBELL, A., & COOPER R. 1999. Do Customer Partnerships Improve New Product Success Rates? *Industrial Marketing Management*, 28(5), 507-519.

CANKURTARAN, P., LANGERAK, F., and GRIFFIN, A. 2013. Consequences of New Product Development Speed: A Meta-Analysis. *Journal of Product Innovation Management*, 30(3): 465-486.

CARAYOL, N. 2003. Objectives, agreements and matching in science-industry collaborations: reassembling the pieces of the puzzle. *Research Policy,* 32**,** 887-908.

CARBONELL, P., RODRIGUEZ-ESCUDERO, A.I., & PUJARI, D. 2009. Customer Involvement in New Service Development: An Examination of Antecedents and Outcomes. *Journal of Product Innovation Management*, 26(5), 536-550.

CARLILE, P. R. 2002. A Pragmatic View of Knowledge and Boundaries: Boundary Objects in New Product Development. *Organization Science*, 13, 442-455.

CARROLL, G. R. 1985. Concentration and Specialization: Dynamics of Niche Width in Populations of Organizations. *American Journal of Sociology*, 1262-1283.

CASSIMAN, B., & VEUGELERS, R. 2002. R&D Cooperation and Spillovers: Some Empirical Evidence from Belgium. *The American Economic Review*,*92*(4), 1169-1184.

CASSIMAN, B., & VEUGELERS, R. 2006. In Search of Complementarity in Innovation Strategy: Internal R&D and External Knowledge Acquisition. *Management Science,* 52**,** 68-82.

CASSIMAN B., VEUGELERS, R., & ZUNIGA, M.P. 2008. In Search of Performance Effects of (in)direct Industry-Science Links. *Industrial and Corporate Change*, 17(4), 611-646.

CASSIMAN, B., Di GUARDO, M.C., & VALENTINI, G. 2009. Organising R& D Projects to Profit from Innovation: Insights From Co-opetition. *Long Range Planning*, 42(2), 216-233.

CASSIMAN, B., Di GUARDO, M.C., & VALENTINI, G. 2010, Organizing Links with Science: Cooperate or Contract? A Project-level Analysis. *Research Policy*, 39, 882-892.

CHEN, J., DAMANPOUR, F., & REILLY, R. R. 2010. Understanding Antecedents of New Product Development Speed: A Meta-analysis. Journal of Operations Management, 28(1): 17-33.

CHESBROUGH, H., & ROSENBLOOM, R.S. 2002. The Role of the Business Model in Capturing Value from Innovation: Evidence from Xerox Corporation's Technology Spin-off Companies. *Industrial and Corporate Change*, 11(3): 529-555.

CHESBROUGH, H.W. 2003. *Open Innovation: The New Imperative for Creating and Profiting from Technology*, Harvard Business School Press, Boston.

CHESBROUGH, H., VANHAVERBEKE, W., & WEST, J. 2006. *Open Innovation: Researching a New Paradigm,* Oxford University Press: Oxford, UK.

CHESBROUGH, H.W., & Schwartz, K., 2007, Innovating Business Models with Co-development Partnerships. *Research-Technology Management*, 50(1), 55-59.

CHESBROUGH, H.W., & GARMAN, A. 2009. Use Open Innovation to Cope in a Downturn. *Harvard Business Review*, 87(12), 68-76.

CHIARONI, D., CHIESA, V., & FRATTINI, F. 2011. The Open Innovation Journey: How Firms Dynamically Implement the Emerging Innovation Management Paradigm. *Technovation,* 31**,** 34-43.

CHRISTENSEN, C. M., & BOWER, J. L. 1996. Customer Power, Strategic Investment, and the Failure of Leading Firms. *Strategic Management Journal*, 17: 197–218.

CHRISTENSEN, C. M. 1997. The Innovator's Dilemma: When New Technologies Cause Great Firms to Fail. *Harvard Business Press,* Boston.

CLARK, K., B., & FUJIMOTO, T. 1991. *Product Development Performance: Strategy, Organization, and Management in the World Auto Industry.* Harvard Business School Press.

CLARK, K.B., & WHEELWRIGHT, S.C. 1990. *Managing New Product and Process Development: Text and Cases*. Harvard Business School.

CLELAND, D I., & KERZNER, H. 1985. *A Project Management Dictionary of Terms*, Van Nostrand Reinhold, New York.

COCKBURN, I., & HENDERSON R. 1998. Absorptive Capacity, Coauthoring Behavior, and the Organization of Research in Drug Discovery. *The Journal of Industrial Economics*, 46(2), 157-182.

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, 1-23.

COHEN, W. M., & LEVINTHAL, D. A. 1990. Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly,* 35**,** 128-152.

COLEMAN, J. S. 1988. Social Capital in the Creation of Human Capital. *American Journal of Sociology,* 94**,** 95-120.

COOPER, R. G. 1979. The Dimensions of Industrial New Product Success and Failure. *The Journal of Marketing,* 43**,** 93-103.

COOPER, R. G. 1990. Stage-gate Systems: A New Tool for Managing New Products. *Business Horizons,* 33**,** 44-54.

COOPER, R. G., & KLEINSCHMIDT, E. J. 1987. New Products: What Separates Winners from Losers? *Journal of Product Innovation Management,* 4**,** 169-184.

COOPER, R. G., EDGETT, S. J., & KLEINSCHMIDT, E. J. 2004. Benchmarking Best NPD Practices-I. *Research Technology Management,* 47(1)**,** 31-43.

COOPER, R. G., & EDGETT, S. J. 2008. Maximizing Productivity in Product Innovation. *Research-Technology Management*, 51, 47-58.

COSH, A., & ZHANG, J.J. 2011. Open Innovation Choices ? What is British Enterprise Doing? UK ~ Innovation Research Centre, University of Cambridge.

CRAWFORD, C, M. 1992. The Hidden Costs of Accelerated Product Development. *Journal of Product Innovation Management*, 9(3), 188-199.

CYERT, R.M., & MARCH, J.G. 1963. Behaviroal Theory of the Firm, Englewood Cliffs, NJ: Prentice-Hall.

DAFT, R. L. 1978. A Dual-Core Model of Organizational Innovation. *Academy of Management Journal*, *21*(2), 193-210.

DAHLANDER, L., & WALLIN, M. W. 2006. A Man on the Inside: Unlocking Communities as Complementary Assets. *Research Policy*, 35, 1243-1259.

DAHLANDER, L., & GANN, D.M. 2010. How Open is Innovation? *Research*

Policy, 39(6), 699-709.

DANNEELS, E. 2002. The Dynamics of Product Innovation and Firm Competences. *Strategic Management Journal*, 23, 1095-1121.

DAS, T.K., & TENG, B.S. 1998. Between Trust and Control: Developing Confidence in Partner Cooperation in Alliances. *The Academy of Management Review*, 23(3), 491-512.

DAS, T. K., & TENG, B.-S. 2001. Trust, Control, and Risk in Strategic Alliances: An Integrated Framework. *Organization Studies,* 22**,** 251-283.

