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On strategies enhancing technological learning and technological performance in R&D-intensive corporations

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Daar de proefschriften in de reeks van de Faculteit Economie en Bedrijfswetenschappen het persoonlijk werk zijn van hun auteurs, zijn alleen deze laatsten daarvoor verantwoordelijk.

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In a Tour de France not every stage is the same. During flat stages, the temptation to doze off in the slow, steady pace of the peloton lies around the corner. Time trials are all about your mission and the ticking stopwatch. A rider who wants to reach the Champs-Elysées with his head held high, however, will inevitably have to tackle the mountain stages as well.

Starting a PhD journey for sure bears some similarities to riding a Tour de France in your rookie year. Eager for adventure, unknowing what will come but hungry for success and loaded with a good dose of courage, you start your journey. You have the opportunity to spend several years on a subject that really fascinates you, you're challenged to discover, to sometimes fall and stand up again. Oftentimes you're tempted to draft, to enjoy the sweet freedom that being a PhD student offers. After all, Paris is far away. There's only one road to success, however, and that path also leads through the mountains.

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Chapter 1
Introduction

1.1 General introduction

In the course of only a few decades, firms in nearly every sector, but especially in high-tech sectors characterized by high dollar amounts of R&D inputs, have conceded that fruitful innovation requires establishing ties with external collaborators (Nelson & Winter, 1982; Stuart & Podolny, 1996; Fleming & Sorenson; 2004; Laursen, 2012). In the light of this transition, flows of knowledge and human talent seem to increasingly transcend organizational and geographic boundaries (Agarwal *et al.*, 2009; Boschma, 2005). Moreover, successful innovators achieve high monetary returns on their investments in innovation by tapping into the skills and talents of others. By doing so, they can speed up the innovation process (Leone & Reichstein, 2012) and unfold unexplored ways to create value for their clients and partners in their innovation ecosystem. One way in which firms can source in externally developed knowledge, is by tapping into the markets for technology (Arora & Gambardella, 2010). The option to turn to markets for technology in order to gain exposure to knowledge and talent outside of one's own organization changes the traditional mindset in which the only available option for a company wishing to introduce an innovation is to develop the technology in-house (Arora *et al.*, 2001). Rather, markets for technology allow firms to search, evaluate and integrate external technology in order to complement in-house technological knowledge and thus facilitate recombining internal and external knowledge components in order to generate novel technology (Arora & Fosfuri, 2003; Fleming, 2001; Hargadon & Sutton, 1997; Laursen & Salter, 2006). Particularly in high-tech and fast-paced industries, the acquisition of external knowledge allows companies to spread their risk and cost and shorten the development of

inventions (Ahuja, 2000), and thus forms an attractive alternative to the option to only develop R&D in-house. Furthermore, given the generality of technologies, established companies may opt to supply their technologies to distant uses that they cannot reach themselves by using their downstream capabilities (Arora & Gambardella, 2010). Markets for technologies may thus provide a platform for firms to generate revenues on otherwise unused technologies. A prime example in this respect is the case of Eastman Kodak in the 1990s. As part of a reorganization effort of their R&D strategy, Kodak invested heavily in the development of basic technologies in nanotechnology, wireless technologies and other fields. While some of these technologies were used internally for new product development, Kodak also actively licensed and created spin-offs in order to use their inventions in other applications that were not core to Kodak. While markets for technologies offer firms interesting alternative routes to monetize on their R&D efforts, however, they are at risk of installing unwanted competitors if they do not act diligently in these markets. Arora & Fosfuri (2003), in this respect, signal a trade-off between a revenue effect (the monetary rewards of trading technology) versus a rent-dissipation effect, which may destroy future firm value by creating competitors in the downstream markets in their core fields. Within the context of markets for technology, several vehicles have emerged that have been shown to be effective ways of tapping into knowledge outside a firm's own organizational context. For instance, firms can gain access to technology and knowledge of partners by means of formal ways of collaboration, such as a decision to co-patent, to engage in technology licensing with a partner (Arora *et al.*, 2001; Link & Scott, 2002; Athreye & Cantwell, 2007), by means of setting up research alliances (Powell *et al.*, 1996; Carayannopoulos & Auster, 2010), or by taking minority equity stakes in another firm by means of CVC investments (Dushnitsky & Lenox, 2005; Dushnitsky, 2006).

Another significant pool of knowledge that innovative companies can tap into resorts in the establishment of industry-science links. The relationship between science and technology has

gained a prominent place within the body of literature on innovation. For instance, multiple studies suggest that a firm's scientific activity is related to their innovative performance, as measured by patent counts (Gambardella, 1992; Arora *et al.*, 2015), average patent quality (Fabrizio, 2009), or the degree of radicalness of subsequent inventions (Della Malva *et al.*, 2015). Scholars have highlighted several advantages of performing (basic) science in-house. For instance, it facilitates the search towards new inventions and provides science-backed direction to more applied research within the firm, while it also increases a firm's ability to absorb externally generated knowledge (Rosenberg, 1990; Arora et al, 2015; Arora *et al.*, 2017). Furthermore, the body of literature suggests a positive mediating impact of involving academic research partners into a firm's own scientific efforts (Cockburn & Henderson, 1998; Belderbos *et al.*, 2004). Basic research institutions play a crucial role in firm's innovations (Bozeman, 2000; Salter & Martin, 2001; Cohen *et al.*, 2002), since they are a cornerstone in the diffusion of basic knowledge that leads to innovations in the industry (Mansfield & Lee, 1996) and the development of ties between universities and industry is believed to be an important driver of innovation processes (Perkman & Walsh, 2007). Establishing science parks, in which R&D-intensive companies are clustered and which provides on-park companies with a direct link to basic research institutions, is believed to function as another vehicle allowing R&D-intensive firms to tap into externally generated knowledge. For instance, it is shown that firms which are located on a science park have a higher likelihood to establish connections with research institutions and other firms, which allows them to increase their recombinatory set on which novel technologies are based (Löfsten & Lindelof, 2002; Weitzman, 1998; Fleming, 2001; Arthur, 2009). Furthermore, the establishment of inter-firm networks and links with science is shown to have a positive impact on the diversity of the knowledge portfolio of science park-based firms (Quintas *et al.*, 1992). Lastly, a science park may provide networking opportunities between scientists due to bringing them geographically

closer to one another, thereby overcoming the fact that knowledge is not 'in the air', but a barrier of tacitness that sticks to knowledge has to be overcome in order to allow for effective diffusion, as this type of knowledge transfer benefits from close interactions in the form of face-to-face contacts (Howells, 2002; Gertler, 2003).

By analyzing different performance criteria across R&D-intensive firms, mainly with a focus on the biotech and pharmaceutical context, this Ph.D. dissertation aims to explore the workings of several of these vehicles that allow firms to tap into technological knowledge generated outside their own organizational boundaries, and tries to uncover strategic benefits for companies undertaking such activities, in terms of learning from their knowledge partners and the likelihood of generating inventions of high significance within the technological field they are active in. Furthermore, based on the findings of the research papers presented in this dissertation, I finish with a set of policy and managerial implications which may assist companies and policy makers in enhancing their strategic innovative goals.

In the following paragraphs, I will present an overview of the different chapters of this doctoral dissertation.

1.2 Overview of the chapters

This doctoral dissertation is a collection of three empirical essays related to innovation strategies of R&D-intensive firms. The first two essays study the technological impact of tapping into market of technologies by means of technology licensing and corporate venture investments, respectively. The third essay looks at the impact of establishing industry-science links by being part of a science park on the propensity of generating inventions with a high technological impact.

Essay 1

The first essay, "Do licensors learn from licensing out? Empirical evidence from the pharmaceutical and biotech industry" investigates the effect of licensing out technology on the subsequent likelihood to learn from the licensee. Prior literature has described the rise of technology licensing over the last decades (Arora *et al.*, 2001), and primarily highlights the potential it offers for firms to offer their technologies on a market for technology instead of commercializing their innovations themselves (Arora & Fosfuri, 2003; Teece, 1986). While the financial performance effects of monetizing on R&D through licensing drawn a lot of attention in prior literature (Katz & Shapiro, 1985; Gambardella *et al.*, 2007; Fosfuri, 2006), the knowledge transfer and possible associated learning effects stemming from licensing have so far exclusively been covered from the licensee point-of-view (Johnson, 2002; Arora & Ceccagnoli, 2006; Leone & Reichstein; 2012; Leone *et al.*, 2016). However, this body of literature generally neglects the fact that a licensing agreement also often establishes further interactions or resource sharing between the licensing partners (Agrawal, 2006; Hagedoorn & Hesen, 2007). For instance, it is estimated that around 60% of licensing agreements in the biotech industry are embedded in broader partnerships, such as collaboration agreements or guidance tracks helping the licensee to implement the transferred knowledge (Hagedoorn *et al.*, 2009; Klueter *et al.*, 2017). Given these frequent interactions between licensor and licensee, it might be worthwhile to explore whether there are 'reverse learning' effects at play as well. Malerba (1992) shows that companies can learn in various ways from one another, including 'learning-from-interaction'. Therefore, in this study, we focus on the potential learning benefits stemming from a licensing agreement to the licensor. Up to our knowledge, this essay is among the first to investigate this 'reverse learning' in licensing agreements. One exception is a study by Srivastava & Wang (2015), who show that a licensor increases its future patenting propensity after licensing but without looking at whether the information flow captured by

patent citations indeed stems from the licensee in a dyadic setup. In that respect, a main contribution of our study is to investigate whether there is indeed a knowledge flow-back from the licensee to the licensor in a licensing agreement, i.e. whether a licensor learns from its licensee.

We use data on 1,861 unique licensing deals of 254 consolidated licensor firms active in the pharmaceutical and biotech industries, with the firms in our sample being top-R&D spenders within their industry. Licensing deals are identified using Clarivate Analytics RECAP, which is a database composed of licensing agreements and other forms of collaboration between firms in the life sciences industry. Our data is further complemented by firm-level data on patenting, which is drawn from the PATSTAT database. Each deal is observed in a 5-year stock of licensing agreements on a dyadic level (i.e. between a licensor and a licensee) We create a dummy variable assuming value '1' if there has been licensing activity in the dyad in the past five years. For each treatment observation in our sample, we sample one matched control observation of in-sample firm dyads that have no recent licensing activity between the two dyad partners. In order to obtain a balanced panel of treatment and control dyad observations, we employ a Coarsened Exact Matching (CEM) approach, based on six matching parameters. Specifically, we match treatment and control groups on (1) the prior citation behavior within the dyad, (2) the technological similarity of the dyad partners, (3) the geographical proximity of the dyad partners, (4) the difference in firm sizes between the dyad partners, (5) the in-licensing activity between the dyad partners and (6) their alliance activity.

Our main equation is a negative binomial model, with the dependent variable specified as the number of backward patent citations from licensee to licensor in the dyad. We match each treatment observation with a counterfactual observation using a Coarsened Exact Matching algorithm based on six relevant dyad-level matching criteria (difference in firm size, technological similarity, geographic proximity, prior alliance link, prior in-licensing link and

citation behavior in the dyad prior to the period in which we measure licensing), so that our panel of treatment and control observations is balanced on these key covariates. We observe that firms that out-license their technology have a higher likelihood of citing patents of their licensee following a licensing agreement as compared to citing patents of firms with whom they have not entered a licensing agreement in the past. This observation provides strong a strong indication of a reverse learning effect by the licensor.

We deepen the insight our main finding by running several robustness checks. First, we find that a reverse learning effect by the licensor is still taking place after removing examiner-given citations. Furthermore, we find find evidence for 'reverse learning' for both pharmaceutical and biotechnology firms. Lastly, we find that the reverse learning by licensors is primarily geared towards to higher-value technologies, and that the majority of licensor citations to licensee's patents are new, i.e. that these patents were not cited before by the patents of the licensor in the prior five years. These supplementary analyses indicate that the interaction with licensees is leveraged by licensors to explore technologies that are new to them and that are above-average valuable.

Essay 2

The first essay in this dissertation associated technology licensing to learning outcomes for the licensor firm. In the second essay in this dissertation, "Dipping a toe before plunging in? The relation between CVC investments and entry into new technology domains", we explore a different vehicle for exploring unfamiliar technology which a firm can subsequently recombine with knowledge components they already possess within their organizational boundaries. In this second essay, we look at the effect of making corporate venture capital (CVC) investments in ventures active in a new-to-the-firm technology domain on the investor firm's subsequent propensity to become active (i.e. start patenting) in that technology domain. Existing research

suggests CVC investments[1] to be an effective tool for investor firms to explore and learn about novel technologies while maintaining a minimal commitment and therefore only being exposed to a limited amount of risk (Van den Vrande, 2009). Furthermore, prior research highlights that CVC investments are associated with better innovation outcomes, which investors may achieve as a result of learning (Dushnitsky & Lenox, 2005; Dushnitsky, 2006). However, organizational learning literature dictates that mere exposure to new-to-the-firm technologies as such are an insufficient basis for innovation. Thus, the question arises whether CVC investments are not only effective as tools for acquiring exploratory knowledge through minority investments in ventures, but also serve as learning channels in the sense that investor firms acquire, but also assimilate and integrate newly acquired knowledge components into their pre-existing knowledge structures in order to start building up competencies in these new technology domains. Therefore, we argue in this paper that investor firms have successfully run through these stages of integrating new knowledge components following a CVC investment in a technology domain, i.e. that they have learned from having made the investment, when they subsequently start inventing in that technology domain.

Our estimation sample consists of longitudinal data (1995-2015) on the technological and CVC activities of 244 consolidated firms active in the pharmaceutical and biotechnology industries. Firms in our sample have been selected as being top-R&D spenders within their respective industries. Data on CVC investments are collected from the SDC VentureXpert database. This database combines information from industry associations with information from the investment banking industry and has been used in several prior studies on the effect of CVC investments (Dushnitsky & Lenox, 2005; Keil *et al.*, 2008; Dushnitsky & Lavie, 2010; Belderbos *et al.*, 2018). We combine this data with firm- and technology-level data on patenting

[1] In a CVC investment, an investor firm makes a minority equity investment in another firm, often a relatively young venture.

(PATSTAT) and other technology sourcing agreements (Clarivate RECAP). Using an IV 2SLS model, we estimate the effect of making CVC investments in a technology domain on the likelihood of becoming active in that technology domain. The variable of interest that is used throughout this essay, a firm's five-year stock of prior CVC deals in a technology domain, is instrumented for by the number of other investors in a technology domain. Under this model specification, we find support for the hypothesis that prior CVC investments in a technology domain increase the subsequent likelihood to start patenting in that domain. Furthermore, in this study we explore several moderating effects on the relationship between CVC investments and entry into a new technology domain. First, we take the quality of the venture that the focal firm has invested in, and the number of co-investors in the focal technology domain into consideration. The idea here is that investors in higher-quality ventures do not only have access to superior knowledge and are more eager to seek the acquisition of this knowledge, but they are furthermore more incentivized to exploit it. A second moderating effect this paper looks at is the number of co-invested CVCs in an investment syndicate. The rationale behind this moderator is that CVC investors that tend to invest as part of a consortium of CVC investors have an additional – horizontal – learning channel, complementing the learning channel from their ventures. Synergies created through the interaction between these two learning channels can be expected to increase the likelihood that the learning which a firm achieves through their CVC investments will lead them to enter novel technological domains. A final moderator in this study is the technological relatedness to the investor's existing knowledge base. The idea behind this moderator is that a firm's ability to learn from a CVC investment, and thus generate novel technology building on the knowledge of a venture, may increase when the new technology domains are technologically closer to what firms already know (Cohen & Levinthal, 1990). While we find no strong empirical evidence for the moderating influence of

investees' quality, we do find that firms that co-invest with other corporate investors are more likely to enter new technology domains.