DEEDS, D. L., & HILL, C. W. L. 1996. Strategic Alliances and the Rate of New Product Development: An Empirical Study of Entrepreneurial Biotechnology Firms. *Journal of Business Venturing,* 11**,** 41-55.

DEKKER, H. C. 2004. Control of Inter-organizational Relationships: Evidence on Appropriation Concerns and Coordination Requirements. *Accounting, Organizations and Society*, *29*(1), 27-49.

DEMING, E. W. 1986. *Out of Crisis*. Cambridge, MA: MIT Press.

DESCHAMPS, J.P., & NAYAK, P.R. 1992. Competing Through Products: Lessons from Winners. *Columbia Journal of World Business*, 27 (2), 38–54.

DIERICKX, I., & COOL, K. 1989. Asset Stock Accumulation and Sustainability of Competitive Advantage. *Management Science,* 35**,** 1504-1511.

DI MININ, A., FRATTINI, F., & PICCALUGA, A. 2010. Fiat: Open

Innovation in a Downturn (1993–2003). *California Management Review*, 52(3), 132–159.

DITTRICH, K., & DUYSTERS, G. 2007. Networking as a Means to Strategy Change: The Case of Open Innovation in Mobile Telephony. *Journal of Product Innovation Management,* 24**,** 510-521.

DODGSON, M. (Ed.). 1989. *Technology Strategy and the Firm: Management and Public Policy*. Longman.

DODGSON, M. 1992. The Strategic Management of R&D Collaboration. *Technology Analysis & Strategic Management,* 4**,** 227 - 244.

DODGSON, M., GANN, D., & SALTER, A., 2006, The Role of Technology in the Shift Towards Open Innovation: the Case of Procter & Gamble. *R&D Management*, 36(3), 333-346.

DOUGHERTY, D. 1992. Interpretive Barriers to Successful Product Innovation in Large Firms. *Organization Science,* 3**,** 179-202.

DOUGHERTY, D. 1992. A Practice-centered Model of Organizational Renewal through Product Innovation. *Strategic Management Journal*, 13, 77-92.

DOUGLASS, K. 2011. *What Does Product Development Really Cost? How Internal Rate of Return for a New Product Improves Substantially With a Decrease in Time to Market*. Pivot International Report.

DOZ, Y. L. 1996. The Evolution of Cooperation in Strategic Alliances: Initial Conditions or Learning Processes?. *Strategic Management Journal*, *17*(1), 55-83.

DOZ, Y. L., & HAMEL, G. 1998. Alliance Advantage: The Art of Creating Value Through Partnering. *Harvard Business Press,* Boston.

DOZ, Y., SANTOS, J., & WILLIAMSON, P. 2001. *From Global to Metanational: How Companies Win in the Knowledge Economy*, Harvard Business School Press.

DROGE, C., JAYARAM, J., & VICKERY, S. K. 2004. The Effects of Internal versus External Integration Practices on Time-based Performance and Overall Firm Performance, *Journal of Operations Management*, 22 (6), 557-573.

DUYSTERS, G., & DE MAN, A. P. 2003. Transitory Alliances: An Instrument for Surviving Turbulent Industries? *R&D Management*, 33(1), pp. 49-58.

DUYSTERS, G., & HAGEDOORN, J. 2000. Core Competences and Company Performance in the World-wide Computer Industry. *The Journal of High Technology Management Research*, *11*(1), 75-91.

DWYER, L., & MELLOR, R. 1991. Organizational Environment, New Product Process Activities, and Project Outcomes. *Journal of Product Innovation Management*, 8, 39-48.

DYER, J. H. 1996. Does governance matter? Keiretsu alliances and asset specificity as sources of Japanese competitive advantage. *Organization Science*, 7, 649-666.

DYER, J. H., & SINGH, H. 1998. The Relational View: Cooperative Strategy and Sources of Interorganizational Competitive Advantage. *The Academy of Management Review,* 23**,** 660-679.

ENKEL, E., GASSMANN, O., & CHESBROUGH, H. 2009. Open R&D and Open Innovation: Exploring the Phenomenon. *R & D Management*, 39(4), pp. 311-316.

EISENHARDT, K. M., & TABRIZI, B. N. 1995. Accelerating Adaptive Processes: Product Innovation in the Global Computer Industry. *Administrative Science Quarterly,* 40**,** 84-110.

EISENHARDT, K. M., & SCHOONHOVEN, C. B. 1996. Resource-Based View of Strategic Alliance Formation: Strategic and Social Effects in Entrepreneurial Firms. *Organization Science,* 7**,** 136-150.

EISENHARDT, K. M., & MARTIN, J. A. 2000. Dynamic Capabilities: What Are They? *Strategic Management Journal*,21 (10–11), 1105–1121.

EMMANUELIDES, P.A., 1993. Towards an Integrative Framework of Performance in Product Development Projects. *Journal of Engineering and Technology Management*, 10(4), 363-392.

ENGWALL, M. 2003. No Project is an Island: Linking Projects to History and Context, *Research Policy*, 32(5), 789-808.

ERNST, H. 2002. Success Factors of New Product Development: A Review of the Empirical Literature. *International Journal of Management Reviews,* 4**,** 1-40.

ESCP Europe & Accenture. 2011. Open Innovation, What Behind the Buzz Word. Public Report.

ESCRIBANO, A., FOSFURI, A., & TRIBÓ, J. A. 2009. Managing External Knowledge Flows: The Moderating Role of Absorptive Capacity. *Research Policy*, *38*(1), 96-105.

FABRIZIO, K. R. 2009. Absorptive capacity and the search for innovation. *Research Policy,* 38**,** 255-267.

FAEMS, D., VAN LOOY, B., & DEBACKERE, K. 2005. Interorganizational Collaboration and Innovation: Toward a Portfolio Approach. *Journal of Product Innovation Management,* 22**,** 238-250.

FAEMS, D., JANSSENS, M., & VAN LOOY, B. 2007. The Initiation and Evolution of Inter-firm Knowledge Transfer in R&D Relationships. *Organization Studies*, *28*(11), 1699-1728.

FAEMS, D., De VISSER, M., ANDRIES, P., & VAN LOOY, B. 2010. Technology Alliance Portfolios and Financial Performance: Value-Enhancing and Cost-Increasing Effects of Open Innovation. *Journal of Product Innovation Management*, 27(6), 785-796.

FELLER, I., & ROESSNER, D. 1995. What Does Industry Expect from University Partnerships. *Issues in Science and Technology*, 12, 80-84.

FILIPPINI, R., SALMASO, L., & TESSAROLO, P. 2004. Product Development Time Performance: Investigating the Effect of Interactions between Drivers. *Journal of Product Innovation Management*, 21(3). 199-214.

FLEMING, L. 2001. Recombinant Uncertainty in Technological Search. *Management Science,* 47**,** 117-132.

FLEMING, L., & SORENSON, O. 2004. Science as a Map in Technological Search. *Strategic Management Journal,* 25**,** 909-928.

FISHER, S. R., & WHITE, M. A. 2000. Downsizing in a Learning Organization: Are there Hidden Costs? *Academy of Management Review*, 244-251.

FLEMING, L. 2001. Recombinant Uncertainty in Technological Search. *Management Science,* 47**,** 117-132.

FONTANA, R., GEUNA, A., & MATT, M. 2006. Factors Affecting University–Industry R&D Projects: The Importance of Searching, Screening and Signalling. *Research Policy*, 35(2), 309-323.

FREEMAN, C. 1987. *Technology Policy and Economic Performance*. Pinter, London.

FUCHS, C., & SCHREIER, M. 2011. Customer Empowerment in New Product Development. *Journal of Product Innovation Management*, 28, 17-32.

GALUNIC, D.C., & RODAN, S.A. 1998. Resource Re-combinations in the Firm: Knowledge Structures and the Potential for Schumpeterian Innovation. *Strategic Management Journal*, 19(12), 1193-201.

GARCIA, R., & CALANTONE, R. 2002. A Critical Look at Technological Innovation Typology and Innovativeness Terminology: A Literature Review. *Journal of Product Innovation Management,* 19**,** 110-132.

GASSMANN, O., KAUSCH, C., & ENKEL, E. 2010. Negative side effects of customer integration. *International Journal of Technology Management,* 50**,** 43-63.

GAVETTI, G. 2004. *Kodak and the Digital Revolution*. Harvard Business School, Boston.

GEMÜNDEN, H. G., SALOMO, S., & KRIEGER, A. 2005. The influence of project autonomy on project success. *International Journal of Project Management,* 23**,** 366-373.

GERWIN, D. 2004. Coordinating New Product Development in Strategic Alliances. *Academy of Management Review*, 29(2), 241–257.

GJERDE, K. A. P., SLOTNICK, S. A., & SOBEL, M. J. 2002. New Product Innovation with Multiple Features and Technology Constraints. *Management Science,* 48**,** 1268-1284.

GLOBE, S., LEVY, G. W., & SCHWARTZ, C. M. 1973. Key Factors and Events in the Innovation Process, Research Management, July, 8-15.

GOKTAN, A.B., & MILES, G. 2011. Innovation Speed and Radicalness: Are They Inversely Related? *Management Decision*, 49(4), 533 – 547.

GOLDER, P.N., & TELLIS, G.J. 1993. Pioneer Advantage: Marketing Logic or Marketing Legend? *Journal of Marketing Research*, 30(2), 158-170.

GRABHER, G., 2004, Learning in Projects, Remembering in Networks? Communality, Sociality, and Connectivity in Project Ecologies, *European Urban and Regional Studies*, 11 (2), 103-123.

GRANSTRAND, O., PATEL, P., & PAVITT, K. 1997. Multi-technology Corporations: Why They have 'Distributed' Rather than 'Distinctive' Core Competences. *California Management Review*, *39*(4), 8-25.

GRANT, R. M. 1996. Prospering in Dynamically-Competitive Environments: Organizational Capability as Knowledge Integration. *Organization Science,* 7**,** 375-387.

GRANT, R. M. 1996. Toward a Knowledge-based Theory of the Firm. *Strategic Management Journal*, 17, 109-122.

GRANT, R. M., & BADEN-FULLER, C. 2004. A Knowledge Accessing Theory of Strategic Alliances. *Journal of Management Studies,* 41(1)**,** 61-84.

GRAVES, S.B. 1989. Why Costs Increase When Projects Accelerate? *Research Technology Management*, 32 (2), 16.

GRAVES, S.B. 1989. The Time-Cost Trade-off in Research and Development: A Review. *Engineering Costs and Production Economics*, 16(1), 1-9.

GREENE, W, H. 2000. *Econometric Analysis*. 4th edition. Upper Saddle River, NJ: Prentice Hall.

GREER, C. R., & LEI, D. 2012. Collaborative Innovation with Customers: A Review of the Literature and Suggestions for Future Research. *International Journal of Management Reviews,* 14**,** 63-84.

GRIFFIN, A. 1993. Metrics for Measuring Product Development Cycle Time. *The Journal of Product Innovation Management*, 10 (2), 112-125.

GRIFFIN, A., & PAGE, A.L. 1993. An Interim Report on Measuring Product Development Success and Failure. *Journal of Product Innovation Management*, 10(4), 291-308.

GRIFFIN, A., & HAUSER, J. R. 1996. Integrating R&D and Marketing: A Review and Analysis of the Literature. *Journal of Product Innovation Management,* 13**,** 191-215.

GRIFFIN, A., & PAGE, A. L. 1996. PDMA Success Measurement Project: Recommended Measures for Product Development Success and Failure. *Journal of Product Innovation Management,* 13**,** 478-496.

GRIFFIN, A. 1997. PDMA Research on New Product Development Practices: Updating Trends and Benchmarking Best Practices. *Journal of Product Innovation Management,* 14**,** 429-458.

GRIFFIN, A. 1997. The Effect of Project and Process Characteristics on Product Development Cycle Time. *Journal of Marketing Research*, 34(1), 24-35.

GRIFFIN, A. 1997. Modeling and Measuring Product Development Cycle Time across Industries. *Journal of Engineering and Technology Management*, 14(1), 1-24.

GRIFFIN, A., & PAGE, A. L. 2003. PDMA Success Measurement Project: Recommended Measures for Product Development Success and Failure. *Journal of Product Innovation Management*, *13*(6), 478-496.

GRONLUND, J., RONNBERG, S. D., & FRISHAMMAR, J. 2010. Open Innovation and the Stage-Gate Process: A Revised Model for New Product Development. *California Management Review*, 52, 106–131.

GRUNER, K. E., & HOMBURG, C. 2000. Does Customer Interaction Enhance New Product Success? *Journal of Business Research*, 49, 1-14.

GUJARATI, D.N. 1995. *Basic Econometrics* (3rd ed). McGraw-Hill Inc.

GULATI, R. 1995. Social Structure and Alliance Formation Patterns: A Longitudinal Analysis. *Administrative Science Quarterly,* 40**,** 619-652.

GULATI, R. 1999. Network Location and Learning: The Influence of Network Resources and Firm Capabilities on Alliance Formation. *Strategic Management Journal,* 20**,** 397-420.

GUPTA, A.K., & WILEMON, D.L. 1990. Accelerating the Development of Technology-based New Products. California Management Review, 32, 24-44.

HACKMAN, J. R., & WAGEMAN, R. 1995. Total quality management: Empirical, conceptual, and practical issues. Administrative Science Quarterly, 40: 309-342.

HAGEDOORN, J., & SCHAKENRAAD, J. 1994. The Effect of Strategic Technology Alliances on Company Performance. *Strategic Management Journal,* 15**,** 291-309.

HAGEDOORN, J. 1995. Strategic Technology Partnering during the 1980s: Trends, Networks and Corporate Patterns in Non-Core Technologies. *Research Policy*, *24*(2), 207-231.

HAGEDOORN, J., LINK, A. N. & VONORTAS, N. S. 2000. Research partnerships. *Research Policy,* 29**,** 567-586.