Essay 3

Whereas the first two chapters of this Ph.D. dissertation have looked at the markets for technology as a way of establishing links with external collaborators to source in knowledge, this last chapter takes a different approach towards the search of external knowledge. It does that by looking at the establishment of industry-science links as a way to source in knowledge from external partners. Prior research has highlighted the pivotal role that academic research plays to complement a firm's own scientific research (Bozeman, 2000; Salter & Martin, 2001; Cohen *et al.*, 2002). In this paper, we therefore study the innovative impact of an invention being generated on a science park. Although the literature adopts multiple definitions about what science parks are, generally they are considered to be high-tech spatial clusters (Oerlemans & Meeus, 2005; Phan *et al.*, 2005; Hansson *et al.*, 2005; Salvador & Rolfo, 2011), aimed at building bridges between basic research institutions and the industry (Fukugawa, 2006; Squicciarini, 2009; Fikirkoca & Saritas, 2012) with a focus on commercializing basic research. Given that science parks are often associated with intense inventive activity, a considerable body of literature has focused on the innovative performance of firms based on science parks (Westhead, 1997; Löfsten & Lindelöf, 2002; Colombo & Delmastro, 2002; Siegel *et al.*, 2003), while other studies have focused on the role of the research institution linked to a science park (Felsenstein, 1994; Westhead & Storey, 1995; Vedovello, 1997; Link & Scott, 2003; Marques *et al.*, 2006). However, all of these studies conceive innovative output as a quantity-oriented measure, while the quality of inventions generated on these science parks remains an open question. Since there generally exists a strong link between science parks and basic research institutions, and prior literature suggests a positive relationship between access

to basic science and generating inventions with a high technological impact (Della Malva *et al.*, 2015), we believe that science parks might be a fertile ground for science park firms to generate high-impact (or breakthrough) inventions. Therefore this essay addresses this question by studying whether on-park inventions of a tenant firm in a given technological domain and year have a higher likelihood of becoming a breakthrough invention than inventions in the same technological field and year generated by the same firm in an off-park location. In line with prior research, we consider a patent which is a three-standard deviation outlier in the number of forward citations received in a 5-year window following its application year to be a breakthrough invention (Singh & Fleming, 2010; Della Malva *et al.*, 2015), since forward citations are generally accepted to be a solid indication of a patent's technological value (Albert *et al.*, 1991; Jaffe *et al.*, 2000).

Throughout our empirical analyses, we employ data on 7,692 US patents filed between 1980 and 2010, filed by science-park based firms on 60 US science parks. Determining whether a patent is on- or off-park is done based on geo-coded disambiguated inventor data (Li *et al.*, 2014). Our main equation is a probit model, where we regress our variable of interest, a dummy variable indicating whether a patent is generated on- or off-park, on our dependent variable, a dummy variable indicating whether the focal patent is a breakthrough patent. We use an exact matching approach to link 3,846 treatment (on-park) patents to an equal number of off-park patents, filed by the same firm, in the same technology domain, in the same application year. Controlling for a set of confounders at the level of the science park, the tenant firms and the science park region as well as for time-, firm-, and technology-invariant unobservable traits, we find patents that have been generated on a science park to have a substantially higher technological impact compared to patents created off-park. We furthermore find that the likelihood of a patent being a breakthrough invention is higher if the invention is made in the proximity of a top-tier university. Lastly, this study finds support for an 'anchor tenant'

hypothesis (Agrawal & Cockburn, 2003), in the sense that the presence of large R&D-intensive tenants, able of generating externalities that smaller innovative firms can benefit from, plays an important role in the propensity of generating a breakthrough invention.

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Chapter 2
Do Licensors Learn from Out-Licensing? Empirical Evidence from the Pharmaceutical Industry[2]

Abstract

The strategic decision to out-license technology has been characterized in the literature as a trade-off for the firm between a direct monetary reward and a unidirectional outflow of knowledge that may erode future profits. In this paper, we provide evidence that this characterization is incomplete. We start from the observation that many licensing contracts contain explicit organizational arrangements for transferring the licensed technology, involving repeated and close interaction between the licensing partners. We argue that these interactions provide opportunities for the licensor to learn from the licensee. Using data on 1,861 licensing deals of 254 pharmaceutical and biotech firms between 1995 and 2015, we show that licensors are more likely to cite the inventions from their licensing partner subsequent to an out-licensing deal than matched control firm-pairs that do not engage in licensing. The paper makes two main contributions to the literature on technology licensing: first, it demonstrates that not only licensees, but also licensors, can learn from licensing. Second, it extends the theoretical framework behind strategic out-licensing decisions by showing that learning from out-licensing is an additional (positive) element in the trade-off faced by licensors, in addition to short-term revenue generation and the risk of long-term rent dissipation.

Keywords: licensing, markets for technology, firm learning, pharmaceutical industry

[2] This chapter is based on a working paper co-authored with Stijn Kelchtermans (KU Leuven), Bart Leten (KU Leuven) and Massimo Riccaboni (IMT Lucca).

2.1 Introduction

The last few decades have witnessed a rapid growth of licensing as a means to transfer technology between firms (Ceccagnoli & Jiang, 2013; Hagedoorn, 2002; Pammolli *et al.*, 2020; Somaya *et al.*, 2011). This is especially true for high-tech industries such as semiconductors, chemicals, electronics, but also pharma and biotech – industries that are characterized by large investments in R&D and high rates of patenting (Arora *et al.*, 2001; Orsenigo *et al.*, 2001). Within these industries, companies frequently engage in out-licensing in order to capitalize on their R&D efforts (Arora & Fosfuri, 2003) as an alternative to commercializing their innovations themselves (Teece, 1986), and licensing revenues have become to represent a considerable share of their profits (Arora & Fosfuri, 2003; Fosfuri, 2006; Rivette & Kline, 2000).

Prior literature has pointed to these financial effects of out-licensing (Gambardella *et al.*, 2007; Katz & Shapiro, 1985) but also found that the competitive position of a firm that engages in out-licensing may be weakened if licensees use the transferred technologies to compete directly with the licensor (Arora *et al.*, 2001; Fosfuri, 2006; Riccaboni & Moliterni, 2009). Licensors thus face a trade-off between the direct monetary rewards from licensing (a short-term *revenue* effect) and the risk of installing a new competitor by licensing out their technology (a long-term *rent-dissipation* effect). The key point of this paper is that this characterization of the trade-off that out-licensing firms face, is incomplete. Technology licensing has traditionally been characterized as an arm's length process whereby a licensor provides a licensee the right to use a technology in exchange for money, lacking any further interactions or resource sharing between the licensing partners (Agrawal, 2006; Hagedoorn & Hesen, 2007). However, many licensing contracts contain explicit arrangements for transferring the licensed technology, e.g. by being part of broader collaboration agreements, by defining technical support to be provided by licensors, or through installing meetings of

supervisory committees that are set up for the specific purpose of the licensing deal and that contain representatives from both firms (Hagedoorn *et al.,* 2009*;* Klueter *et al.*, 2017; Leone *et al.*, 2016; Van Kranenburg *et al.*, 2014). Hagedoorn *et al.* (2009) estimate that 60% of the licensing deals in the biopharmaceutical industry are embedded in such broader partnerships.

These 'partnership-embedded' licensing deals involve purposeful and frequent interactions between the licensor and the licensee, which gives way to opportunities for learning; so-called *learning from interaction* (Malerba, 1992). While the more straightforward learning effects accruing to the licensee have been highlighted extensively in the literature (Johnson, 2002; Arora & Ceccagnoli, 2006; Leone *et al.*, 2016; Wang and Li-Ying, 2014), the learning effects for the licensor have so far remained underexplored, making this paper among the first to delve into this relationship[3]. In particular, in this study we consider whether a licensor learns from its counterparty, the licensee, after a licensing agreement. We will refer to this type of learning as 'reverse learning' to distinguish it from the knowledge flow *from* the licensor to the licensee (i.e. learning on behalf of the licensee).

We test for the occurrence of reverse learning using data on licensing agreements signed between 1995-2015 and patent (citations) of 254 large R&D spending pharmaceutical and biotech firms. Our empirical analysis provides support for our hypothesis on learning-by-interacting with the licensee: using coarsened exact matching (CEM) and a multivariate

[3] A noticeable exception is the study by Srivaskava and Wang (2015), which reports a positive correlation between technology transfer (including various types of activities, such as formal licensing, but also contract R&D, and R&D consulting and services) and a firm's patent filing propensity. Our work differentiates itself from this study by i) focusing only on the role of technology licensing, and ii) relying on data on patent citations to construct a direct measure of learning by the licensor about technologies of their licensees.

analysis, we find that a licensing deal increases subsequent citations by the licensor to patents of the licensee by 146%, indicating knowledge flows and reverse learning.

This study contributes to the literature on technology licensing. First, we show that not only licensees (Leone & Reichstein, 2012; Leone *et al.*, 2016; Moreira *et al.*, 2018; Wang & Li-Ying, 2014) but also licensors can learn from interacting under a license agreement. Second, we broaden the discussion on the rationale behind firms' decisions to out-license technology (Arora *et al.*, 2001; Fosfuri, 2006). In particular, we show that reverse learning from out-licensing is an additional, positive element in the trade-off faced by licensors, which has traditionally been casted only in terms of rent dissipation versus revenue effects.

2.2 Theoretical background

2.2.1 Learning from in-licensing

The way that firms organize themselves for the development of new technologies has undergone significant changes over the last years (Cassiman & Veugelers, 2006). While innovation traditionally used to occur in the closed environment of an individual firm, we have witnessed a gradual shift towards a system of open innovation, emphasizing the internal use of externally developed knowledge and the use of external markets for internal technologies (Chesbrough, 2003; Chesbrough *et al.*, 2006). As a result of the shift to open innovation and the embracement of externally developed knowledge by firms (Chesbrough, 2003; Enkel *et al.*, 2009), technology licensing has seen a steep rise in volume and importance over time (Arora *et al.*, 2001; Anand & Khanna, 2000b; Athreye & Cantwell, 2007; Arora & Gambardella, 2010; Ceccagnoli & Jiang, 2013; Riccaboni & Pammolli, 2002) and has become one of the most important vehicles for transferring technology between firms and for the diffusion of technological knowledge (Anand & Khanna, 2000a; Arora & Fosfuri, 2003).

There are different reasons for firms to engage in technology licensing (Arora & Gambardella, 2010; Gambardella *et al.*, 2007; Sakakibara, 2010; Zuniga & Guellec, 2008; Radauer & Dudenbostel, 2013). From the perspective of the licensor, licensing can generate revenues (Radauer & Dudenbostel, 2013), can increase the demand for a technology (Shepard, 1987) and set technology standards (Zuniga & Guellec, 2009), or can be a mechanism for capturing a share of future inventions of the licensee (Ahuja *et al.*, 2013; Leone & Reichstein, 2012; Laursen *et al.*, 2017). From the perspective of the licensee, licensing can stop infringement of intellectual property and ensure freedom-to-operate, and can allow firms to learn about new technologies (Radauer & Dudenbostel, 2013).

The knowledge flows and associated learning aspects of licensing have been studied quite extensively in the last years, with the available literature focusing on the learning effects for the *licensee* (Arora & Ceccagnoli, 2006; Johnson, 2002; Laursen *et al.*, 2010; Leone & Reichstein, 2012; Leone *et al.*, 2016; Moreira *et al.*, 2018; Wang & Li-Ying, 2014). For instance, using data on 160 Chinese high-tech firms, Wang and Li-Ying (2014) found a positive association between in-licensing of foreign technology and innovation performance. Leone and Reichstein (2012) collected data on 133 patent license agreements and used a matching methodology to show that licensees are faster at innovating than non-licensees, provided that contracts do not contain grant-back clauses and licensees are familiar with licensed technologies. In a follow-up study, Moreira *et al.* (2018) found that the speed by which firms can absorb unfamiliar licensed technologies and develop new innovations depends on the diversity and density of the intra-firm inventor network. Finally, Laursen *et al.* (2010) demonstrated that the combination of technology in-licensing and experience in technology exploration allows firms to engage in more distant technology exploration.

2.2.2 Learning from out-licensing

While the learning effects of in-licensing have gained a lot of attention, surprisingly little empirical research has been conducted with respect to the possibility of 'reverse learning' i.e. learning by the licensor. One reason to expect why firms may learn from out-licensing is that a large share of licensing agreements are embedded in a broader partnership (Hagedoorn *et al.*, 2009; Leone *et al.*, 2016), which implies that the licensor and licensee closely interact with each other in order to ensure that the exchange of knowledge and its subsequent implementation are successful (Luo, 2008). Malerba (1992) argues that firms are able to learn in a variety of ways from each other, including *learning by doing* and *learning from spillovers* (the types of learning generally assumed to take place in technology in-licensing), but also *learning from interaction*. This viewpoint of interactive learning is also supported in other research on inter-firm learning (Kogut & Zander, 1992; Mowery *et al.*, 1996; Lane & Lubatkin, 1998; Oxley & Wada, 2009; Yang *et al.*, 2010). Interactive learning assumes that the 'learning' firm gets in close contact with the 'teacher' firm in order to not just foster the transfer of codified and articulable knowledge, but also to acquire tacit knowledge components i.e. the 'how and why' knowledge (Polanyi, 1966).

It is argued that technologies that are characterized by high levels of 'tacit' or 'sticky' knowledge require higher amounts of interaction and face-to-face contacts between scientists and engineers of firms in order to be effectively transferred (Polanyi, 1966; von Hippel, 1994). These interactions are especially important in complex industries, such as the bio-pharmaceutical industry, in which tacit knowledge transfer is a crucial aspect of innovation (Lundvall, 1998, Lundvall & Johnson, 1994; von Hippel, 1988; Kline & Rosenberg, 1986). Therefore, we argue that an important dimension of the learning process of a licensor in the bio-pharmaceutical industry resides in the close interactions with the licensees.

Leone *et al.* (2016) refer in this context to the existence of 'thick' licensing contracts, which provide the legal basis for the disclosure and exchange of additional information and knowledge beyond what is described in the patented technologies that are subject to transmission from the licensor to the licensee. In other words, technology licensing contracts often not merely involve the right to use a certain technology, but also include clauses that specify the modalities of reasonable assistance and information sharing (Leone *et al.*, 2016; Macho-Stadler *et al.*, 1996).[4] While licensees may learn from the assistance of licensors, licensors can also learn from interacting with licensees in the technology transfer process. Such 'reverse learning' may take the form of generating insights into novel applications of the out-licensed technologies or ideas for recombining licensor and licensee technology. Therefore, we expect that licensors can learn from out-licensing technologies to licensees.

2.3 Data and Methodology

2.3.1 Sample

In order to study the impact of licensing on reverse learning by the licensor, we collected longitudinal data (1995-2015) on 254 European, US and Japanese top-R&D spending firms in the bio-pharmaceutical industry. These firms are identified from the 2004 and 2015 editions of the EU Industrial R&D Investment Scoreboard that provides listings of the top R&D spending firms in the world across industries.

Information on license agreements for the firms is obtained from the Thomson Reuters RECAP database (now part of *Clarivate Analytics' Cortellis platform*), which includes information on licensing deals and other forms of collaboration between firms in the pharma industry. In RECAP, each deal is identified by a combination of codes in order to specify the

[4] In our analysis we matched 116 licensing deals in which one of our firms acted as licensor with contract information. A total number of 66 out of these 116 deals (56.9%) contained a technological assistance clause.

nature of the collaboration. Since we are interested in identifying licensing deals that have a technology background rather than commercial agreements in which the licensee is merely responsible for marketing or distribution of a licensed drug, we excluded licensing deals marked by codes that indicate a marketing-driven license agreement, resulting in 1,861 unique licensing deals among the 254 sample firms.[5] Table 2.1 provides an overview of the 20 largest licensors and licensees by the number of licensing deals. While the licensors includes both pharmaceutical and biotechnology firms, most licensees are pharmaceutical companies.

Table 2.1. Overview of 20 largest licensors and licensees, by number of licensing deals

	Licensor	**# obs**		**Licensee**	**# obs**
1	Roche	**80**	*1*	Pfizer	**139**
2	Crucell	**68**	*2*	Novartis	**133**
3	Elan	**58**	*3*	Roche	**127**
4	Affymetrix	**57**	*4*	Glaxosmithkline	**126**
5	Incyte	**56**	*5*	Abbott Laboratories	**88**
6	Cephalon	**55**	*6*	Sanofi	**87**
7	Morphosys	**55**	*7*	Astrazeneca	**81**
8	Abgelix	**53**	*8*	Merck Co	**73**
9	Bristol Myers Squibb	**51**	*9*	Johnson & Johnson	**71**
10	Celltech	**44**	*10*	UCB	**60**
11	Array Biopharma	**43**	*11*	Takeda Pharma	**55**
12	Glaxosmithkline	**42**	*12*	Bayer	**54**
13	Immunogen	**42**	*13*	Astellas Pharma	**53**
14	Pfizer	**41**	*14*	Amgen	**49**
15	Shire	**39**	*15*	Aventis	**46**
16	Novartis	**37**	*16*	Boehringer Ingelheim	**41**
17	Pharmagene	**35**	*17*	Watson Pharma	**39**
18	Astrazeneca	**34**	*18*	Elan	**35**
19	Seattle Genetics	**33**	*19*	Qiagen	**34**
20	Infinity Pharma	**33**	*20*	Recordati	**33**

We rely on patent data from the PATSTAT database (version May 2018) to measure the technological activities of our sample firms. Patents are a good indicator in our context, as

[5] We obtain similar results when marketing-driven licensing agreements are included in the analysis.

the propensity to patent innovations is high in the bio-pharmaceutical industry (Arundel and Kabla, 1998), and patents correlate strongly with other innovation indicators, such as new product announcements (Narin & Noma, 1987; Hagedoorn & Cloodt, 2003). Licensing agreements and patent data are collected at the consolidated firm level, i.e. we take into account not only the parent firms but also their consolidated (majority-owned) subsidiaries. The motivation for performing the consolidation lies in the fact that both patenting and licensing is often performed on the level of the subsidiary. We identify firm subsidiaries based on yearly lists of majority-owned subsidiaries (minimum 50% ownership) reported in the Orbis financial database (Bureau Van dijk). We perform this consolidation exercise annually to account for shifts in company group structures that occur over time due to M&As or spin-offs.