HAGEDOORN, J. 2002. Inter-firm R&D Partnerships: An Overview of Major Trends and Patterns Since 1960. *Research Policy,* 31**,** 477-492.

HALL, B., GRILICHES, H.Z., & HAUSMAN,J.A. 1986. Patents and R&D: Is There A Lag? *International Economic Review*, 27(2), 265-284.

HALL, B.H., JAFFE A.B., & TRAJTENBERG, M. 2005. Market Value and Patent Citations, *Rand Journal of Economics,* 36: 16-38.

HAMEL, G. 1991. Competition for Competence and Interpartner Learning within International Strategic Alliances. *Strategic Management Journal*, 12(1), 83-103.

HAMEL, G. 1994. *The Concept of Core Competence*, in Hamel, G and Heene, A (eds.), Competence-Based Competition, The Strategic Management Society, Sussex: John Wiley and Sons, 11-33.

HAMEL, G., DOZ, Y. L., & PRAHALAD, C. K. 1989. Collaborate with Your Competitors and Win. *Harvard Business Review*, 67(1), 133-139.

HARRISON, D., & WALUSZEWSKI, A. 2008. The Development of a User Network as a Way to Re-launch an Unwanted Product. *Research Policy*, 37, 115-130.

HARRY, M. J., & SCHROEDER, R. 2000. *Six Sigma: The breakthrough management strategy revolutionizing the world's top corporations*. New York: Currency.

HARTLEY, J.L., ZIRGER, B.J., KAMATH, R.R. 1997. Managing the Buyer-Supplier Interface for On-Time Performance in Product Development. *Journal of Operations Management*, 15(1), 57-70.

HAUPT, R., KLOYER, M., & LANGE, M. 2007. Patent Indicators for the Technology Life Cycle Development. *Research Policy*, 36, 387-398.

HEIMAN, B. A., & NICKERSON, J. A. 2004. Empirical Evidence Regarding the Tension between Knowledge Sharing and Knowledge Expropriation in Collaborations. *Managerial and Decision Economics*, *25*(6-7), 401-420.

HOANG, H., & ROTHAERMEL, F. T. 2005. The Effect of General and Partner-Specific Alliance Experience on Joint R&D Project Performance. *The Academy of Management Journal,* 48**,** 332-345.

HOBDAY, M. 2000. The Project-based Organization: An Ideal Form for Managing Complex Products and Systems? *Research Policy*, 29, 871-893.

HOPKINS, M. M., TIDD, J., NIGHTINGALE, P., & MILLER, R. 2011. Generative and degenerative interactions: positive and negative dynamics of open, user-centric innovation in technology and engineering consultancies. *R&D Management,* 41**,** 44-60.

HOSKISSON, R.E., & HITT, M.A. 1994. *Down-Scoping: How to Tame the Diversified Firm*. Oxford University Press, Oxford, UK.

HOWELLS, J. 2008. New Directions in R&D: Current and Prospective Challenges. *R&D Management*, 38(3), 241–252.

HUIZINGH, E.K.R.E. 2011. Open Innovation: State of the Art and Future Perspectives. *Technovation*, 31(1), 2-9.

HUSTON, L., & SAKKAB, N. 2007. *Implementing Open Innovation*. Industrial Research Institute, Inc.

INKPEN, A. C., & TSANG, E. W. 2007. 10 Learning and Strategic Alliances. *The Academy of Management Annals*, *1*(1), 479-511.

IRELAND, R. D., HITT, M. A. & VAIDYANATH, D. 2002. Alliance Management as a Source of Competitive Advantage. *Journal of Management,* 28(3)**,** 413-446.

ISHIKAWA, K. 1985. *What is Total Quality Control? The Japanese Way*. Englewood Cliffs, NJ: Prentice-Hall.

JAFFE, A. 1989. Real Effects of Academic Research. *American Economic Review*, 79(5), 957-970.

JAWORSKI, B. J., & KOHLI, A. K. 1993. Market Orientation: Antecedents and Consequences. *Journal of Marketing,* 57(3)**,** 53-70.

KAHN, K. B., BARCZAK, G., & MOSS, R. 2006. PERSPECTIVE: Establishing an NPD Best Practices Framework. *Journal of Product Innovation Management,* 23**,** 106-116.

KALE, P., & SINGH, H. 2007. Building Firm Capabilities through Learning: the Role of the Alliance Learning Process in Alliance Capability and Firm-level Alliance Success. *Strategic Management Journal*, *28*(10), 981-1000.

KARAGOZOGLU, N., & BROWN, W. B. 1993. Time-based Management of the New Product Development Process. *Journal of Product Innovation Management*, 10(3), 204-215.

KARLSSON, C., & AHLSTROM, P. 1999. Technological Level and Product Development Cycle Time. *Journal of Product Innovation Management*, 16(4), 352-362.

KATILA, R., & AHUJA, G. 2002. Something Old, Something New: A Longitudinal Study of Search Behavior and New Product Introduction. *Academy of Management Journal*, *45*(6), 1183-1194.

KATZ, R., & ALLEN, T. J. 1982. Investigating the Not-Invented-Here (NIH) Syndrome - A Look at the Performance, Tenure, and Communication Patterns of 50 R&D Project Groups. *R & D Management,* 12(1)**,** 7-19.

KESSLER, E. H., & CHAKRABARTI, A. K. 1996. Innovation Speed: A Conceptual Model of Context, Antecedents, and Outcomes. *The Academy of Management Review*, 21, 1143-1191.

KESSLER, E. H., BIERLY, P. E. & GOPALAKRISHNAN, S. 2000. Internal vs. External Learning in New Product Development: Effects on Speed, Costs and Competitive Advantage. *R&D Management,* 30**,** 213-224.

KESSLER, E.H., & BIERLY, P.E., III. 2002. Is Faster Really Better? An Empirical Test of the Implications of Innovation Speed. *IEEE Transactions on Engineering Management*, 49(1), 2-12.

KEUPP, M. M., & GASSMANN, O. 2009. Determinants and Archetype Users of Open Innovation. *R&D Management*, *39*(4), 331-341.

KIM, W.C. & MAUBORGNE, R. 2005. Blue Ocean Strategy : How to Create Uncontested Market Space and Make the Competition Irrelevant, Harvard Business School Press.

KING, W.R. & CLEALAND, D.I., 1983, *Life Cycle Management*. In D.I.Cleland & W.R.King (Eds.), *Project Management Handbook*, New York: Van Nostrand Reinhold Co.

KIRSCHBAUM, R. 2005. Open Innovation in Practice. *Research Technology Management,* 48 (4)**,** 24-28.

KLEVORICK, A.K., LEVIN, R., NELSON, R., WINTER, S., 1995. On the

Sources and Significance of Inter-industry Differences in Technological Opportunities. *Research Policy,* 24, 185–205.

KNUDSEN, M. P. 2007. The Relative Importance of Interfirm Relationships and Knowledge Transfer for New Product Development Success. *Journal of Product Innovation Management,* 24(2)**,** 117-138.

KNUDSEN, M.P., & MORTENSEN, T. B. 2011. Some Immediate – But Negative – Effects of Openness on Product Development Performance. *Technovation*, 31(1), 54-64.

KOGUT, B. 1991. Joint Ventures and the Option to Expand and Acquire. *Management science*, *37*(1), 19-33.

KOGUT, B., SHAN, W., & WALKER, G. 1992. The Make-or-Cooperate Decision in the Context of an Industry Network. *Networks and organizations*, 348-65.

KOGUT, B., & ZANDER, U. 1992. Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology. *Organization Science,* 3**,** 383-397.

LABAHN, D.W., ALI, A., & KRAPFEL, R. 1996. New Product Development Cycle Time: The Influence of Project and Process Factors in Small Manufacturing Companies. *Journal of Business Research*, 36(2), 179-188.

LANGERAK, F. & HULTINK, E. J. 2005. The Impact of New Product Development Acceleration Approaches on Speed and Profitability: Lessons for Pioneers and Fast Followers. *IEEE Transactions on Engineering Management*, 52, 30-42.

LANGERAK, F., & HULTINK, E.J. 2006. The Impact of Product Innovativeness on the Link between Development Speed and New Product Profitability. *Journal of Product Innovation Management*, 23(3), 203-214.

LANGERAK, F., HULTINK, E.J., & GRIFFIN, A. 2008. Exploring Mediating and Moderating Influences on the Links among Cycle Time, Proficiency in Entry Timing, and New Product Profitability. *Journal of Product Innovation Management*,25(4), 370-385.

LAURSEN, K., & SALTER, A. 2006. Open for innovation: the Role of Openness in Explaining Innovation Performance among U.K. Manufacturing Firms. *Strategic Management Journal,* 27 (2)**,** 131-150.

LECOCQ, C., & VAN LOOY, B. 2009. The Impact of Collaboration on the Technological Performance of Regions: Time Invariant or Driven by Life Cycle Dynamics? *Scientometrics*, 80(3), 845- 865.

LEI, D., HITT, M. A., & BETTIS, R. 1996. Dynamic Core Competences through Meta-Learning and Strategic Context. *Journal of management*, *22*(4), 549-569.

LEONARD-BARTON, D. 1992. Management of Technology and Moose on Tables, *Organization Science*, 3(4), 556-558.

LETEN, B., BELDERBOS, R., & VAN LOOY, B. 2007. Technological Diversification, Coherence, and Performance of Firms. *Journal of Product Innovation Management*, 24(6), 567-579.

LETTL, C., HERSTATT, C. & GEMUENDEN, H. G. 2006. Users' Contributions to Radical Innovation: Evidence from Four Cases in the

Field of Medical Equipment Technology. *R&D Management,* 36**,** 251-272.

LEVINTHAL, D. A., & MARCH, J. G. 1993. The Myopia of Learning. *Strategic Management Journal*, 14(2), 95-112.

LHUILLERY, S. & PFISTER, E. 2009. R&D Cooperation and Failures in Innovation Projects: Empirical Evidence from French CIS Data. *Research Policy,* 38**,** 45-57.

LICHTENTHALER, U. 2008. Open Innovation in Practice: An Analysis of Strategic Approaches to Technology Transactions. *IEEE Transactions of Engineering Management*, 55(1), 148-157.

LICHTENTHALER, U. 2011. Open Innovation: Past Research, Current Debates, and Future Directions. *Academy of Management Perspective*, 25(1), 75-93.

LIEBERMAN, M. B. & MONTGOMERY, D. B. 1988. First-mover advantages. *Strategic Management Journal,* 9**,** 41-58.

LIEBESKIND J.P., OLIVER A.L., ZUCKER L., & BREWER M. 1996. Social Networks, Learning, and Flexibility: Sourcing Scientific Knowledge in New Biotechnology Firms. *Organization Science,* 7(4), 428-442.

LINK, A.N. & SCOTT, J. T. 2005.Opening the Ivory Tower's Door: An Analysis of the Determinants of the Formation of U.S. University Spin-off Companies, *Research Policy*, 34(7), 1106-1112.

LINK, A.N. & SIEGEL, D.S.2005.University-based Technology Initiatives: Quantitative and Qualitative Evidence, *Research Policy*, 34(3), 253-257.

LITTLER, D., LEVERICK, F., & BRUCE, M. 1995. Factors Affecting the Process of Collaborative Product Development – A Study of UK Manufacturers of Information and Communications Technology Products. *Journal of Product Innovation Management*. 12(1): 16-32.

LOKSHIN, B., HAGEDOORN, J. & LETTERIE, W. 2011. The Bumpy Road of Technology Partnerships: Understanding Causes and Consequences of Partnership Mal-functioning. *Research Policy,* 40**,** 297-308.

LORANGE, P., ROOS, J. & BRØNN, P. S. 1992. Building Successful Strategic Alliances. *Long Range Planning*, 25, 10-17.

LUNDVALL, B.A. 1992. *National Systems of Innovation: Towards a Theory of Innovation and Interactive Learning*. Pinter Publishers, London.

MADHOK, A. & TALLMAN, S. B. 1998. Resources, Transactions and Rents: Managing Value through Interfirm Collaborative Relationships. *Organization Science,* 9(3)**,** 326-339.

MAIDIQUE, M. A. & ZIRGER, B. J. 1990. A Study of Success and Failure in Product Innovation: The Case of the U.S. Electronics Industry. *IEEE Transactions on Engineering Management,* 31(4), 192-203.

MALERBA, F. 2002. Sectoral Systems of Innovation and Production, *Research Policy*, 31, 247–264.

MALERBA, F. (eds.) 2004. *Sectoral Systems of Innovation: Concepts, Issues and Analyses of Six Major Sectors in Europe*. Cambridge University Press, Cambridge , UK.

MALONE, T.W. 1987. Modeling Coordination in Organizations and Markets. *Management Science*, 33(10), 1317-1332.

MANSFIELD, E. 1988. The Speed and Cost of Industrial Innovation in Japan and the United States: External vs. Internal Technology. *Management Science*, 34(10),1157-1168.

MANSFIELD, E. 1995. Academic Research Underlying Industrial Innovations: Sources, Characteristics, and Financing. *The Review of Economics and Statistics*, 77, 55-65.

MANSFIELD, E. 1998. Academic research and industrial innovation: An update of empirical findings. *Research Policy,* 26**,** 773-776.

MARCH, J. G. 1991. Exploration and Exploitation in Organizational Learning. *Organization Science*, *2*(1), 71-87.

MCDONALD, J. F., & MOFFITT, R. A. 1980. The Uses of Tobit Analysis. *The Review of Economics and Statistics*, *62*(2), 318-321.

MCDONOUGH, E.F., III, & SPITAL, F.C. 1984. Quick-Response New Product Development. *Harvard Business Review*, 62, 52-62.

MCDONOUGH, E.F., III, & BARCZAK, G. 1990. Speeding Up New Product Development: The Effects of Leadership Style and Source of Technology. *Journal of Product Innovation Management*, 8(3), 203-211.