2.3.2 Matching

To examine whether a licensor can learn from licensing to a specific licensee, we have constructed a *licensor-licensee* x *year* dataset. This dataset includes all 4,255 observations for which we observe a licensing agreement in the prior five years. The choice for the period of five years is determined by the fact that it takes time for a licensor to convert the insights obtained through interaction with a licensee into new patented innovations. Licensing is no random event and is determined by a number of factors. In a next step, we therefore construct a control group of firms that have no licensing agreement by matching each of the *licensor-licensee x year* observations with a counterfactual *firm-firm dyad x year* observation using the sample firms that did not enter into a licensing agreement with each other.

We use coarsened exact matching (CEM), an imbalance-reducing matching method proposed by Blackwell *et al.* (2009), that splits the matching variables into different 'bins' and then matches treated and control observations based on these coarsened values. An advantage of the CEM procedure is that it allows the user to decide on the degree of covariate balance *ex ante*, bearing in mind that an increasingly fine-grained coarsening will reduce the number of

matches. Also, expanding the set of matching variables will reduce the chances to identify a "close" counterfactual, so there is a trade-off between the quality of the match and external validity (Azoulay *et al.*, 2011). We match on the following dyadic-level variables which are all expected to impact on the likelihood that two firms have a licensing agreement: *difference in patent stock, technological similarity, geographic proximity, prior alliance link, prior in-licensing link* and *citation behavior within the dyad prior to the period in which we measure licensing (t-6)*. We discuss each of these variables in detail below. Using this matching procedure, we are able to identify a matching control dyad for 1,608 of the 'treated' dyads, which results in a total of 3,216 treated and control observations that we use in our analysis.

2.3.3 Dependent variable: Number of backward patent citations

We rely on patent citations to examine whether a licensor has learned from outlicensing. Patent citations restrict the scope of patent claims to novelty and represent a link to the pre-existing knowledge base upon which patents have been built. This feature has been used by prior studies (e.g. Almeida & Kogut, 1999; Rosenkopf & Nerkar, 2001; Singh & Agrawal, 2011) to justify patent citations as a measure of knowledge flows between firms.

One critique to the use of patent citations as a measure of knowledge flows is that patent citations combine citations provided by the patent applicant and those added by the patent examiner. Therefore patent applicants (firms) may not know some of the references added by the patent examiner (Alcacer & Gittelman, 2006; Criscuolo & Verspagen, 2008). However, surveys of USPTO patent inventors (Jaffe *et al.*, 2000) have shown that patent inventors are familiar with 50% of the cited patent references. Since, on average, 63% of patent citations in USPTO patents are provided by patent examiners (Alcacer & Gittelman, 2006), this indicates that patent inventors (firms) are even aware of some of the references that are added by patent examiners as relevant prior art for their patents.

In order to have a complete measure of knowledge flows and learning, we therefore rely on all (applicant and examiner) patent citations in our basic analysis. Afterwards, we show that we obtain similar results if we only use applicant-given citations to measure knowledge flows. Our measure of reverse learning by a licensor from a licensee is calculated as the count of patent citations in patent applications of the licensor in year t to prior patent applications of the licensee. To avoid double counting in patent citation counts, we integrate citing and cited patent at the PATSTAT patent family level (Martinez, 2011).

2.3.4 Explanatory variable: Out-licensing

The matching procedure generates a dummy variable which indicates whether there has been any licensing activity between a pair of firms in the past five years (t-5; t-1). This dummy takes a value one for the treatment observations and zero for the control observations.

2.3.5 Matching variables

We use the following variables in the matching procedure.

Δ Patent Stock. The difference (Δ) in patent stock of licensor and licensee is measured as the difference in the prior five year patent stocks of both firms. This variable controls for the fact that there may be differences in the size of the patent portfolio of licensors and licensees, with the latter often being larger than the former.[6]

Technological similarity. Firms that display a higher degree of similarity in technologies in their patent portfolios have a higher propensity to engage in technology licensing as they share an interest in the same technologies (Stuart, 1998). We measure the technological similarity of the five year patent portfolios of firm *i* and firm *j* using Jaffe's

[6] Note that in the subsequent regression analysis of firms' propensity to cite the patents of the other firm in the dyad (section 4.2), we control for the absolute size of both firms in the dyad rather than merely accounting for the size difference.

(1986) cosine distance measure at the 6-digit IPC-level. The technological similarity measure takes the value 1 in case of a perfect overlap between both firms' technology portfolios, while it equals 0 if they have no IPC classes in common.

Geographic proximity. Geographic proximity between firms facilitates 'localized learning' (Malmberg & Maskell, 2006) while it also captures localized knowledge spillovers outside of formal inter-firm relations (Griliches, 1979; Owen-Smith & Powell, 2004). In other words, the closer inventors of both firms in the dyad are, the more opportunities they have to physically meet and collaborate with each other, creating opportunities for identifying candidate technologies for out-licensing. We measure geographic proximity by calculating the cosine distance between the firms' geocoded patent portfolios of the past five years. We obtain the data for this measure from the OECD REGPAT database, which links addresses of patent inventors to the regional NUTS-level 3.

In-licensing. Firms may develop mutual licensing relationships whereby firms act both as licensor and licensee (Laursen *et al.,* 2017). The in-licensing variable is measured as the number of in-licensing deals between both firms during the previous five years.

Alliance. Firms may adopt an open innovation strategy and source knowledge via different open innovation channels. We therefore consider two firms that collaborated in the past more likely to engage in technology licensing today (Leone *et al.*, 2016). The alliance variable is calculated as a count of the number of *collaborations*, *co-developments* and *alliances* (as reported in the RECAP database) during the previous five years.

Prior citation count. Finally, we control for prior patent citations between two firms as indicator of the strength of the existing technological relationship between these firms prior to the engagement in technology licensing. This allows us to examine whether outlicensing results in an *increase* in patent citations from a licensor to a licensee. Since technology licensing is

measured over a period of five years, *prior citation count* measures the number of patent citations from the licensor to the licensee in patents in year t-6.

2.4 Empirical Results

2.4.1 Matching

The results of the CEM procedure are shown in Table 2.2. The left panel shows that there are important pre-matching differences for the matching variables in treatment and control samples. Firms that engage in licensing (i.e. the treatment group) display, on average, a larger difference in patent stock and higher values for technological similarity, geographic proximity, alliances, in-licensing and prior citations than firm pairs that have no license agreement (i.e. the control sample). The differences between the matching variables are no longer significant after matching, as shown in the right panel of Table 2.2.[7]

Table 2.2. Comparison of licensing and control samples

	Pre-CEM				Post-CEM			
	Licensing dyads	Non-licensing dyads	Diff.	Pr (|T>|t|)	Licensing dyads	Non-licensing Dyads	Diff.	Pr (|T>|t|)
Observations	4,113	865,401			1,608	1,608		
Δ patent stock	-879.42	4.17	883.60	0.00***	-590.41	-584.01	6.39	0.93
Technological similarity	0.62	0.37	-0.24	0.00***	0.58	0.58	0.00	0.92
Geographic proximity	0.31	0.14	-0,16	0.00***	0.22	0.22	0.00	0.75
Alliance	0.44	0.00	-0.44	0.00***	0.00	0.00	0.00	1.00
In-licensing	0.09	0.01	-0,08	0.00***	0.17	0.17	0.00	1.00
Prior citation count (t-6)	12.03	0.52	-11.51	0.00***	0.43	0.39	-0.04	0.40
Number backward citations	19.49	0.91	-18.58	0.00***	3.49	1.66	-1.83	0.00***

** p<0.05; ** p<0.01; *** p<0.001, two-tailed.*

The bottom row of Table 2.2 shows average values of the dependent variable after matching, providing a first test of reverse learning by the licensor. A licensor makes on average

[7] The default automatic binning method in CEM ('Scott' binning) did not result in a balanced sample for the *prior citation link* variable, unlike the other five matching variables. Given that *prior citation link* is an integer and heavily skewed towards zero, we used the flexibility of CEM to manually bin this variable into 300 equal strata, which resulted in a balanced sample for all matching variables.

3.49 citations to patents of a licensee (treatment sample), more than twice the average number of patent citations between two non-licensing firms (1.66, for the control sample).

2.4.2 Regression Analysis

As a formal test of our hypothesis on reverse learning, we conduct a regression analysis using the matched observations in which we regress the dependent variable on the licensing dummy. Since our dependent variable takes on discrete non-negative values, non-linear count data models are preferred over standard linear regression models. We use negative binomial count data models, which control for over-dispersion in the dependent variable (Cameron & Trivedi, 1998). We include the matching variables in the regression to control for remaining imbalance between treated and control dyads, which is common practice after applying CEM (Conti & Graham, 2020; Forti *et al.*, 2020; Jeon, 2017). The correlations between the control variables (Appendix 2.1) are low and do not raise multicollinearity concerns.

Model 1 (Table 2.3) only includes the control variables. All controls are statistically significant and, except for the alliance variable. In Model 2, we add the dummy for out-licensing activity between the two firms in the five preceding years. As indicated by the log-likelihood ratio test, adding this variable improves the model fit. The estimated coefficient is positive and highly significant ($p<0.001$), indicating that firms that out-license their technology have a higher likelihood of citing the patents of their licensee subsequent to the licensing agreement than the patents of firms that are similar to the licensee but to whom they have not out-licensed any technology in the recent past. The magnitude of this effect is large: by outlicensing technology to a specific firm there is an increase in the number of subsequent patent citations to this firm by 146 percent[8]. These results provide strong indications of our

[8] This marginal effect if out-licensing is calculated as the exponent of the regression coefficient for the licensing dummy minus 1 (Cameron & Trivedi, 2005).

hypothesis on 'reverse learning' by the licensor, i.e. a knowledge flow from the licensee back to the licensor, that can be attributed to recent licensing deals.

Table 2.3: Negative binomial regressions, dependent variable: all patent citations (applicant- and examiner-given)

VARIABLES	Model 1	Model 2
Out-licensing from firm A to B		0.902***
		(0.149)
Prior citation count	0.178***	0.213***
	(0.044)	(0.047)
Patent stock firm A	0.000***	0.000***
	(0.000)	(0.000)
Patent stock firm B	0.001***	0.001***
	(0.000)	(0.000)
Technological similarity	1.188***	1.303***
	(0.308)	(0.297)
Geographical proximity	1.213***	1.104***
	(0.302)	(0.268)
In-licensing	0.702*	0.896*
	(0.298)	(0.413)
Alliance	0.619	0.972
	(0.597)	(0.672)
Constant	-1.588***	-2.211***
	(0.269)	(0.230)
Observations	3,216	3,216
Log likelihood	-4,781	-4,727
LR chi-squared		106.95***
Pseudo R-squared	0.05	0.06

Robust-clustered SE in parentheses
*** $p<0.001$, ** $p<0.01$, * $p<0.05$

2.4.3 Robustness Checks and Supplementary Analyses

We conducted a number of additional analyses. First, we performed a robustness check in which we take into account only patent citations made by patent applicants to construct our measure of knowledge flows, excluding those patent citations that are added by a patent

examiner during the patent review process. By doing so we address the concern that not all citations made in the licensor's patents to the licensee may reflect knowledge flows from the licensee to the licensor (Jaffe *et al.*, 2000; Alcacer & Gittelman, 2004; Alcacer *et al.*, 2009). Therefore, we recalculated our patent citation variables to retain only those citations for which the origin field in PATSTAT indicates that it was made by the patent applicant. Afterwards, we ran the CEM procedure again, resulting in 3,884 matched observations.

Table 2.4: Negative binomial regression, dependent variable: applicant-given citations only

VARIABLES	Model 1	Model 2
Out-licensing from firm A to B		0.689***
		(0.119)
Prior citation count	0.001***	0.001***
	(0.000)	(0.000)
Patent stock firm A	0.001***	0.001***
	(0.000)	(0.000)
Patent stock firm B	1.459***	1.498***
	(0.369)	(0.381)
Technological similarity	1.462***	1.417***
	(0.272)	(0.274)
Geographical proximity	0.410	0.547
	(0.309)	(0.392)
In-licensing	1.196*	1.145*
	(0.548)	(0.487)
Alliance	0.317**	0.372**
	(0.100)	(0.141)
Constant	-1.785***	-2.223***
	(0.284)	(0.262)
Observations	3,884	3,884
Log likelihood	-6,846	-6,803
LR chi-squared		70.35***
Pseudo R-squared	0.07	0.08

Robust-clustered SE in parentheses
*** $p<0.001$, ** $p<0.01$, * $p<0.05$

The regression results are reported in Table 2.4 and confirm that licensors can learn from their licensees. The magnitude of the licensing effect is a bit smaller than the one reported

in Table 2.3: outlicensing a technology to a licensee results in an increase of the subsequent number of patent citations to the licensee by 99 percent i.e. almost doubles it.

Second, we conducted a supplementary analysis in which we differentiate between pharmaceutical and biotechnology firms as licensors. In order to determine whether a firm is a pharmaceutical or biotechnology company, we have identified the main industry code (NACE Rev.2) in the Orbis database. Using this classification, 189 firms in our set of 254 firms are classified as pharmaceutical firms (NACE C21), 44 firms are biotech firms (NACE M72) whereas 21 firms in our sample are labeled as 'Other' and are therefore not included in the split sample analyses.[9] As shown in Table 2.5, we find evidence for 'reverse learning' for both pharmaceutical and biotechnology firms. Estimating the model on the pharma and biotech subsamples as a system of linear equations (i.e. as a SUR model, table not reported) shows that the out-licensing coefficient is smaller ($\chi^2 = 3.17$; $p = .0749$) for pharmaceutical than biotechnology licensors. A possible explanation may be that pharmaceutical firms sometimes out-license non-core technologies (which are no longer considered essential) for which they do no longer undertake R&D, which limits the opportunities to learn from licensees.

Third, we conducted several supplementary analyses to shed further light on the source of reverse learning by the licensor. First, we determined whether licensee patents that are cited by licensors after the licensing agreement are on average more valuable in terms of forward citations relative to licensee patents that are not cited by the licensor.

[9] Firms categorized as 'Other' have their primary activity in other fields than the pharma or biotech industry. Examples of such firms are diversified firms such as Bayer or Monsanto, or firms whose primary activity is in medical devices and screening. If these 21 firms are left out of the main analysis, the results remain robust.

Table 2.5: Negative binomial regression: pharma versus biotech firms

VARIABLES	Firm A = pharma	Firm A = biotech
Out-licensing (0/1)	0.718***	1.173***
	(0.175)	(0.273)
Prior citation count	0.184***	0.113
	(0.048)	(0.152)
Firm size licensor	0.001***	0.003*
	(0.000)	(0.001)
Firm size licensee	0.001***	0.000***
	(0.000)	(0.000)
Technological similarity	1.348***	1.678*
	(0.372)	(0.761)
Geographical proximity	1.075***	-0.120
	(0.317)	(0.681)
In-licensing	1.082*	-1.925*
	(0.441)	(0.891)
Alliance	1.108	-18.235***
	(0.650)	(0.539)
Constant	-2.260***	-2.153***
	(0.281)	(0.506)
Observations	2,392	631
Log likelihood	-3,629	-865
Pseudo R-squared	0.07	0.06

Robust-clustered SE in parentheses
*** $p<0.001$, ** $p<0.01$, * $p<0.05$

We find that the reverse learning by licensors is primarily geared towards to higher-value technologies: licensee patents not cited by licensors receive on average 8.18 forward citations in the five years after their filing[10] while licensee patents that are cited by the licensor after the licensing agreement receive an average of 18.61 forward citations in the same time window. In addition, we analyzed to which extent licensors cite 'breakthrough' technologies

[10] In order to calculate this number, we take into account only licensee patents which are cited at least once, since our comparison group by default only contains patents that are cited at least once (i.e. by the licensor)

of licensees. In line with prior work (Shane, 2001), a licensee patent is considered a breakthrough patent if it is in the 99th percentile of the forward citation distribution of all licensee patents in our sample. We find that 1.5% of the licensee patents that are not cited by a licensor are breakthrough patents compared to 5.8% of the licensee patents that licensors do cite.