MCKINSEY & Co.. 1985. Blitzkrieg Product Development: Cut Development Time in Half (by REINERTSEN, D.G.). *Electronic Business*, Jan.15.

MENON, A., CHOWDHURY, J., & LUKAS, B. A. 2002. Antecedents and Outcomes of New Product Development Speed: An Interdisciplinary Conceptual Framework. *Industrial Marketing Management*, 31 (4), 317-328.

MEYER, M. 2007. What Do I Know about Innovation in Nanotechnology? Some Propositions about an Emerging Field between Hype and Path-dependency. *Scientometrics*, 70(3), 779-810.

MILLSON, M.R., RAJ, S.P., & WILEMON, D. 1992. A Survey of Major Approaches for Accelerating New Product Development. *Journal of Product Innovation Management*, 9(1), 53-69.

MIOTTI, L. & SACHWALD, F. 2003. Co-operative R&D: Why and with Whom?: An Integrated Framework of Analysis. *Research Policy,* 32**,** 1481-1499.

MORTARA, L., & MINSHALL, T. 2011. How Do Large Multinational Companies Implement Open Innovation? *Technovation*, 31(10–11), 586-597.

MOWERY, D. C. 1988. *International Collaborative Ventures in US Manufacturing*. Ballinger Pub Co.

MOWERY, D. C., OXLEY, J. E., & SILVERMAN, B. S. 1998. Technological Overlap and Inter-firm Cooperation: Implications for the Resource-based View of the Firm. *Research policy*, *27*(5), 507-523.

MOWERY, D. C. 1998. Collaborative R&D: How Effective is it? *Issues in Science & Technology,* 15(1)**,** 37-46.

MUNNS, A. K. & BJEIRMI, B. F. 1996. The Role of Project Management in Achieving Project Success. *International Journal of Project Management,* 14**,** 81-87.

MURMANN, P. A. 1994. Expected Development Time Reductions in the German Mechanical Engineering Industry. *Journal of Product Innovation Management*, 11(3), 236-252.

MYERS, S., & MARQUIS, D. G. 1969. *Successful Industrial Innovations: A Study of Factors Underlying Innovation in Selected Firms*. Washington, DC: National Science Foundation.

NARIN F., HAMILTON K., OLIVASTRO D. 1997. The Increasing Linkage between U.S. Technology and Public Science. *Research Policy*, 26, 317-330.

NARVER, J. C. & SLATER, S. F. 1990. THE EFFECT OF A MARKET ORIENTATION ON BUSINESS PROFITABILITY. *Journal of Marketing*, 54, 20-35.

NELSON, R. R., & WINTER, S. G. 1982. *An Evolutionary Theory of Economic Change*, Belknap press.

NELSON R.R. 1993. *National Innovation Systems: A Comparative Analysis*. Oxford University Press, New York.

NONAKA I., 1994. A Dynamic Theory of Organizational Knowledge Creation. *Organization Science* 5(1), 14-37.

OGAWA, S. & PILLER, F. T. 2006. Reducing the Risks of New Product Development. *MIT Sloan Management Review*, 47-65.

OLSON, E.M., WALKER, O,C., RUEKERF, R.W., & BONNERD, J.M. 2001. Patterns of Cooperation during New Product Development among Marketing, Operations and R&D: Implications for Project Performance. *Journal of Product Innovation Management*, 18(4), 258-271.

PAGE, A.L. 1993. Assessing New Product Development Practices and Performance: Establishing Crucial Norms. *Journal of Product Innovation Management.* 10(4):273–290.

PATEL, P., & PAVITT, K. 1997. The Technological Competencies of the World's Largest Firms: Complex and Path-dependent, But Not Much Variety. *Research Policy*, 26(2), 141-156.

PATEL, P., & VEGA, M. 1999. Patterns of Internationalisation of Corporate Technology: Location vs. Home Country Advantages. *Research Policy*, *28*(2), 145-155.

PAVITT, K. 1985. Patent Statistics as Indicators of Innovative Activities: Possibilities and Problems. *Scientometrics*, 7(1-2), 77-99.

PENROSE, E. T. 1959. *The Theory of the Growth of the Firm*, 3rd edition. Oxford University Press, Oxford, UK.

PERKMANN, M., & WALSH, K. 2007. University-industry Relationships and Open Innovation: Towards a Research Agenda. *International Journal of Management Reviews,* 9**,** 259-280.

PETERAF, M. A. 1993. The Cornerstones of Competitive Advantage - A Resource-Based View. *Strategic Management Journal,* 14**,** 179-191.

PINTO, J. K., & PRESCOTT, J. E. 1988. Variations in Critical Success Factors Over the Stages in the Project Life Cycle. *Journal of Management,* 14**,** 5-18.

PISANO, G. P. 1990. The R&D Boundaries of the Firm: An Empirical Analysis. *Administrative Science Quarterly*, 35(1), 153-176.

POETZ, M. K., & SCHREIER, M. 2012, The Value of Crowdsourcing: Can Users Really Compete with Professionals in Generating New Product Ideas? *Journal of Product Innovation Management*, 29: 245–256.

POLANYI M. 1966. *The tacit dimension*. Doubleday Anchor, New York.

POWELL, W. W., KOPUT, K. W. & SMITH-DOERR, L. 1996. Interorganizational Collaboration and the Locus of Innovation: Networks of Learning in Biotechnology. *Administrative Science Quarterly,* 41**,** 116-145.

PRAHALAD, C. K., & HAMEL, G. 1990. The Core Competence of the Corporation. *Harvard Business Review*, May-June, 79-91.

PRAHALAD, C.K., & RAMASWAMY, V. 2004. Co-Creating Unique Value with Customers. *Strategy & Leadership*, 32(3), 4-9.

PRAHALAD, C. K., & RAMASWAMY, V. 2004. Co-creation Experiences: The Next Practice in Value Creation. *Journal of Interactive Marketing*, 18: 5–14.

RAGATZ, G. L., HANDFIELD, R. B., & SCANNELL, T. V. 1997. Success Factors for Integrating Suppliers into New Product Development. *Journal of Product Innovation Management,* 14**,** 190-202.

REICH, R. B., & MANKIN, E. D. 1986. Joint Ventures with Japan Give Away My Future, *Harvard Business Review*, 29, 78-86.

RIVKIN, J.W. 2001. Reproducing Knowledge: Replication without Imitation at Moderate Complexity. *Organization Science,* 12, 274–293.

RODRIGUEZ-PINTO, J., CARBONELL, P., & RODRIGUEZ-ESCUDERO, A, I. 2011. Speed or Quality? How the Order of Market Entry

Influences the Relationship between Market Orientation and New Product Performance. *International Journal of Research in Marketing*, 28(2), 145-154.

ROHRBECK, R. 2010. Harnessing a Network of Experts for Competitive Advantage: Technology Scouting in the ICT Industry. *R&D Management*, 40(2), 169-180.