Licensors not only single out the licensees' more valuable technologies to learn from: we also find that 73.3% of licensor citations to a licensee's patents are 'new', i.e. these patents were not cited before by the patents of the licensor in the 5 preceding years. The high share of such first-time citations indicates that licensing provides a 'window on new technology' for the licensor on which they tend to build in subsequent inventions. Overall, these supplementary analyses indicate that the interaction with licensees is leveraged by licensors to explore technologies that are new to them and that are above-average valuable.

2.5 Conclusion and discussion

This study sheds light on whether a licensor benefits from the interaction with the licensee, a feature that characterizes the execution of many licensing agreements (Hagedoorn *et al.*, 2009; Leone *et al.*, 2016; Van Kranenburg *et al.*, 2014). We demonstrate that the interactions between inventors from the licensor with their counterparts at the licensee provide a fertile ground for knowledge flows, back from the licensee to the licensor. Such 'reverse learning' may take the form of generating insights into novel applications of the out-licensed technology or developing new innovations that recombine licensor and licensee technology.

We contribute to the literature on technology licensing and markets for technology by extending the scope of the theoretical framework underlying out-licensing decisions (Arora *et al.,* 2001; Gambardella *et al.*, 2007; Fosfuri, 2006). In particular, besides the short-term revenue

effect, we argue that there is an additional positive element to be weighed against the risk of creating future competitors through the out-licensing of technology, and that is that the licensor may learn from interacting with their licensees. The key message of this paper is therefore that the characterization of the trade-off that out-licensing firms face is incomplete and that it should factor in the possibility of 'reverse learning' effects for licensors.

Naturally, such reverse learning will rarely be automatic and requires effort from the side of the licensor. But a clear implication for managers is that the assistance that licensees request to ensure proper transfer of technology actually represent learning opportunities for the licensor rather than being mere (contractual) obligations. A practical advice that follows from our analysis is for licensors to be prepared to reap the benefits from interactions with the licensee, for example by instructing own staff to be alert and use technology licensing as an opportunity to engage into meaningful discussions with their counterparts at the licensee.

Although our findings offer interesting insights, we acknowledge the following limitations of our analysis, which also highlight ideas for follow-up research. First, while we control for the similarity of firms' technology portfolios in our matching procedure, we lack information about the licensed technologies (i.e. at the level of the licensing deals)[11], which prevents us from analyzing how the out-licensed technology fits into the technology portfolio of the licensee and identifying the proposed learning mechanism in a more detailed way. More specifically, if a license agreement concerns a core technology for the licensee, this may increase the willingness of the licensee to interact with the licensor during knowledge transfer, which in turn may increase the probability of feedback learning to the licensor.

[11] While the RECAP data offers information on broad classes of technological fields and disease indications to characterize licensing deals, it does not allow linking them to patent (IPC) classes.

Second, we do not investigate whether learning effects of out-licensing are influenced by the design of licensing contracts. For example, one may expect that the degree of interaction between a licensor and licensee depends on the inclusion of a grant-back clause (Laursen *et al.*, 2017; Leone & Reichstein, 2012) or a technical assistance clause (Leone *et al.*, 2016) in the license agreement. While a technical assistance clause provides a legal obligation for a licensor to interact with a licensee, a grant-back clause may incentivize a licensor to interact with a licensee as this clause gives the licensor the right to any improvements to the licensed technology developed by the licensee. We consider it an interesting avenue for further research to examine how the learning effects from out-licensing are influenced by the design of licensing contracts. As firms do not have the obligation to disclose licensing contracts, such analysis would inevitably be restricted to a small subset of firm's licensing agreements.

Finally, future research should address the generalizability of our findings. While the pharmaceutical and biotech sector heavily relies on patents as vehicles to transfer technology, this is not always the case in other industries. It would therefore be interesting to see if the reverse learning effects that we find can be corroborated in different industries.

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2.7 Appendices

Appendix 2.1: *Correlation table (n=3,216)*

		1	2	3	4	5	6	7	8	9
1	Backward citations (DV)	1.00								
2	Out-licensing (0/1)	0.10	1.00							
3	Prior citation count	0.19	0.01	1.00						
4	Patent stock firm A	0.13	0.04	0.06	1.00					
5	Patent stock firm B	0.20	0.03	0.10	-0.25	1.00				
6	Technological similarity	0.15	0.00	0.17	0.08	-0.10	1.00			
7	Geographical proximity	0.07	0.01	0.03	0.01	-0.04	0.17	1.00		
8	In-licensing	0.04	0.00	-0.03	0.06	-0.06	0.07	-0.07	1.00	
9	Alliance	-0.00	0.00	-0.03	0.00	0.00	-0.04	-0.05	-0.01	1.00

Chapter 3
Dipping a Toe before Plunging in? The Relation between CVC Investments and Entry into New Technology Domains[12]

Abstract

Existing research has prescribed corporate venture capital (CVC) investments as effective tools for firms to explore new technologies. However, it remains unclear to what extent firms can use CVC investments to build capabilities to create technology in previously unfamiliar domains as this requires that they go through an extensive learning process. This paper argues that CVC investment not only allows exploring new technologies but sets in motion a chain of learning events linked by four stages in a knowledge absorption framework, and which is moderated by investee quality and the presence of other corporate investors. We test our propositions using a panel of 244 large pharmaceutical firms that make 847 unique CVC investments during 2000-2015 in ventures patenting in technology domains in which the firms were not active in the 5 years preceding the investment. We show that firms who make CVC investments in ventures active in technology domains which are unfamiliar to them, have a higher likelihood to subsequently start patenting in these new domains. Furthermore, we show that this likelihood is positively moderated by the relatedness of the technology to the firm's existing knowledge base. These results add to the literature on CVC investments and technological entry by furthering our understanding on the role of CVC investments not only as a tool for technological exploration, but also as an effective vehicle for technological exploitation through learning.

[12] This chapter is based on a working paper co-authored with Stijn Kelchtermans (KU Leuven), Bart Leten (KU Leuven) and Hamzeh Obeid (Vlerick Business School).

Keywords: CVC investments, technological entry, innovation

3.1 Introduction

Management scholars have argued, drawing on the knowledge-based view of the firm, that firms achieve competitive advantage through "what they know and in their ability to acquire, maintain, and use knowledge." (Keil, 2000: 20). In other words, differences in the knowledge stocks of firms, and differences in their ability to process this knowledge, can explain performance variation across firms (Nahapiet & Ghoshal, 1998). This rationale is particularly salient in knowledge-intensive environments, where firms' failure to respond to technological opportunities and threats can result in the erosion of their competitive advantage as new value propositions and discontinuous innovation render their own solutions increasingly obsolete (Leten *et al.*, 2016). Likewise, their inability to seize technological opportunities can leave firms vulnerable to competitors that were able to exploit these opportunities sooner. What determines their responsive potential is a dynamic capability by which "repetition and experimentation enable tasks to be performed better and quicker and new production opportunities to be identified" (Teece & Pisano, 2003: 10), that is, by learning.

Learning increases firms' adaptability to uncertain environmental conditions. In high-velocity technological environments, where emerging technologies continuously displace existing ones, to learn more efficiently is to achieve and be able to sustain competitive advantage and ultimately, survive (Eisenhardt & Bourgeois, 1988). Organizational learning is "a purposive quest to retain and improve competitiveness, productivity, and innovativeness in uncertain technological and market circumstances" (Dodgson, 1993: 378). In practice, this often translates into the pursuit of knowledge in technological domains that are unfamiliar to the firm. This is a task laden with uncertainty (March, 1991). Firms must be able to sense the

emergence of technologies that pose strategic opportunities or threats to their business, assess their potential impact, and adapt by internalizing these technologies in a timely manner (Cohen & Levinthal, 1990; Lane & Lubatkin, 1998), requiring not only the acquisition of technical knowledge, but also the internal capabilities necessary to translate, integrate, and combine this knowledge with the existing technology assets of firms in order to generate new technology. This task is, unsurprisingly, challenging. But when firms' innovation efforts succeed in generating technology in technology domains previously unfamiliar to them, they can be regarded as having entered those domains (Leten *et al.*, 2016).

Existing research has prescribed corporate venture capital investments (CVC henceforth) as effective tools for exploring and learning about novel technologies. This form of interorganizational relationship involves what are typically incumbent firms on the one hand, and entrepreneurial ventures, on the other. For investors, they allow 'dipping a toe' into the knowledge of investees at a limited degree of integration and therefore, limited exposure to risk (Van de Vrande *et al.*, 2009). For these reasons, CVC researchers have typically portrayed these investments as 'windows on new technology' (Dushnitksy, 2006). Yet, it is well-established in organizational learning literature that mere exposure to novel technology is insufficient as a basis for innovation, especially when this innovation targets technologies that are unfamiliar to the firm. Here, a question arises about the efficacy of CVC investments not only as devices for exploratory knowledge acquisition, but also as more sophisticated channels that facilitate learning so firms truly "acquire, maintain, and use knowledge". In this work we seek to answer this question by investigating the effect that CVC investments in new-to-the-firm technology domains have on the likelihood of entry into these new-to-the-firm technology domains afterwards. Establishing this effect would imply that CVC investors not only gain in exploratory knowledge, but that they also improve their capabilities in interpreting, transforming, and exploiting this explored knowledge in their operations.

We test our predictions by drawing on a set of 244 top-R&D spenders in the pharmaceutical and biotech industry, who have together made 847 CVC investments in patenting ventures, during the years 1995-2015. We measure technologies of CVC investors and the ventures that they invest in by patent data. We observe CVC investment- and entry-behavior of our firms in new technology domains at the *firm-technology domain-year* level, resulting in 2,325,264 observations where the firm is 'at risk' of entering the technology domain i.e. it doesn't show any patenting activity in the domain the past 5 years. To identify the effect of CVC investments on the subsequent decision to enter (i.e. to start patenting) in a new technology domain, we add covariates at the level of the investor firm, the technology domain and the investees. We furthermore use a set of firm-, technology domain-, and year-dummies. To account for the fact that prior CVC investments might be endogenous to the firm's ex ante intention to enter the technology domain in which the investee has proven expertise, we instrument a firm's stock of CVC investments in a technology domain by the one undertaken by the other sample firms during the same time period, drawing on the literature on peer effects in firms' financial decision making.

Our results suggest that prior CVC investments in a new-to-the-firm technology domain are in a positive and significant way related to the firm's likelihood to generate technology in that domain afterwards. Furthermore, we observe that the more technologically related the technology domain is to the firm's current patent portfolio, the stronger the positive effect is. This research makes two main contributions. Firstly, it adds to the literature on entry into new-to-the-firm technology domains (e.g. Leten *et al.*, 2016) by demonstrating the effectiveness of CVC investments as a tool for entry into novel technology domains. Secondly, it contributes to the stream of literature on the performance consequences of CVC investments (e.g. Dushnitsky & Lenox, 2005) by demonstrating that CVC investments – especially when taking

place in syndicates with other corporates - can be used to absorb the knowledge of investees and to build up competencies in new technology domains.

3.2 Theoretical Background and Hypotheses

Firms enter novel technology domains when they expand their technological assets to areas that differ from those in which they have been active (Leten *et al.*, 2016). Depicting firms' successful entry into novel technology domains using the lens of organizational learning reveals the importance of the ability to overcome the constraints imposed by existing knowledge bases (Ahuja and Lampert, 2001; Leten *et al.*, 2016) and to absorb and leverage unfamiliar knowledge. . The logic of capabilities in exploring and exploiting novel knowledge harkens back to the seminal work of March (1991) on organizational learning. He argued that firms' cognitive and behavioral adaptation (i.e. learning) is the result of their seeking to introduce greater variety in their knowledge and experience by way of increasing their exposure to novelty (McGrath, 2001). They thus search, experiment, take risks, discover, and innovate, before institutionalizing the lessons learned from this process through implementation and repetition (March, 1991). Zahra & George (2002) later expounded on this exploration by depicting it as a process that begins with the acquisition of new knowledge, then its assimilation, transformation, and exploitation within the firm, leading to the production of novel technology.

The discussion on this learning process naturally evolves into one that deals with the locus of the knowledge that feeds each of these stages. Here, Leten *et al.* (2016) argue that firms detect opportunities in novel technology domains by reading scientific journals and through observation of the activities of competitors. They find that the greater the number of these opportunities, the greater the likelihood that firms will commit the resources necessary to generate technology in novel domains. Their detection, therefore, can be considered as an

instigator of the process that eventually results in technology generation. This process, we argue in this work, is a process of learning that spans firm boundaries. Indeed, there seems to be a consensus among innovation management scholars, particularly those who study absorptive capacity in firms, to locate knowledge exploration outside firm boundaries (Zahra & George, 2002). This often leads to firms sourcing this exploratory knowledge from organizational actors outside their boundaries in what researchers refer to as acquisitive learning (Dess *et al.*, 2003; Zahra & Bogner, 1999), which is a widely practiced strategy employed by firms (Van de Vrande *et al.*, 2009). Acquisitions, strategic alliances, joint ventures, licensing agreements, and equity investments all are different governance modes that are employed for explorative learning purposes under different conditions (Van de Vrande *et al.*, 2009).

3.2.1 Corporate Venture Capital defined

This study focuses on the efficacy of a particular mode of venturing as a precursory device to entry into novel technological domains. That is, through establishing equity-based relationships with innovative, entrepreneurial ventures through corporate venture capital investments. In the remainder of this section, we will argue that CVC investments enhance firms' performance along the four dimensions of external knowledge absorption depicted by Zahra and George (2002), thus increasing firms' ability to generate novel technology.

Corporate venture capital (CVC) refers to direct minority equity investments made by established companies in privately-held entrepreneurial ventures (Gompers & Lerner, 1998). The provision of these funds can be administered through an internal body within organizations, through an external, more independent investment fund, or through participation in pooled investment funds organized by other venture capitalists. With these investments, corporates can pursue financial or strategic (i.e. learning) objectives, or a combination of both

where one is stressed more than the other. Generally, however, strategic objectives tend to dominate financial ones (Dushnitsky, 2006).

Existing research has thus long associated CVC investments with better innovation outcomes, which investors achieve as a result of learning (Dushnitsky & Lenox, 2005). The extent to which CVC investments can be effective devices for generating technology in a novel domain remains unclear. This particular learning outcome is unique because it implies that firms have undergone an extensive learning process that goes beyond the simple acquisition of exploratory knowledge and extends to the range of processes which firms must apply efficiently in order to transform this exploratory knowledge to novel technology. This process can be described in terms of the technology absorption process described in innovation management literature (Zahra & George, 2002), which consists of knowledge acquisition, assimilation, transformation, and exploitation.

3.2.2 CVC and knowledge acquisition

CVC investments arguably have their strongest effect on the frontend of the technology absorption process, that is, on knowledge acquisition. According to Zahra & George (2002), acquiring knowledge requires a firm's capability to "identify and acquire externally generated knowledge that is critical to its operations" (p. 189).

Pre-investment

The mainstream view in CVC research is one that emphasizes the effectiveness of CVC investments insofar as knowledge acquisition is concerned. Researchers have long considered CVC investments as 'windows on new technology' (Dushnitsky, 2006). For investors thus, CVC investments are devices for increasing exposure to knowledge on a novel technology domain. But first, and even before firms direct their attention to sourcing technical knowledge on a novel technology, they must become aware of the presence of this technology, and

appreciate, even to a meager extent, the strategic relevance this technology may harbor for their operations. This 'awareness' of technological opportunities is what may drive firms to dedicate resources to further exploration, and eventually exploitation of a novel technology (Leten *et al.*, 2016). Entrepreneurial ventures need to attract investors to finance their business growth. They do this by advertising the innovativeness of their technologies and the commercial potential of their solutions. This information is then disseminated throughout the venture capital community and is often first captured by independent venture capitalists who continuously monitor new investment opportunities. These players then leverage their extensive networks to draw co-investors whose involvement would reduce their risk exposure and enrich the pool of complementary resources that is available to an investee (Hochberg *et al.*, 2007; Keil *et al.*, 2010). This process often leads to inviting CVCs to invest. This process also effectively translates into passive intelligence gathering or an additional scanning device mechanism for firms that reduces the likelihood that they are left unaware of an emerging technology.

In a second stage, but still prior to investment, CVC investors can gather exploratory knowledge of a novel technology during what is known in venture capital as the 'due diligence' stage (Keil *et al.*, 2008). Here, entrepreneurial ventures must disclose enough information on their technologies and business to lure potential investors. This is a well-known dilemma for entrepreneurs seeking investment and is known in research as the paradox of disclosure (Arrow, 1962). Entrepreneurs risk the misappropriation of their intellectual assets by potential investors when sharing this knowledge, but they are forced to do so in order to compete for funding (Dushnitsky & Shaver, 2009). From the perspective of CVC investors, this indeed offers a rich context for learning in which they may gather much information on potential technology and its commercialization potential.

Post-investment

Post-investment, interaction between CVC investors and investees can be at once passive, relating to monitoring investees and evaluating their performance at agreed-upon milestones (Gompers, 1995), as well as active aimed at supporting investees by sharing complementary resources and participating in their strategic decision-making (Katila *et al.*, 2008; Lockett *et al.*, 2006). The main channel facilitating this interaction is the board of directors of investee ventures, on which their CVC investors would typically be represented with voting rights or simply as observers (Bottazzi *et al.*, 2004). CVC investors learn from investees, post-investment, to the extent that they not only gain a closer look into the knowledge bases and technologies of investees at the moment of investment, but also in that they continue to monitor the development of this knowledge as ventures exploit them in their innovation processes. This dynamic has led some scholars to describe CVC investments as "disembodied experimentation" (Keil *et al.*, 2008). Thus, the more ventures experiment with innovation in a novel technology domain, the greater the depth of knowledge to which their CVC investors are exposed. Also, the greater the number of investments firms make in ventures active in a novel technology domain, the greater the breadth of solutions to which they are exposed in that domain. Taken together, more CVC activity can be expected to result in an exploratory knowledge base that can be better leveraged towards generation of technology in novel technology domains.

3.2.3 CVC and assimilation of knowledge

In order to enter novel technology domains, firms must understand the knowledge which they acquired from external sources in the first stage (Cohen & Levinthal, 1990). Zahra & George (2002) depict this assimilation of acquired knowledge as the second stage of the

knowledge absorption process, and argue that in order to be successful, firms must possess "routines and processes that allow it to analyze, process, interpret, and understand the information obtained from external sources" (p. 189). A larger number of CVC investments in a novel technology domain implies that investors have performed repetitive analysis of a number of technologies and solutions of different ventures from that unfamiliar technology domain. More extensive experience with the due diligence process implies that investors are better able to fathom the underlying technologies of potential investees and evaluate their investment potential. The ability of CVC investors to comprehend externally sourced knowledge thus improves over time, increasing the efficiency of the process that leads to entry into novel technology domains.

Firms structure their CVC activities in a number of ways. Some delegate the provision and management of CVC investments to business unit managers, whereas other firms establish wholly-owned subsidiaries to handle these investments (Dushnitsky, 2006). In either case, the personnel at CVC investors is embedded in the corporate structure of their parent companies, and more often than not, they do not have the autonomy that their counterparts in independent venture capital enjoy when making decisions on potential investment deals[13] (Dushnitsky, 2006; Souitaris *et al.*, 2012). Instead, their decisions must be approved by more senior executives, which introduces an intermediate interpretive stage whereby CVC personnel must explain to their superiors the relevance of particular CVC deals to the parent firm. This repetitive task requires a translation of the knowledge acquired from investment targets during the due diligence stages into a language that is understood by the firm, because this knowledge may embody heuristics that differ significantly from those used by the firm, which delays its

[13] A survey by Siegel *et al.* (1988) found that 66 percent of the surveyed CVC managers have to get approval from their more senior managers in order to make investments

comprehension (Zahra & George, 2002). This interpretation stage should then promote the assimilation of knowledge within the firm. The greater the number of CVC investments under their management, the more CVC personnel will refine the capability of analyzing and comprehending the knowledge acquired from investment targets, prior to as well as post investment, then translating it to the language of their parent firms.

3.2.4 CVC and transformation of knowledge

A subsequent step to assimilating knowledge is to combine it with the existing knowledge base of the firm. This is the stage which Zahra & George (2002) refer to as knowledge transformation, defining it as the ability to "develop and refine the routines that facilitate combining existing knowledge and the newly acquired and assimilated knowledge" (p. 190). The importance of this stage in dealing with entry into novel technology domains is easily discernible, since it increases opportunities for firms to combine knowledge in novel ways, which is the impetus of innovation (Fleming, 2001; Leten *et al.*, 2016). A question arises on the impact CVC investments may have on this stage in the process of entry into novel technology domains. Here, we argue that the more a firm invests in an unfamiliar domain, the more enhanced its ability to transform externally acquired domain-specific knowledge internally by identifying linkages with its existing knowledge base.

Previously we described the structure of CVC units within their parent organizations. We argued that CVC investment managers must translate external knowledge in order to communicate it to their superiors and galvanize interest in a potential investment. Firstly, and in due course of obtaining these approvals, CVC investment units may reach out to specialized subsidiaries within the parent firm in order to obtain their evaluation of a technology held by a potential investment target. Once approvals are given and investments are made in ventures, CVC managers continue to act as bridges between investees and the different stakeholders

within their parent firm. In part, this is done to offer investees complementary value, such as access to production plants, R&D laboratories, and specialized expertise, which is one of the main reasons why ventures take on CVC investors to begin with (Katila *et al.*, 2008; Alvarez-Garrido & Dushnitsky, 2015). Since the investment unit does not possess these resources, it must communicate the needs of investees to other units within the parent.

Taken together, these actions by CVC units help disseminate external knowledge within the parent, and with repetition, strengthen ties between the CVC unit, investees and other corporate units, improving the translation process of external knowledge, and making the process of entry into novel technology domains more efficient.

3.2.5 CVC and exploitation of knowledge

The final stage in the process of entry into novel technology domains can be considered as a stage where the knowledge which has been acquired, assimilated, and transformed is then used to create new knowledge, goods, or capabilities. Zahra & George (2002) refer to this as the exploitation stage and define it as a capability that "allows firms to refine, extend, and leverage existing competencies or to create new ones by incorporating acquired and transformed knowledge into its operations" (p. 190). Undoubtedly, firms that successfully generate technology in novel technology domains can be considered as having successfully exploited knowledge they acquired from external sources, such as through partnerships with other firms. Although CVC investments are typically depicted as tools for exploration, here we make the argument that they can enhance investors' ability to exploit knowledge as well. This effect is driven by the institutional logics of entrepreneurial ventures, which are distinguishable from those of investors in that they favor the commercialization of technology.

Continued interaction with entrepreneurial ventures may instill in the investor some of the logics that make these ventures more successful at commercializing (or indeed exploiting)

innovation. Existing research has suggested that incumbent corporations tend to be technically- rather than commercially-oriented (Pahnke *et al.*, 2015). It has also been shown that CVC investments can render one partner more similar in their behavior to their counterpart by way of 'organizational imprinting' (Kim & Park, 2017). With repeated CVC investments in a particular technology domain, firms are more likely to capture some of these entrepreneurial heuristics that facilitate the exploitation of knowledge in those domains. In addition, interaction with entrepreneurs in novel technology domains can help CVC investors learn about the exploitative potential of technology in that domain. In net effect, those investors are then better able, and more willing to commit resources to the exploitation of those technologies.

In sum, we have argued that CVC investments are effective tools for learning about a novel technology domain, and that investors will be more likely to enter those technology domains as a result. We based this expectation on the impact CVC investments are expected to have on the four stages of the knowledge absorption framework: knowledge acquisition, assimilation, transformation, and exploitation. With a greater number of CVC investments in a novel technology domain, investors will not only gain the technical knowledge necessary to generate technology in that domain, but investors will also increasingly lay the internal foundations that enable an efficient and more successful exploitation of sourced knowledge on technology development in those novel domains.

We thus expect that:

Hypothesis 1: *The greater the number of CVC investments which a firm makes in a new-to-the-firm technology domain, the greater the likelihood that the firm will enter and generate technology in that technology domain.*

3.2.6 Quality of venture's technology

We argued above that CVC investments are effective devices for entering novel technology domains because they offer investors explorative external knowledge on these domains as well as hone their skills in assimilating, transforming, and exploiting that knowledge. In this section we will argue that this effect is sensitive to the quality of the technological knowledge possessed by investee ventures.

Like any market, substantial variation is discernible on both the supply and demand sides of the venture capital model. Here, supply and demand can be thought of in terms of financing, with VC and CVC investors acting as suppliers, and ventures as customers. From a technological standpoint, however, firms that employ CVC investments as learning devices can be seen as customers in a market where entrepreneurial ventures supply novel and potentially disruptive technologies. Here, it is well-documented that ventures that receive venture capital differ significantly in the viability of their value propositions as well as in the quality of technologies that underlie them (Cumming & Dai, 2013). Knowledge that is transferred from ventures with richer and more innovative technologies is more effective in learning than that sourced from ventures with weaker knowledge bases. To investors, better knowledge translates into a larger variety of knowledge elements to explore, and a more reliable knowledge base to assimilate, translate and exploit later in the knowledge absorption process. CVC investors that have access to ventures that possess higher quality knowledge enjoy a knowledge advantage that improves their chances of leveraging that knowledge towards generating technology in new technology domains. Simultaneously, CVC investors in higher-quality ventures are more incentivized to learn from their investees due to the latter's prominence in the entrepreneurial landscape. Relatedly, ventures that generate innovative technologies garner prominence in their respective domains (Baum & Silverman, 2004). Investors in higher-quality ventures not only have access to superior knowledge and are more eager to seek the acquisition of this

knowledge, they are also more incentivized to exploit it. This effect is due to the prominence of their investees, which correlates with the perceived potential of their technologies (Wadhwa & Basu, 2013).

In sum, we argue here that ventures with richer and more valuable knowledge bases are better ambassadors in terms of convincing investors to enter novel technology domains.

Thus, we expect that:

Hypothesis 2: *The higher the quality of investee ventures' technology, the stronger the positive effect of CVC investments in a new-to-the-firm technology domain on the likelihood that a firm will enter and generate technology into that technology domain.*

3.2.7 Number of co-invested CVCs

Syndicating investments by dividing the total equity raised for investment into stakes held by different investors is a well-established practice in venture capital. In this section we argue that CVC investors that invest alongside a greater number of CVC co-investors, on average, will achieve greater learning benefits from their CVC investments, and will be more likely to enter novel technological domains as a result. Upon close analysis, syndicates facilitate learning on two levels. First, there is well-established bidirectional learning taking place between investors and investees (Di Lorenzo & Van de Vrande, 2019; Dushnitsky & Lenox, 2005). A less explored avenue for learning is that which takes place within the investment syndicate and involving its members. This, we argue, offers a second avenue where co-investors learn from each other as they interact within the context of the syndicate (Malerba, 1992). These interactions take place both pre-investment and post-investment. Pre-investment, it is common practice that a lead firm of an investment syndicate solicits new investors to join the syndicate, and in this process interacts with these investors on investees' technologies. Post-investment, co-investors interact during formal board meetings, but also frequently consult each other

informally on the evolution of investees' technologies. Since it involves principals and agents (i.e. investors and investees), the former can be regarded as vertical learning, while the latter, involving only investors, can be regarded as horizontal learning.

Horizontal learning is certainly not independent of vertical learning. Knowledge that is transferred vertically from investees to investors can be 'better learned' through horizontal learning, that is, through interaction with co-investors in relation to this knowledge. An example that illustrates this is the CVC investor that was able to learn of a novel approach to solving a certain problem through interaction with an investee. This explored knowledge is then better defined and complemented with knowledge from a firm co-invested in the same investee, helping therefore the focal investor with implementation of the investee's knowledge. In this sense, each of the two levels can act as a conduit for acquiring knowledge of a particular technology or of processes to exploit this knowledge, or both, although it can be expected that explorative learning will be more pronounced on the vertical level, while the horizontal level is more likely to be channel for exploitative learning given the greater experience CVC investors have, as industry incumbents, in exploiting technology.

In sum, CVC investors that tend to invest as part of larger consortia of corporate investors have an additional channel of learning that complements their learning from their investee ventures. This channel is created through interaction with co-investors, and increases in its efficacy the greater the number of those firms with which a CVC investor invests, on average. The synergies created through the interaction between the two learning channels can be expected to increase the likelihood that the learning which a firm achieves through their CVC investments will lead them to enter novel technological domains.

We therefore expect that,

Hypothesis 3: *The greater the number of corporate co-investors which a CVC investor has invested with, the stronger the positive effect of CVC investments in a new-to-the-firm technology domain on the likelihood that a firm will enter and generate technology into that technology domain.*

3.2.8 Technological relatedness to investor's existing knowledge base

Above, we argued that CVC investments allow investor firms to search, evaluate and integrate external technology in order to complement in-house technological knowledge and thus facilitate the recombination of internal and external knowledge components in order to generate novel technology (Fleming, 2001). However, prior work has shown that the extent to which firms can reap the benefits offered by technological opportunities in novel technology domains is dependent on their existing knowledge base (Leten *et al.*, 2016). Pursuing technologies in domains which are distant to the firm's existing technology portfolio may offer less opportunities for effective knowledge recombinations, since the creation of knowledge is a cumulative, path-dependent process which is influenced by the capabilities already in place within the firm (Cohen & Levinthal, 1990; Teece *et al.*, 1997). Hence, the ability to learn from a CVC investment, and thus generate novel technology building on the knowledge of a venture may increase when the new technology domains are technologically closer to what firms already know (Cohen & Levinthal, 1990). For this reason, we hypothesize that:

Hypothesis 4: *The higher the technological relatedness between a technology domain and the firm's current technology portfolio, the stronger the positive effect of CVC investments in a new-to-the-firm technology domain on the likelihood that a firm will enter and generate technology into that technology domain.*

3.3 Data and Methodology

3.3.1 Sample

In order to study the impact of prior investments in ventures on the subsequent likelihood to enter new technological domains, we collected longitudinal data (1995-2015) on the technological and CVC activities of 244 pharmaceutical and biotechnology firms. Firms in our sample are Japanese, US and European top-R&D spenders within this industry, and have been identified from the 2004 and 2015 editions of the EU Industrial R&D Investment Scoreboard. This ranking provides listings (1000 firms in 2004, and 2500 firms in 2015) of the top R&D spenders in the world across all industries. This results in an unbalanced panel of 244 firms in which we observe firms in a 21-year period (1995-2015).

Information on CVC investments is derived from SDC VentureXpert, which is a comprehensive dataset combining information from industry associations (e.g. National Venture Capital Association, European Venture Capital Association) with information from the investment banking industry. The VentureXpert dataset has been frequently used in prior studies related to CVC investments (Dushnitsky & Lenox, 2005; Keil *et al.*, 2008; Dushnitsky & Lavie, 2010; Belderbos *et al.*, 2018). Furthermore, we have identified whether firms in our sample have been active in other forms of external technology sourcing during the years of observation, by means of in-licensing agreements and other forms of collaboration agreements, such as alliances. To identify these other forms of external technology sourcing, we gathered data from Clarivate Analytics RECAP.

We rely on patent data from the PATSTAT database (version May 2018) to measure the technologies of our sample firms and their counterparts. These counterparts can either be ventures that our sample firms have invested in or companies they have engaged with in other forms of technology sourcing, such as in-licensing or alliances. All data (patent data as well as

investment/deal data) for our sample firms have been collected at the consolidated parent firm level. This means that we take into account both activity on the level of the parent firm as well as their consolidated (majority-owned) subsidiaries. We identify firm subsidiaries based on yearly lists of majority-owned subsidiaries (minimum 50% ownership) reported in the ORBIS financial database. We perform this consolidation exercise on a yearly basis to account for shifts in consolidated group structures that may occur over time due to M&A activity or spin-offs. The choice of using firm data at the consolidated level is motivated by the fact that both patenting and technology sourcing often occur at the level of the subsidiary instead of the parent firm. For instance, a study by Magerman *et al.* (2005) estimates that on average 20 percent of unique patents in a firm's technology portfolio has been applied for under the name of the subsidiary or a different name than the current name of the parent firm.

By collecting patent data for our consolidated firms and their investment/deal counterparts, we have set up our database in a *parent firm * year * technology domain* structure. The technology domain is defined at the IPC-4digit level. Hence, our dataset consists of 244 firms in 636 possible IPC-4digit technology domains. For the purpose of our analyses, we use the years 1995-1999 in our panel to calculate 5-year stocks of several of our key variables. Therefore, the panel used in our analyses spans 16 years (2000-2015). This results in 2,443,904 possible *firm-year-technology domain* combinations. Since we are interested in *entry*, we only include observations for technology domains in which the firm did not patent in the previous five years, in line with prior work (Leten *et al.*, 2016). Furthermore, we remove observations for panel years during which the 244 firms were not consolidated, as well as observations for technology domains in which none of our sample firms have ever made a technological entry over the course of our panel years. Hence, the resulting sample for our analyses comprises 1,835,446 observations.