ROIJAKKERS, N., & HAGEDOORN, J. 2006. Inter-firm R&D Partnering in Pharmaceutical Biotechnology Since 1975: Trends, Patterns, and Networks. *Research Policy*, 35, 431-446.

ROSENBERG, N. 1990. Why do Firms Do Basic Research (with Their Own Money)? *Research Policy*, 19(2), 165-174.

ROTHWELL, R., FREEMAN, C., HORLSEY, A., JERVIS, V. T. P., ROBERTSON, A. B., & TOWNSEND, J. 1974. SAPPHO Updated - Project SAPPHO Phase II. *Research Policy,* 3**,** 258-291.

ROTHAERMEL, F. T., & DEEDS, D. L. 2006. Alliance Type, Alliance Experience and Alliance Management Capability in High-technology Ventures. *Journal of Business Venturing*, 21, 429-460.

RUMELT, R.P. 1974. *Strategy, Structure, and Economic Performance, Division of Research*, Harvard Business School, Boston.

RYCROFT, R.W., & KASH, D.E. 1999. *The Complexity Challenge: Technological Innovation for the 21st Century*. Cassell Academic Publishers.

SAMPSON, R. C. 2007. R&D Alliances and Firm Performance: The Impact of

Technological Diversity and Alliance Organization on Innovation. *Academy Management Journal*, 50(2), 364-386.

SCHILLING, M. A., & HILL, C. W. L. 1998. Managing the New Product Development Process: Strategic Imperatives. *The Academy of Management Executive (1993-2005),* 12**,** 67-81.

SCHILLING, M. A., & PHELPS, C. C. 2007. Interfirm Collaboration Networks: The Impact of Large-Scale Network Structure on Firm Innovation. *Management Science,* 53**,** 1113-1126.

SCHULZE, A., & HOEGL, M., 2008, Organizational Knowledge Creation and the Generation of New Product Ideas: A Behavioral Approach. *Research Policy*, 37(10), 1742-1750.

SCHUMPETER, J.A. 1939. Business Cycles : Theory, History, Indicators, and Forecasting, Cambridge University Press.

SHAN, W., WALKER, G., & KOGUT, B. 1994. Interfirm Cooperation and Startup Innovation in the Biotechnology Industry. *Strategic Management Journal,* 15**,** 387-394.

SHENHAR, A. J. & DVIR, D. 1996. Toward a Typological Theory of Project Management. *Research Policy,* 25**,** 607-632.

SINGH, J. & FLEMING, L. 2010. Lone Inventors as Sources of Breakthroughs: Myth or Reality? *Management Science,* 56**,** 41-56.

SIVADAS, E. & DWYER, F. R. 2000. An Examination of Organizational Factors Influencing New Product Success in Internal and Alliance-based Processes. *Journal of Marketing,* 64**,** 31-49.

SLEVIN, D.P. & PINTO, J.K. 1986. The Project Implementation Profile: New Tool for Project Managers. *Project Management Journal*, 18, 57–71.

SMITH, P. G., & REINERTSEN, D. G. 1992. Shortening the Product Development Cycle. *Research-Technology Management*, 35(3), 44-49.

SOFKA, W. & GRIMPE, C. 2010. Specialized Search and Innovation Performance – Evidence across Europe. *R&D Management,* 40**,** 310-323.

SONG, X. M. & PARRY, M. E. 1997. The Determinants of Japanese New Product Successes. *Journal of Marketing Research,* 34(1)**,** 64-76.

SONG, M. & THIEME, J. 2009. The Role of Suppliers in Market Intelligence Gathering for Radical and Incremental Innovation. *Journal of Product Innovation Management*, 26(1), 43-57.

SONG, J., ALMEIDA, P., & WU, G. 2003. Learning–by–Hiring: When Is Mobility More Likely to Facilitate Inter-firm Knowledge Transfer? *Management Science*, *49*(4), 351-365.

STALK, G., & HOUT, T.M. 1990. *Competing against Time: How Time-based Competition is Reshaping Global Markets*. New York: Free Press.

STERN S. 2004. Do Scientists Pay to Be Scientists? *Management Science*, 50(6), 835-
853.

SWINK, M. 2003. Completing Projects On-Time: How Project Acceleration Affects New Product Development. *Journal of Engineering and Technology Management*, 20 (4), 319–344.

SWINK, M., TALLURI, S., & PANDEJPONG, T. 2006. Faster, Better, Cheaper: A Study of NPD Project Efficiency and Performance Trade-offs. *Journal of Operations Management,* 24(5)**,** 542-562.

SYDOW, J., LINDKVIST, L., & DEFILLIPPI, R. 2004. Project-based Organizations, Embeddedness and Repositories of Knowledge: Editorial. *Organization Studies*, 25(9), 1475–89.

TABRIZI, B.N. 2005. *Accelerating Transformation Process Innovation in the Global Information Technology Industry*. USA: Universal Publishers.

TAO, J, & MAGNOTTA, V. 2006. How Air Products and Chemicals "Identifies and Accelerates". *Research Technology Management*, 49(5), 12–18.

TEECE D.J., PISANO, G., SHUEN, A. 1997. Dynamic Capabilities and Strategic Management. *Strategic Management Journal*, 18(7), 509–533.

TEECE, D. J. 1998. Capturing Value from Knowledge Assets. *California Management Review*, 40(3), 55-79.

TEECE, D. J. 2007. Explicating Dynamic Capabilities: The Nature and Micro-Foundations of (Sustainable) Enterprise Performance. *Strategic Management Journal*, 28(13), 1319-1350.

TETHER, B.S. 2002. Who Co-operates for Innovation, and Why: An Empirical Analysis. *Research Policy*, *31*(6), 947-967.

TETHER, B.S., & TAJAR, A. 2008. Beyond Industry–University Links: Sourcing Knowledge for Innovation from Consultants, Private Research Organisations and the Public Science-Base, *Research Policy*, 37(6–7), 1079-1095.

The Economist. 2007. The Love-in, The Move Toward Open Innovation is Beginning to Transform Entire Industries. http://www.economist.com/node/9928227

The Economist. 2009. InnoCentive— A Market for Ideas, A Pioneering " Innovation Marketplace" is Making Steady Progress. http://www.economist.com/node/14460185

The New York Times. 2008. If You Have a Problem, Ask Everyone. http://www.nytimes.com/2008/07/22/science/22inno.html?pagewanted=print

TIDD, J., BESSANT, J. & PAVITT, K. 2006. *Managing Innovation,* New York, John Wiley & Sons, Ltd.

TRIPSAS, M., SCHRADER, S., & SOBRERO, M. 1995. Discouraging Opportunistic Behavior in Collaborative R&D: A New Role for Government. *Research Policy*, *24*(3), 367-389.

TROTT, P., & HARTMANN, D. 2009. Why "Open Innovation" is Old Wine in New Bottles. *International Journal of Innovation Management*, 13(4), 715-736.

TSAI, K.-H. 2009. Collaborative Networks and Product Innovation Performance: Toward a Contingency Perspective. *Research Policy,* 38(5)**,** 765-778.