3.3.2 Measures

a. Dependent variable: Entry in new technological domain

In this study, our dependent variable is an "entry in a new technological domain" (NTD)-dummy. We define a technological domain as "new to the firm" if the firm has not had any patenting activity in that given technological domain (IPC 4-digit) in the five years prior to the focal year. The assumption behind this entry-variable is that a technological domain presents a new technology to the firm if the firm has not been active in that domain for a considerable time (Leten *et al.*, 2016). In industries that are characterized by a rapid pace of technological change, such as the pharma and biotech industry, inactivity in a given technological domain leads to quick depreciation of a firm's technology stock (Ahuja & Lampert, 2001). Therefore, prior research in technology-intensive industries suggests a window of five years as suitable for assessing the 'newness' of technological domains for firms (Ahuja & Lampert, 2001; Belderbos *et al.*, 2010; Leten *et al.*, 2016). Our entry-variable into a given technological domain assumes the value '0' when a firm has not undertaken any patenting activity in that technology domain and year, and switches to '1' when the firms files a patent coded in this technology domain. Once the firm has become active in this field, we eliminate this particular field as being 'new' to the firm in subsequent years. A specific technology domain can only be 'new' to the firm again when – after inactivity of at least 5 years as described above – they would undertake new patenting activity in this technology field.

b. CVC investments in new technology domain

Our variable of interest is a count of the number of CVC investments that a firm has made in ventures which are active (i.e. has filed patents) in a given technology domain, in the five years preceding the focal year. We choose to adopt a 5-year moving window in our independent variable to allow for the fact that access to new-to-the-firm knowledge by means of venturing

into new technological fields might take several years to substantiate into internal R&D activity within the parent firm (Dushnitsky & Lenox, 2005; Wadhwa *et al.*, 2016).

Only a subset of our sample firms (38 out of 244)[14] are active in corporate venturing during our sample period and have CVC investments recorded in the SDC VentureXpert database. These 38 CVC investors have altogether made 902 CVC investments in 716 unique ventures, with the number of CVC investments per venture varying between 0 and 4. In line with prior work (e.g. Colombo & Shafi, 2016), we restrict the definition of ventures to young firms that are less than 10 years old at the time of CVC investments. Most of the CVC investments (847 of 902) take place in ventures that are technology-active and have filed for patents prior to CVC investments. The *stock of CVC investments in a new-to-the-firm technology domain* measures the number of CVC investments that a firm has made in the prior 5 years in technology-active ventures that have filed for patents in that technology domain. In the regression analyses, we make use of demeaned values for this variable.

c. Quality of venture's technology

We measure the quality of technologies of ventures that a firm has invested in a particular technology domain by forward citations to the patents of the ventures. Forward citations have a longstanding association with a patent's technological and commercial value (Trajtenberg, 1990; Albert *et al.*, 1991; Harhoff *et al.*, 1999; Hall *et al.*, 2005). In this study, we use the average number of forward patent citations that a venture's patent portfolio receives as proxy for the quality of the venture's technology.

We measure the patent portfolio of a venture as the sum of all PATSTAT patent families of the venture prior to a focal CVC investment. Forward patent citations are measured in a fixed five-year window. Our variable *quality of venture's technology* averages the

[14] 35 of the 38 CVC investors have invested in ventures that filed for patents prior to the CVC investment.

demeaned number of forward citations per patent over all ventures that a CVC investor has invested in during the last five years in a technology domain.

d. Number of CVC co-investors

We measure the potential for 'horizontal' learning on investees' technologies by the presence of CVC co-investors in investment syndicates. The variable *number of CVC co-investors* is calculated as the demeaned average number of CVC co-investors in CVC investments undertaken by a firm in the last 5 years in a technology domain.

e. Technological relatedness

We include a control which measures the 'relatedness' of a new technological domain with the investor firm's existing patent portfolio, to control for the path dependency and local search that characterizes technology development of firms (Helfat, 1994; Kim and Kogut, 1996; Leten *et al.*, 2016; Nelson and Winter, 1977). Two technology domains are considered related if they share a similar underlying knowledge base, which can be measured by the frequency of patent cross-citations between domains (Leten *et al.*, 2007). Frequent patent cross-citations between two technology domains indicate the importance of knowledge of one technology domain as inputs for the development of new inventions belonging to the other technology domain, and vice versa.

In line with the approach followed by Leten *et al.* (2016), we start by constructing technology relatedness measures for all pairs of IPC 4-digit technology domains, by relying on citation data for the universe of all patent filings (disentangled at patent family level) for the period 1995 to 2015. We calculate our measure for technological relatedness from > 15 million cited patent families listed on > 11 million citing patent families. We construct symmetric pair-wise technology-relatedness measures, by calculating the ratio of the observed and expected (random) number of cross-citations between two technology domains. Let O_{ij} be the observed

number of patents belonging to technology domain *j* which are cited by patents belonging to technology domain *i*, with $O_i = \sum_j O_{ij}$. The likelihood that a technology domain will be cited increases as the number of patents classified in that domain is higher. Let N_j be the number of patents that are classified in technology domain *j*, with the total number of citable patents $T = \sum_j O_{ij}$. Without assumptions on the distribution of citations across technology domains, we can therefore express the expected number of cited patents belonging to technology domain *j* which are cited by patents of technology domain *i* as $(E_{ij}) = O_i*(N_j/T)$. We can subsequently calculate the relatedness of any two technology domains i and j (R_{ij}) as the ratio between the number of citations ($O_{ij} + O_{ji}$) that are actually observed, and the expected number of citations ($E_{ij} + E_{ji}$). The pairwise relatedness measures are used in a second step to calculate the average weighted technological relatedness between a technology domain that is new to the firm and its existing five-year technology portfolio, with the shares of patents in technology domains used as weights.

f. Control variables

Next, we introduce a list of control variables to isolate the effect of CVC investments in ventures which have expertise in a given technology domain on the propensity of the focal firm subsequently entering this technology domain. Specifically, we add controls on three different levels: at the level of the firm, a set of technology domain-specific controls and a set of dummy variables which control for firm-, technology domain-, and time-invariant unobserved heterogeneity.

External technology sourcing. In their technology exploration process, firms often use CVC investments in a simultaneous way with other strategies of technology sourcing, such as technology in-licensing or the formation of technological alliances and formal collaboration agreements with other firms (Dushnitsky & Lavie, 2010; Van de Vrande & Vanhaverbeke,

2013). Both CVC investments and these alternative ways of technology sourcing share several characteristics, such as a certain degree of flexibility in termination and relatively moderate levels of commitment (Dushnitsky, 2006; Belderbos *et al.*, 2018). Whereas CVC investments or technology in-licensing rather imply providing financial remuneration for the "right of use" of a technology while R&D activities are mainly carried out at the level of the venture, other forms of technology sourcing rely to a larger extent on mutual efforts in terms of R&D between partners, as is the case in formal collaborations or technological alliances (Dushnitsky & Lavie, 2010). Prior research in the field of pharma and biotech has shown that external technology sourcing is positively related to the development of a firm's technological capabilities, which in turn increases a firm's likelihood of entering new technology domains (Anand *et al.*, 2010).

To control for the influence of other technology sourcing strategies on entry into new technology domains we add a variable *external technology sourcing* to our models. To create this variable, we make use of the RECAP database, which provides information on technology licensing, technology alliances and other agreements of technological collaboration between firms. In RECAP, every deal is coded with at least one code, indicating the type of agreement. To construct our variable, we include all deals which are coded as deals which carry an external technology sourcing component[15]. Our external technology sourcing measure is a count of deals that the firm has engaged in in the five years prior to the focal year with partners which have prior technological experience (patents) within that technology domain.

Firm size. At the level of the firm, we include the log-transformed five-year stock of patents that the firm has applied for in the years prior to the focal year. This patent stock proxies for the size of the firm. We expect larger firms in terms of patent portfolio to have built up more

[15] Specifically, we use RECAP deals coded as Licensing (L), Collaborations (Col) and Co-Developments (CoD).

experience in R&D, which in turn may make them better positioned to leverage this experience when exploring new technological domains.

Firm patent self-citations. Innovation is typically a cumulative process where new innovations largely build on prior innovations (Scotchmer, 1991; Shapiro, 2001). Viewing cumulativeness as a chain of innovations linked by citations, self-citations measure these instances in which a firm relies on internally developed prior knowledge in their development of new technological knowledge elements. Self-citations in this respect seem to suggest that a firm is well-equipped to internalize knowledge spillovers which are created by their own internal developments (Hall *et al.*, 2005). Therefore, we add a control for the average number of self-citations per patent that the focal firm has applied for in the five years prior to the focal year.

Firm technological diversification. We add a measure of a firm's technological diversification, i.e. the extent to which its existing technology portfolio is dispersed over different technology domains. Firms with a broader technology portfolio possess a broader set of knowledge elements which they can activate in the recombinant process of new knowledge creation (Fleming, 2001, Leten *et al.*, 2007). Firms that are technologically diversified therefore have a higher likelihood to enter new technology domains. To develop a measure for a firm's technological diversification, we calculate the concentration of patents in a firm's five-year patent stock over IPC 4-digit technology classes. Let N_j be the number of patents in technology class *j* in the five years prior to the focal year, with N being the total number of patents a firm has filed. The level of a firm's technological diversification is then calculated as $1-\sum_j(N_j/N)^2$. A value equal to '1' indicates perfect diversification of a firm's patent portfolio over technology classes, while a value equal to '0' indicates perfect concentration.

Firm science intensity. The science intensity of the firm, i.e. the degree to which the firm's R&D activities are rooted in science, arguably also plays a role in the firm's propensity to enter

new technological domains. Inventions frequently do not only build on previously patented inventions, but also refer to scientific publications, which are not patented. The use of non-patent references as a proxy for scientific activity has a long-standing tradition in prior literature (i.e. Gittelman & Kogut, 2003; Callaert *et al.*, 2006; Cassiman *et al.*, 2008), and empirical work considers non-patent citations in patents as a robust indicator for the usage of science in technology (Tijssen, 2001; Sorenson & Fleming, 2004). Therefore, we include a measure of the firm's science intensity in our models, which we proxy for by calculating the average number of non-patent references made in patents filed by the focal firm, in the 5 years preceding the focal year. To calculate this variable, we restricted NPRs to those NPRs in PATSTAT which are coded as scientific NPRs. We expect firms with a higher degree of science intensity to have a higher likelihood of entering new technological domains, since these firms have demonstrated skills to acquire, assimilate and convert scientific insights into new technological inventions.

Technological opportunities. We include a measure which proxies for the level of technological opportunities in a technology domain. Prior literature suggests that a firm's innovation capabilities are dependent upon the interaction between internal R&D processes and the extent to which they can exploit external opportunities for their own purposes (Cohen, 1995; Cohen & Levin, 1989; Kline & Rosenberg, 1996). A significant amount of these technological opportunities find their origins in scientific research (i.e. Klevorick *et al.*, 1995; Levin *et al.*, 1985). Scientific references made in patents are a substantiation of firms' exposure to scientific research and the opportunities for technological advancement that are related to it. These technological opportunities, in turn, have been shown to be an important incentive for firms to enter into new technological domains. For instance, a study by Leten *et al.* (2016) shows that the larger the technological opportunities in a new technology domain, the higher the likelihood that firms will enter these new technology domains. In this study, we measure

the technological opportunities that are embedded in a technology domain by calculating the average number of references to non-patent literature made per patent in a given IPC 4-digit domain in the 5 years prior to the focal year. To calculate this measure, we take into account the universe of patents in 1995-2015, deduplicated at the patent family level.

Technology concentration. We measure the attractiveness of entering a technology domain and the competition level from incumbent firms that firms may expect after entry by the level of concentrated technology ownership in the technology domain. The more technology development and ownership in a technology domain is concentrated in the hands of a limited number of incumbent firms, the more likely that these incumbent firms will defend their strong technology positions against new entrants (Leten *et al.*, 2016). Specifically, we calculate the concentration of patents over patent owners (assignees) within IPC 4-digit technology domains. Let N_j be the number of patents that assignee *j* has filed in a technology domain in the five years prior to the focal year, with N being the total number of patents in a technology domain. The level of technology concentration within a technology domain is then calculated as $\sum_j (N_j/N)^2$. This is a Herfindahl-Hirschman Index, where a value of the technology concentration measure equal to '1' indicates perfect concentration (only one sample firm active in the technology field), while a value equal to '0' indicates perfect dispersion of patents over patent owners (assignees) within the technology domain.

Technology size. We include the size of the technology domain, measured by the total number of patents filed in an IPC 4-digit domain to control for differences across technology domains in the size of technological activities, and the importance of patents as R&D appropriation mechanism (Cohen *et al.*, 2000).

3.4 Results

3.4.1 Instrument: Number of other CVC investors in the technology domain

In this study, we aim to predict entry in a new technology domain as a function of prior CVC investments in ventures active in that domain.

Prior CVC investments in a technology domain are however likely to be (partly) the outcome of a strategic decision process within firms (Ceccagnoli *et al.*, 2018) and therefore an endogenous predictor of entry in a new technology domain[16]. For this reason, we instrument the stock of CVC investments of the focal firm in a technology domain by the total number of other CVC investors (besides the focal firm) in the same technology domain. The underlying logic of our instrument is that firms face substantial uncertainty when making CVC investment decisions in technology domains in which they have no prior expertise. Investors may cope with this uncertainty on the technology domain's potential by investing in many different technologies. In addition, in line with evidence of peer effects in corporate financial decisions (Leary & Roberts, 2010), firms may partly base their CVC investments on those made by their competitors, which they are able to observe. While CVC investment choices by competitors are expected to influence CVC investment choices of a focal firm, they are expected to be exogenous with respect to the decision of a focal firm to enter and generate technology in a new technology domain.

3.4.2 Descriptive statistics

In total, data on 244 pharmaceutical and biotechnology firms has been collected, of which 35 firms (14.3%) have made a total of 847 CVC investments in patenting ventures during the time period 1995-2015. Firms who engaged in CVC investments made on average 24.2 investments

[16] We confirmed the endogeneity of the prior CVC investment variable using a Hausman test, to verify that our variable of interest is correlated with the error term (not reported in paper).

during these years.[17] Tables 3.1 and 3.2 show descriptive statistics and correlations for the dependent and independent variables used in our models. In about 0.5% of our *firm-year-technology domain* observations, a firm entered a technological domain in which they have not patented in the prior five years. Furthermore, we observe that the average number of CVC investments made by a firm in a technology domain (0.001) is low as opposed to the average number of other external technology sourcing deals made by a firm. This discrepancy is however driven by the fact that CVC investments are usually made in very small firms with a limited patent stock, while our firms tend to also engage in in-licensing or collaboration agreements with companies with more extensive patent portfolios, covering multiple technology domains. Finally, it is worthy to point out that on average a technology domain has 0.17 CVC investors from our sample, when measured over a 5-year time window.

Table 3.1: Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Dependent variable					
Entry in new technology domain (0/1)	2,325,264	0.005	0.067	0	1
Firm-related variables					
Prior CVC deals (5Y stock)	2,329,168	0.001	0.072	0	16
External technology sourcing (5Y)	2,329,168	0.190	0.823	0	11
Firm's technological relatedness	2,329,168	0.005	0.024	0	0.999
Firm size parent (5Y, log-scaled)	2,329,168	3.179	2.255	0	9.333
Firm self-citations (5Y)	2,329,168	0.016	0.092	0	2.227
Technological diversification	2,329,168	0.850	0.137	0	1
Firm science intensity	2,329,168	0.656	3.137	0	93
Technology domain-related variables					
Technological opportunities	2,329,168	0.169	0.525	0	21.302
Technology concentration	2,329,168	0.284	0.360	0	1
Technology size (log-scaled)	2,329,168	6.847	1.742	0	11.168
Investors per tech domain (5Y)	2,329,168	0.173	0.878	0	22
Interaction variables					
Investee prestige	2,329,168	.283	2.146	0	55.500
Co-investors	2,329,168	.000	.008	0	2

[17] See Appendix 3.1 for an overview of firms that have made CVC investments during 2000-2015.