TUSHMAN, M. L., & ROMANELLI, E. 1985. Organizational Evolution: A Metamorphosis Model of Convergence and Reorientation. *Research in Organizational Behavior,* 7, 171-222.

TUSHMAN, M. L., & ANDERSON, P. 1986. Technological Discontinuities and Organizational Environments. *Administrative Science Quarterly*, 439-465.

TUSHMAN, M., & O'REILLY, C. 1996. Evolution and Revolution: Mastering the Dynamics of Innovation and Change. *California Management Review*, *38*(4), 8-30.

TUSHMAN, M. L. & O'REILLY, C. A. 1996. Ambidextrous Organizations: Managing Evolutionary and Revolutionary Change. *California Management Review*, 38, 8-30.

UK~IRC Report (by A, Cosh., & J, Zhang). 2011. Open Innovation Choices – What is British Enterprise doing? UK ~ Innovation Research Centre, University of Cambridge.

ULWICK, A. W. 2002. Turn Customer Input into Innovation. *Harvard Business Review*, 80, 91-97.

UN, C. A., CUERVO-CAZURRA, A. & ASAKAWA, K. 2010. R&D Collaborations and Product Innovation. *Journal of Product Innovation Management,* 27**,** 673-689.

UTTERBACK, J.M., & ABERNATHY, W. J. 1975. A Dynamic Model of Process and Product Innovation. *Omega*, 33(6), 639–656.

VAN DEN BIESEN, J., 2008, Open Innovation @ Philips Research, Business Symposium "Open Innovation in Global Networks" OECD & Danish Enterprise and Construction Authority, Copenhage.

VAN DE VRANDE, V., VANHAVERBEKE, W. & DUYSTERS, G. 2009. External technology sourcing: The effect of uncertainty on governance mode choice. *Journal of Business Venturing,* 24**,** 62-80.

VAN DE VRANDE, V., DE JONG, J.P.J., VANHAVERBEKE, W., & DE ROCHEMONT, M. 2009. Open Innovation in SMEs: Trends, Motives and Management Challenges. *Technovation*, 29(6–7), 423-437.

VAN DER MEER, H. 2007. Open Innovation – The Dutch Treat: Challenges in Thinking in Business Models. *Creativity and Innovation Management,* 16**,** 192-202.

VANHAVERBEKE, W., & CLOODT, M. 2006. Open Innovation in Value Networks', in H. Chesbrough, W. Vanhaverbeke and J. West (eds), *Open Innovation: Researching a New Paradigm*. Oxford: Oxford University Press, 258-281.

VANHAVERBEKE, W., GILSING, V., BEERKENS, B., & DUYSTERS, G. 2008. The Role of Alliance Network Redundancy in the Creation of Core and Non-core Technologies. *Journal of Management Studies*, 46(2), 215-244.

VANHAVERBEKE, W., VAN DE VRANDE, V. & CHESBROUGH, H. 2008. Understanding the Advantages of Open Innovation Practices in Corporate Venturing in Terms of Real Options. Creativity and Innovation Management, 17, 251-258.

VANHAVERBEKE, W., GILSING, V., & DUYSTERS, G. 2012. Competence and Governance in Strategic Collaboration: The Differential Effect of Network Structure on the Creation of Core and Noncore

Technology. *Journal of Product Innovation Management,* 29(5), 784-802.

VAN OORSCHOT, K., SENGUPTA, K., AKKERMANS, H., & VAN WASSENHOVE, L. 2010. Get Fat Fast: Surviving Stage-Gate® in NPD, *Journal of Product Innovation Management*, 27(6), 828-839.

VEGA-JURADO, J., GUTIERREZ-GRACIA, A., FERNANDEZ-DE-LUCIO, I., & MANJARRES-HENRIQUEZ, L. 2008. The Effect of External and Internal Factors on Firms' Product Innovation. *Research Policy*, *37*(4), 616-632.

VERBEEK, A., DEBACKERE, K., LUWEL, M., ANDRIES, P., ZIMMERMANN, E., & DELEUS, F. 2002. Linking Science to Technology: Using Bibliographic References in Patents to Build Linkage Schemes. *Scientometrics*, 54(3), 399-420.

VERONA, G. 1999. A Resource-Based View of Product Development. *The Academy of Management Review,* 24**,** 132-142.

VESEY, J. T. 1992. Time-to-market: Put Speed in Product Development. *Industrial Marketing Management*, 21(2): 151-158.

VILLENA, V. H., REVILLA, E. & CHOI, T. Y. 2011. The Dark Side of Buyer-supplier Relationships: A Social Capital Perspective. *Journal of Operations Management*, 29, 561-576.

Vinnova Report (by T, Fredberg., M, Elmquist., & S, Ollila -Chalmers). 2008. Managing Open Innovation, Present Findings and Future Directions. ISBN:978-91-85959-07-5.

VON HIPPEL, E. 1988. *The Sources of Innovation,* New York, Oxford University Press.

VON HIPPEL, E. 2002. *Democratizing Innovation,* Cambridge, MIT Press.

VON ZEDTWITZ, M., & GASSMANN, O. 2002. Market versus Technology Drive in R&D Internationalization: Four Different Patterns of Managing Research and Development. *Research policy*, 31(4), 569-588.

WERNERFELT, B. 1984. A RESOURCE-BASED VIEW OF THE FIRM. *Strategic Management Journal,* 5**,** 171-180.

WEST, J., VANHAVERBEKE, W., & CHESBROUGH, H. 2006. Open Innovation: A Research Agenda, in H. Chesbrough, W. Vanhaverbeke and J. West (eds), 2006. *Open Innovation: Researching a New Paradigm*. Oxford: Oxford University Press.

WEST, J. & LAKHANI, K. R. 2008, Getting Clear About Communities in Open Innovation. *Industry & Innovation*, 15(2), 223-231.

WOODRUFF, R. 1997. Customer value: The next source for competitive advantage. *Journal of the Academy of Marketing Science*, 25, 139-153.

ZAHAY, D., GRIFFIN, A. & FREDERICKS, E. 2004. Sources, uses, and forms of data in the new product development process. *Industrial Marketing Management,* 33**,** 657-666.

ZAHEER, A., GOZUBUYUK, R. & MILANOV, H. 2010. It's the Connections: The Network Perspective in Interorganizational Research. *Academy of Management Perspectives,* 24**,** 62-77.

ZAHRA, S. A., & GEORGE, G. 2002. Absorptive Capacity: A Review, Reconceptualization, and Extension. *Academy of Management Review*, 27(2), 185-203.

ZHANG, J., & BADEN-FULLER, C. 2009. The Influence of Technological Knowledge Base and Organizational Structure on Technology Collaboration. *Journal of Management Studies*, 47(4), 679-704.

ZIRGER, B. J., & MAIDIQUE, M. A. 1990. A Model of New Product Development: An Empirical Test. *Management Science*, *36*(7), 867-883.

ZIRGER, B.J., & HARTLEY, J.L. 1994. A Conceptual Model of Product Development Cycle Time. *Journal of Engineering and Technology Management*, 11(3–4), 229-251.