Table 3.2: Correlation matrix

		1	2	3	4	5	6	7	8	9	10	11	12
1	Entry in new technology domain (0/1)	1.000											
2	Prior CVC deals (5Y stock)	0.032	1.000										
3	External technology sourcing (5Y)	0.029	0.022	1.000									
4	Firm's technological relatedness	0.243	0.026	-0.012	1.000								
5	Firm size parent (5Y)	0.076	0.012	0.299	0.029	1.000							
6	Firm self-citations (5Y)	0.016	0.011	0.031	0.035	0.121	1.000						
7	Technological diversification	0.005	0.005	0.015	-0.034	-0.083	-0.018	1.000					
8	Firm Science intensity	0.003	-0.003	-0.012	0.026	0.027	0.084	-0.086	1.000				
9	Technological opportunities	0.078	0.036	-0.021	0.344	-0.048	-0.005	-0.003	-0.003	1.000			
10	Technology concentration	-0.017	-0.010	0.009	-0.066	0.018	0.002	-0.001	-0.004	-0.071	1.000		
11	Technology size	0.054	-0.014	-0.031	0.152	-0.028	-0.015	-0.018	-0.012	0.053	0.099	1.000	
12	CVC investors per tech domain (5Y)	0.064	0.174	-0.008	0.110	-0.014	-0.003	-0.004	-0.004	0.149	-0.056	-0.026	1.000

3.4.3 Multivariate analyses

Table 3.3 reports on OLS regressions which evaluate the likelihood to enter a technology domain that is new to the firm, based on their CVC activity in that technology domain in the prior five years. Model 1 shows a panel OLS regression in which only the control variables are included and serves as a base of comparison for the other models where we add the effect of prior CVC investments in a technology domain on the subsequent likelihood to start patenting in that given technology domain. We observe that firms that engage less in external technology sourcing and have a larger and more diversified patent stock are more likely to enter new technology domains. Confirming that technology development is path-dependent, we find that firms are more likely to enter technology domains that are related to their existing technologies. Firm self-citations, which proxies for the degree of cumulativeness of the firm's internal R&D efforts, is correlated in a statistically significant negative way to the likelihood to enter firm-new domains. Furthermore, on the level of the technology domain, we observe that firms are more likely to enter new technology domains that are large in size of technological activities. In Model 2, we examine the effect of prior CVC investments in a technology domain on the likelihood of the firms' subsequent entry in that technology domain. We observe a positive and statistically significant effect for the relationship between prior CVC investments and entry. A unit change in prior CVC investments in a technology domain increases the likelihood to enter that domain with 3.8%. This confirms hypothesis 1. The effects of the firm-level controls remain consistent with the findings of Model 1, where only controls were included.

In order to further explore the circumstances under which CVC investments in a new technology domain lead to subsequent entry, we test three interaction effects: the moderating effect of the quality of ventures' technologies, the number of CVC co-investors and the technological relatedness of the new technology domain to the firm's existing knowledge base. Models 3 through 6 explore these interactions. In Model 3, we interact prior CVC investments

with the quality of the investee(s). The coefficient of the interaction effect is positive and statistically significant. The interaction effect is however no longer significant in Model 6 that includes the interaction terms with investee quality, the number of CVC co-investors and a firm's relatedness to the technology domain together. We therefore reject hypothesis two that CVC investments in a technology domain have a larger effect on subsequent entry if these investments take place in ventures with high quality technologies. Model 4 shows the results of an interaction between CVC investments and the number of CVC co-investors. We observe a positive and significant coefficient for our interaction variable. This coefficient is however no longer statistically significant in the full Model 6, thereby rejecting our third hypothesis that CVC investors that invest alongside a greater number of co-investors in a technology domain, on average, will achieve greater learning benefits from their CVC investments. Lastly, Model 5 shows the results of an interaction between CVC investments and the technological relatedness of the technology domain to the firm's existing knowledge portfolio. The coefficient of this interaction variable is positive and significant in Model 5 and remains positive and significant in Model 6. We therefore accept our fourth hypothesis, that the higher the technological relatedness between a technology domain and the firm's current technology portfolio, the stronger the positive effect of CVC investments in a new-to-the-firm technology domain on the likelihood that a firm will enter and generate technology into that technology domain.

Table 3.3: Results of OLS regressions on *Entry into new technology domain (NTD)*.

	(1)	(2)	(3)	(4)	(5)	(6)
Firm-level variables						
Prior CVC deals (5Y stock)		0.038***	0.031***	0.032***	0.024***	0.017**
		(0.006)	(0.007)	(0.006)	(0.005)	(0.006)
External technology sourcing (5Y)	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm's technological relatedness	0.706***	0.706***	0.706***	0.706***	0.703***	0.704***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Firm size parent (5Y)	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm self-citations (5Y)	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Technological diversification	0.001***	0.001***	0.001***	0.001***	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm Science intensity	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Technology domain-level variables						
Technological opportunities	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Technology competition	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Technology size	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Interaction variables						
Investee quality			0.000			0.000
			(0.000)			(0.000)
Prior CVC*Investee quality			0.002*			0.002
			(0.001)			(0.001)
Co-investors				-0.000		0.017
				(0.031)		(0.033)
Prior CVC*Co-investors				0.037*		0.014
				(0.018)		(0.024)
Prior CVC*Tech relatedness					0.110**	0.099*
					(0.036)	(0.042)
Constant	-0.022	-0.022	-0.022	-0.022	-0.022	-0.022
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
N	1,832,115	1,832,115	1,832,115	1,832,115	1,832,115	1,832,115
R-squared	0.06	0.06	0.05	0.06	0.06	0.06
Technology Domain FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

* $p<0.05$; ** $p<0.01$; *** $p<0.00$; Robust standard errors in parentheses

3.4.4 Robustness check: control function approach

To address the endogeneity concern regarding our CVC investment-variable above and test the robustness of our base results, we employ a control function approach where we instrument CVC investments by the number of other investors in the technology domain. In the models discussed below, we have performed a manual two-step estimation of the model. First, we predict our prior CVC investments-variable based on a linear regression on all confounders. Next, this predicted residual term of this regression is fitted into a second-stage model. Since a manual control function estimation by means of two OLS regressions yields invalid estimated standard errors, we calculate bootstrapped standard errors, which fixes the standard errors via re-sampling (Guan, 2003; Cameron & Trivedi, 2009). In the models presented below, we use 200 bootstrap-replications.

Table 3.4 reports on the first-stage OLS regression of this control function approach. As can be seen from the regression output, our instrumental variable, the number of other CVC investors active in a technology domain is a significant positive predictor of the likelihood of a focal firm to make CVC investments in that technology domain. Furthermore, we see that firms that are smaller in size undertake more CVC investments, while at the level of the technology domain, we see that the degree of technological competition and the size of the technology domain both seem to be negatively related to the likelihood of making CVC investments in that domain.

Table 3.4: Results of first-stage control function regression

	CVC deals in tech domain (5Y)
Instrumental variable	
Other investors in tech domain (5Y)	0.009***
	(0.001)
Firm-level variables	
External technology sourcing (5Y)	-0.001
	(0.000)
Firm's technological relatedness	0.004
	(0.009)
Firm size parent (5Y)	-0.000***
	(0.000)
Firm self-citations (5Y)	0.003
	(0.002)
Technological diversification	0.000
	(0.000)
Firm Science intensity	-0.000
	(0.000)
Technology domain-level variables	
Technological opportunities	0.000
	(0.001)
Technology competition	-0.000*
	(0.000)
Technology size	-0.001**
	(0.000)
Constant	-0.001
	(0.213)
N	1,835,446
R-squared	0.07
Technology Domain FE	YES
Firm FE	YES
Year FE	YES

* $p<0.05$; ** $p<0.01$; *** $p<0.001$
Robust standard errors in parentheses

Table 3.5 reports on the second-stage OLS regressions of the control function approach. Model 1 presents our main set-up. From this model, we can observe that prior CVC investments, when instrumented by the number of other investors in the focal technology domain, are positively and significantly associated to the likelihood of subsequent technological entry into that technology domain. Furthermore, we see that the firm's technological relatedness to the focal technology domain, the size of the parent firm and the technological diversification of their patent stock are all positively related to the firm's likelihood to start patenting in the focal

domain, while firm self-citations and the firm's degree of external technology sourcing activities are negatively associated to the likelihood to enter a new technology domain.

Next, we look deeper into the conditions under which CVC investments in a technology domain lead to an increased likelihood of entry in that technology domain. In Models 2 through 5, we present the interactions that have also been included in Table 3.4, but this time under the control function assumption. In Model 2 we observe a positive and significant coefficient for the interaction term, suggesting that making CVC investments in investees of a higher quality is associated with a stronger likelihood of entering into new technological domains. However, in Model 5, we see that when we include all interaction terms together, the interaction between CVC investments and the quality of the investee is no longer significant. Similarly, we observe a positive and significant coefficient for the interaction between CVC investments and the number of co-investors in an investment syndicate. However, in Model 5 also this interaction term loses significance at the 5% level. Lastly, in Model 4 we observe a positive interaction between CVC investments in a technology domain and a firm's technological relatedness to the focal technology domain, suggesting that a higher technological relatedness increases a firm's likelihood of becoming active in a technology domain after having made CVC investments. Like with the other two interactions that we explored, however, this interaction term is no longer significant when considered jointly with the other two interaction terms. We therefore cannot find support for our three moderating effects under a control function approach.

Table 3.5: Results of control function OLS regressions on Entry into new technology domain (NTD). Prior CVC deals (5Y stock) instrumented by Other investors in tech domain (5Y).

	(1)	(2)	(3)	(4)	(5)
Prior CVC deals (5Y stock)	0.109*	0.104*	0.105*	0.101*	0.094*
	(0.047)	(0.043)	(0.047)	(0.044)	(0.037)
External technology sourcing (5Y)	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm's technological relatedness	0.705***	0.705***	0.705***	0.703***	0.703***
	(0.014)	(0.015)	(0.013)	(0.013)	(0.013)
Firm size parent (5Y)	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm self-citations (5Y)	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Technological diversification	0.001***	0.001***	0.001**	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm Science intensity	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Technological opportunities	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Technology competition	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Technology size	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Investee quality		0.000			0.000
		(0.000)			(0.000)
Prior CVC*Investee quality		0.002*			0.002
		(0.001)			(0.001)
Co-investors			-0.001		0.017
			(0.029)		(0.029)
Prior CVC*Co-investors			0.037*		0.014
			(0.017)		(0.025)
Prior CVC*Tech relatedness				0.110**	0.099
				(0.038)	(0.053)
Residuals	-0.072	-0.072	-0.073	-0.077	-0.076
	(0.046)	(0.043)	(0.047)	(0.043)	(0.039)
Constant	-0.017	-0.021	-0.021	-0.021	-0.022
	(0.004)	(0.003)	(0.003)	(0.004)	(0.002)
N	1,832,115	1,832,115	1,832,115	1,832,115	1,832,115
R-squared	0.17	0.17	0.17	0.17	0.17
Technology Domain FE	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

* $p<0.05$; ** $p<0.01$; *** $p<0.001$; Bootstrapped standard errors in parentheses

3.5 Conclusion and Discussion

This study examines whether CVC investments can be used by firms as effective tools for entering into new technology domains. Exploring and building up competencies in new technology domains is important for firms to survive in turbulent business environments. Adopting an organizational learning perspective, we argue that CVC investments can be used as a means of learning about new technology domains. By investing in ventures that have expertise in new technology domains, firms can acquire, assimilate, translate and exploit the ventures' knowledge that is necessary to build up competencies in these domains. Relying on a panel dataset (1995-2015) on the CVC and patent activities of 244 top R&D spending European, US and Japanese firms in the pharmaceutical industry, we find that prior CVC investments in a new technology domain are in a positive and statistically significant way related to the firm's likelihood to enter and build up competencies in that domain.

Furthermore, we argue that the relationship between CVC investments and subsequent entry in new technology domains is moderated by the quality of technologies of investees, the number of CVC co-investors in investment syndicates and the relatedness of the technology domain to the investor's existing knowledge base. Firms that have access to ventures that possess higher quality technologies enjoy a knowledge advantage that improves their changes of leveraging knowledge of ventures to build up competencies in new technology domains. Investors that co-invest with other CVC firms may benefit from a 'horizontal' learning channel whereby they can rely on the assistance of co-investors to implement ventures' knowledge in new technology domains. When the new technology domains are technologically close to what the investor already knows, the investor may be able to learn more from the CVC investment, thus increasing its likelihood of becoming active in that technology domain at a later stage. We find no strong empirical evidence for the moderating influence of investees' quality or the number of co-investors in a syndicate. However, we do find that firms that invest in ventures

with expertise in technology domains which are technologically close to the investor's own technological expertise, are more likely to enter new technology domains.

Our research contributes to two streams of research. First, our study adds to the literature on entry into new-to-the-firm technology domains (e.g. Leten *et al.*, 2016) by exploring the intersection with the research on corporate venturing, as it examines the relationship between making CVC investments in ventures active in unfamiliar domains and the subsequent likelihood to become active in that domain. More specifically, our study shows that CVC investments are an effective tool for firms to leverage the knowledge of ventures and to build up competencies in new technology domains.

Second, our study contributes in several ways to the literature on CVC investments, which has established an association between CVC activities and investor innovation performance at the firm-level (e.g. Dushnitsky & Lenox, 2005). We test whether this applies to the particular process of entering into novel technology domains. Attention to this particular phenomenon is warranted since it involves a wide range of innovation-related activities, which firms must apply in order to generate technology in those domains. It shows that with more CVC investments, firms not only increase their knowledge inflows and the variety of the knowledge to which they are exposed, but also learn from these investments. In other words, CVC investors are not only able to identify promising investment opportunities, they also manage to speak the language of entrepreneurial ventures in order to successfully leverage their knowledge (Brown & Duguid, 1991). Additionally, this study adds to this stream of literature by deepening our understanding of the circumstances under which CVC investments may lead to an increased likelihood of entering a domain that a firm was not active in before, by looking at interactions of the CVC investment decision with characteristics of the venture such as its perceived quality, the average number of co-investors active in the venture, and the technological relatedness of the investor to the ventures' technology.

This study has several limitations, which open up avenues for further research. Firstly, the findings of our study are -by design- limited to the context of the pharmaceutical industry. Whereas CVC investments are a popular vehicle for technology exploration in this context (Van de Vrande *et al.*, 2009), it might be interesting to expand this study to other industries, particularly these industries which are characterized by a high level of R&D activity. Furthermore, the firms in our sample are selected as being the top-R&D spenders in the industry. It therefore remains to be studied to what extent the findings of the present study can be generalized to smaller firms in the pharmaceutical industry.

Secondly, our study has identified three moderators of the relationship between CVC investments and subsequent entry in new technology domain. An avenue for future research is to get a broader understanding (beyond the moderators studied) of the contingencies under which firms can learn from CVC investments in new technology domains. One suggestion in this respect is to study the role of the geographical distance between the investees and the investor firm. The idea is that investor firms which are located geographically closer to their investees may benefit to a larger extent from the knowledge of their investees in building up competencies in new technology domains. Prior literature shows in this respect that geographical proximity between firms facilitates 'localized learning' (Malmberg & Maskell, 2006) while at the same time capturing localized knowledge spillovers outside of formal relations (Griliches, 1979; Owen-Smith & Powell, 2004), for instance during informal meetings between scientists which may give way to localized knowledge spillovers from the venture to the investor firm.

Finally, while our study examined the relationship between CVC investments and entry in new technology domains, we did not study to which extent CVC investments lead to 'successful' entry and development of strong technological capabilities in new domains.

Further research may take up this challenge by studying the impact of CVC investments post-entry on the technological performance of firms in new technology domains.

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3.7 Appendix

Appendix 3.1. Total number of CVC investments in patenting ventures made by CVC-active parent firms (n=35)

PARENT FIRM	Unique CVC deals
1. MITSUBISHI PHARMA CORPORATION	130
2. CHIRON CORP	68
3. NOVO NORDISK	65
4. NOVARTIS	53
5. JOHNSON & JOHNSON	48
6. QUINTILES	48
7. MEDIMMUNE	47
8. TAKEDA PHARMACEUTICAL	40
9. GLAXOSMITHKLINE	39
10. SUMITOMO DAINIPPON PHARMA CO, LTD	38
11. H LUNDBECK A/S	35
12. PFIZER	34
13. AMGEN	24
14. PERRIGO CO	21
15. ASTELLAS PHARMA	19
16. MERCK & CO	15
17. ELI LILLY	15
18. ROCHE	14
19. ABBVIE	12
20. MONSANTO	12
21. BIOGEN IDEC	12
22. INCYTE	10
23. FUJISAWA PHARMACEUTICAL	8
24. BOEHRINGER INGELHEIM	8
25. SANOFI	7
26. ABBOTT LABORATORIES	5
27. OTSUKA	4
28. SHIRE	4
29. FOSUN INTERNATIONAL	4
30. CELGENE	3
31. AFFYMETRIX INC	1
32. BRISTOL-MYERS SQUIBB	1
33. CELL GENESYS INC	1
34. CIPLA	1
35. BECTON DICKINSON & CO	1

Chapter 4
Does science park presence generate breakthrough inventions? The case of US science park-based firms

Abstract

Science Parks have gained considerable attention in the recent years due to their claimed effect on the increased innovative performance of Science Park-based firms. While prior literature has primarily zoomed in on the quantity of innovative output, the quality of on-park inventions by firms who are present on a science park remains relatively under-investigated. This paper aims to empirically show the effect of being generated on a science park on the technological impact of inventions. To this end, we have compiled a database on patents filed by firms across different industries based on 60 US science parks, for the years 1980-2010. Our results show that inventions which are generated on a science park have a higher likelihood of being a breakthrough patent, as compared to inventions done by the same tenant in an off-park subsidiary. Furthermore, we identify proximity to a nearby (top-tier) research university as an important mechanism through which SP presence affects the generation of BT inventions. These results further our understanding of the role that science parks play in the innovative performance of firms and add to the literature on knowledge spillovers and industry-science links.

Keywords: Science parks, breakthrough inventions, industry-science links

4.1 Introduction

Science parks and their effects on firm innovation have sparked an interest among policy makers and academics in recent years (McCann & Folta, 2008). This interest is largely based on their potential for cross-fertilization between science and technology (Löfsten & Lindelöf, 2002). While basic research conducted at a university or research institution is often characterized as risky for firms due to market failures that come along with this type of research (Arrow, 1962), science parks aim to overcome this problem by fostering spillovers between universities and the industry (Colombo & Delmastro, 2002), allowing basic research to be put in productive use in an applied firm setting (Bower, 1993).

There is no generally accepted definition on what a science park is, and the concept of a science park is often used intertwined with concepts like research parks, technology parks and business incubators (Albahari *et al.*, 2017). However, recurring elements are that science parks are (1) high-tech spatial clusters (Oerlemans & Meeus, 2005; Phan *et al.*, 2005; Hansson *et al.*, 2005; Salvador & Rolfo, 2011), that are (2) managed by specialized professionals (Westhead, 1997), whose aim is (3) to build bridges between universities and the industry (Squicciarini, 2008; Fikirkoca & Saritas, 2012; Fukugawa, 2006), and (4) aim at the commercialization of basic research (Bozeman, 2000). The beneficial effects of science parks on the innovative capabilities of their tenants have been highlighted in recent literature. For instance, it is shown that firms which are located on a science park have a higher likelihood to establish connections with research institutions and other firms, which allows them to increase their recombinatory set on which novel technologies are based (Löfsten & Lindelof, 2002; Weitzman, 1998; Fleming, 2001, Arthur, 2009). Furthermore, the establishment of inter-firm networks and links with science is shown to have a positive impact on the diversity of the knowledge portfolio of science park-based firms (Quintas *et al.*, 1992), since it improves technology sharing (Singh, 2005). Next to that, science parks provide their tenants with an environment in which

practicalities and infrastructure are arranged for them by park management, allowing the tenant firms to focus on their core activities (McAdam & McAdam, 2008). In conclusion, prior literature suggests that science parks help in fostering an effective innovative environment for its tenant firms.

Since science parks are frequently associated with intense inventive activity, prior literature has also given considerable attention to the innovative performance of science park-based firms (Westhead, 1997; Löfsten & Lindelof, 2002; Colombo & Delmastro, 2002; Siegel *et al.*, 2003). For instance, Westhead (1997) examined whether firms which are located on a science park achieve a higher research productivity than firms which are not based on a science park and found that science park-based firms were not able to out-perform off-park firms in terms of R&D outputs, while another study found that being located on a science park is associated with more innovation and more investments in R&D (Lamperti et al, 2015). Furthermore, a study by Siegel *et al.* (2003) shows that the research productivity of on-park firms is greater than that of off-park firms, while Squicciarini (2009a, 2009b) finds that the innovative performance of firms located inside a science park is greater due to knowledge spillovers.

Other studies have looked into the role of the university or research institution that is connected to the science park (Felsenstein, 1994; Westhead & Storey, 1995; Vedovello, 1997; Link & Scott, 2003; Marques *et al.*, 2006). For instance, Westhead and Batstone (1998) empirically show that the location on a science park is driven by a firm's need to acquire research facilities and scientists at the university. On-park firms furthermore seem to have more research links with universities than off-park firms (Malairaja & Zawdie, 2008), and establishing these links seems to pay off. For instance, it is shown that firms that pursue formal agreements and informal interactions with the science park-related university tend to increase their innovative capacity (Diez-Vial & Montoro-Sanchez, 2016), while the presence of a

university in the science park is shown to have a positive effect on the number of patent applications of the tenant firms (Albahari *et al.*, 2013).

Although prior literature which looks at the innovative output of science park-based firms suggests mixed voices in confirming the claimed benefits of science parks in the generation of innovative productivity, the literature which looks into the role of universities in knowledge diffusion and innovative performance of tenant firms within a science park seems to find primarily positive outcomes from on-park firms establishing links with universities and research institutions. However, one common approach in these prior studies is that innovative output is conceived as a quantity-oriented measure, such as the number of patent applications, while the quality of the innovative output produced by on-park firms remains to be investigated.

Furthermore, the way that being present on a science park links to the likelihood of generating inventions with a high technological impact has so far not been given attention in prior literature. However, given the generally strong link between science parks and research institutions or universities and hence the presence of basic research on science parks, we presume that science parks might be a fertile ground for tenants to generate inventions with a higher impact, since prior literature (i.e. Della Malva *et al.*, 2015) suggests a positive relationship between access to basic science and generating impactful inventions.

Therefore, in this paper, we aim to address these gaps by looking whether inventions of firms which are active on a science park have a higher technological impact than inventions by the same firm in the same technological field which are generated off-park and thus whether science park presence becomes advantageous for the tenant firm in their propensity to generate impactful inventions.

To proxy for the impact of a patent, we will adopt a quality-oriented measure (Della Malva *et al.*, 2015; Verhoeven *et al.*, 2016) that assesses whether a patent can be considered as a

'breakthrough' or radical invention. Breakthrough inventions can be characterized as inventions that surpass a critical threshold of forward citations in a given year and technology sector (Conti *et al.*, 2014; Kerr, 2010; Singh & Fleming, 2010). We believe that breakthrough inventions are an important parameter to take into account in discussing the innovative performance of science parks' tenant firms, given their pivotal role in the innovation process. Breakthrough inventions are believed to be welfare-enhancing (Harhoff *et al.*, 1999; Trajtenberg, 1990), possess a high usefulness for both consumers and producers (Arts & Veugelers, 2015) and are highly profitable for inventors (Hall *et al.*, 2005). In this study, we operationalize breakthrough inventions by using patent-level data, in which we consider breakthrough patent as a patent that is among the two standard deviations-outliers in terms of forward citations received within a five-year time frame from the application year. By adopting this quality-oriented measure, we aim to answer the question to what extent inventions of a tenant firm which are created on-park are more likely to have a substantial impact as compared to similar patents by the same tenant firm, but which are developed off-park. By addressing this research question, we shift away from the existing literature, which compares on-park and off-park firms, while we compare on-park and off-park patents of the same firm, which has different subsidiaries on-park and off-park.

We test our prediction by using a matched sample of 7,692 US patents filed between 1980 and 2010. More specifically, our sample contains patents filed by science park-based firms established on 60 US science parks. Based on geo-coded disambiguated inventor data derived from patents (Li *et al.*, 2014), we categorize these patents as either on- or off-park. Using an exact matching approach, we link each on-park patent to an off-park patent, filed by the same firm, in the same year, in the same technology class (at the IPC-3 digit level). This results in 3,846 on-park patents and 3,846 off-park patents, which constitute our treatment and control group on which we have performed our analyses.

Our results suggest that a firm's patents which are created on-park have a significantly higher chance of having a high impact, as measured by being a two-standard deviations outlier in the number of forward citations received within five years of the application date. We observe that these effects hold when controlling for whether the patent is invented close to a research university, in which case the higher impact of the patent might be attributable to a 'university nearby' effect rather than driven by the presence of a science parks.

4.2 Theoretical Background

4.2.1 Towards a conceptualization of Science Parks

Prior literature provides no general, uniform definition of what a science park is. Therefore, we witness that the terms Science Park, Technology Park and Research Park are often used intertwined (Amirahmadi & Saff, 1993; Link & Scott, 2003). However, merging several definitions, we are able to extract the main characteristics of a science park. In the definition of the UK Science Park Association (UKSPA), a science park is "*a cluster of knowledge-based businesses, where support and advice are supplied to assist in the growth of the companies. In most instances, Science Parks are associated with a centre of technology such as a university or research institute."* (UKSPA, 2019).

Spatial Proximity

Prior literature puts the idea of spatial proximity forward as a key characteristic of a science park (Oerlemans & Meeus, 2005; Phan *et al.*, 2005; Hansson *et al.*, 2005, Salvador & Rolfo, 2011). This spatial proximity allows firms to benefit from different types of agglomeration externalities (Albahari *et al.*, 2017). Agglomeration externalities on science parks may come in the form of specialization - a cluster of firms belonging to the same industry - where firms may reap the benefits of Marshal externalities (Marshal, 1920). On the other hand, science

parks may have a very diverse set of tenants, and this technological diversity may allow tenants to take advantage of Jacobs' externalities (Jacobs, 1969). The location of a park may allow tenants to have access to specialized inputs, such as specialized labour or contacts with academics (Prevezer, 1997). Moreover, prior literature suggests that spatial proximity can be an important driver for innovation due to reduced geographical distances, which may enhance the establishment of links (Hervas-Oliver & Albors-Garrigos, 2009; Albahari, 2017), and foster (tacit) knowledge transfer (Howells, 2002; Gertler, 2003), as this type of knowledge transfer benefits from close interactions in the form of face-to-face contacts.

Linking Science and Industry

A second characteristic of science parks is that they aim to bridge research and industry (Squicciarini, 2007; Fikirkoca & Saritas, 2012, Fukugawa, 2006). For example, Link & Scott (2006) suggest that *'universities not only transfer knowledge but expect to develop knowledge more effectively given the association with the tenants in the research park'* (Link & Scott, 2006, p. 44). This suggests that science parks seem to promote spillovers by means of formal and operational links between universities and firms (Yang *et al.*, 2009). Universities play a crucial role in firm's innovations (Bozeman, 2000; Salter & Martin, 2001; Cohen *et al.*, 2002), since they are a cornerstone in the diffusion of basic knowledge that leads to innovations in the industry (Mansfield & Lee, 1996) and the development of ties between universities and industry is believed to be an important driver of innovation processes (Perkman & Walsh, 2007). Prior literature acknowledges that in the aim of bridging research and industry, the spatial proximity again is a crucial component. It is argued that knowledge spillovers from university research to the applied knowledge of the industry are often geographically localized (e.g. Jaffe, 1993; Maurseth & Verspagen, 2002), in order to overcome the tacit nature of this knowledge. Furthermore, this geographical proximity of highly innovative firms to the university is an important driver in commercializing the academic knowledge that universities

possess (Bozeman, 2000). This commercialization could be achieved in a more formal way, such as patenting or establishing active collaborations between university researchers and corporate researchers; or in informal ways of collaborations, such as the provision of networking opportunities between scientists and practitioners. (Perkmann *et al.*, 2013).

Park Management Support

A third characteristic of science parks is that often management and administrative support is provided for tenants (Westhead, 1997; Westhead & Batstone, 1999). Science parks' management teams can assist tenants by identifying relevant external funding opportunities, either through private or public sector sources (Ferguson & Olofsson, 2004; Westhead, 1997). Furthermore, science park management can assist in finding appropriate third-party business support actors (Grayson, 1993), or by providing business advice and training programmes itself (Westhead & Batstone, 1999). Next, science park management can provide tenants with access to and stimulate the use of research institutions' intellectual resources, such as their libraries or academic databases. Lastly, Westhead & Batstone (1999) suggest that park management can help tenants by providing managed support in order to ensure the tenant's rental growth.

4.2.2 Linking science parks to breakthrough invention

Going back to the seminal work by Schumpeter (1942), technological breakthrough inventions are considered as having a pivotal role in value creation and growth (Schumpeter, 1942). This type of inventions, which are characterized by their discontinuity to prior art (Anderson & Tushman, 1990; Dahlin & Behrens, 2006), are believed to have a high market value for the firm (Hall *et al.*, 2005) and to have a high usefulness for producers and consumers (Arts & Veugelers, 2014). Furthermore, prior literature argues that breakthrough inventions serve as a starting point for subsequent inventions (Fleming, 2001; Ahuja & Lampert, 2001), providing prior art for these new technological avenues.

Different studies have been dedicated to factors enhancing the creation of breakthrough inventions. For instance, Ahuja & Lampert (2001) present a model which explains how breakthrough inventions are created by established firms. They find that firms which experiment with novel and emerging technologies, in which they lack prior experience, can foster the creation of breakthrough inventions. Another study by Singh and Fleming (2010) looks at the creation of breakthroughs from an inventor-perspective. They suggest that collaborative innovation in inventor teams may benefit the creation of breakthrough innovations, in opposition to lone inventors.

The relationship between science parks and the invention of breakthrough patents has however not been given attention in prior literature. Still, we believe that it is worthwhile to delve into this relationship. Tenant firms on science parks benefit from considerable exposure to basic research, both in formal and informal ways due to the close link of science parks with research institutions and universities. Furthermore, prior work by Della Malva *et al.* (2015) shows a positive relation between firms actively involved with basic research and the generation of breakthrough inventions. Due to this exposure that science parks' tenants receive to basic research, we hypothesize that patents which are created on-park are more likely to be breakthrough patents.

Whether a patent is a breakthrough patent is often identified in prior literature by using forward citations (Ahuja & Lampert, 2001; Fleming, 2001; Singh & Fleming, 2010), since the number of forward citations is positively correlated to a patent's technological impact (Albert *et al.*, 1991; Jaffe *et al.*, 2000). In this study, we follow this approach on identifying breakthrough inventions and consider a patent as a breakthrough patent if it is among the two standard deviation-outliers in the number of forward citations received in a five year-time window following the application year of the patent.

4.3 Data and Methodology

4.3.1 Data

The sample for this study is constructed in several steps. First, we have identified all science parks located in the US, based on the UNESCO list of science parks[1]. In the definition of UNESCO, a 'Science Park' refers to "*property development that is designated to support the clustering of knowledge-based enterprises in order to commercialize science and technology*" (UNESCO, 2010, p.4). For all science parks included in the UNESCO list, we have manually verified on their website whether (1) the science park collaborates with at least one local university or research institution, (2) whether the science park stimulates the growth of new innovative firms, and (3) whether the activities on the science park do not merely relate to incubation (not only houses start-ups but also incumbent firms). For the science parks that met these criteria[2], we have manually looked up all tenant firms located on the science park. We did this by checking the science park website, which enabled us to identify the tenant firms on the parks as of February 2018. In a next step, we have collected all patents that the tenant firms of our science parks have filed for with the USPTO between 1980 and 2010[3]. All patent-related data in this study are collected from PATSTAT. Furthermore, we have linked all the filed patents to the address information of the inventors listed on the patents, based on the dataset composed by Li *et al.* (2014). This database contains - for all USPTO patents - disambiguated inventor-level information, including the geographic coordinates of the inventors based on their home addresses which inventors living in the US are required to provide in their US patent application form. Using these geographic coordinates and having manually geocoded the

[1] http://www.unesco.org/new/en/natural-sciences/science-technology/university-industry-partnerships/science-parks-around-the-world/

[2] UNESCO lists a total of 72 science parks on its website, of which we retain 60 science parks in our final sample. For the remaining 12 science parks, either no website information could be retrieved so that the science park could not be evaluated against the three inclusion criteria set forward, or it became clear from their website that the 'science park' was in no way related to a research institution or university. Either way, these 12 cases did not fulfill the inclusion criteria and hence have not been included in our sample.

[3] In our analyses, we have dropped panel years before the year of establishment of the science park.

location of each science park in our sample by looking up the longitude and latitude coordinates of their post address, we are able to calculate the geographical distance between inventor address and science park location, thus determining whether a patent of a science park tenant was created on the science park or outside. To determine whether a patent was created on a science park, we have used a radial distance of 30 kilometers around the science park as our cut-off point for the patent to be included as a science park-patent. The resulting variable is a dummy indicating if the patent of a tenant is on-park (< 30 km) or off-park. The cut-off point of 30 km is determined based on a prior exercise of Bakker & Verhoeven (2017), which determined that a maximum distance of 30 km performed best in terms of validity for a sample of inventors around the Research Triangle Park in Durham, North Carolina. The resulting sample contains data on patents created on 60 US science parks by 544 patenting tenants during the years 1980-2010, which we will match in a next step to off-park patents with the same technological characteristics and were applied for in the same year.

4.3.2 Measures

a. Matching

The purpose of this study is to explore whether being present at a science park generates inventions with a comparatively higher technological impact than inventions that are developed off-park. In order to establish a representative treatment and control group, we match each on-park patent in our sample with an off-park patent that carries the same properties. Specifically, we identify a non-treatment observation based on exact matching. To perform the matching exercise, we use three different matching covariates on which we want to achieve a balance between treated and non-treated observations, and for which we require an exact match between treatment and control group. Specifically, we require that the selected non-treatment observation provides an exact match on (1) tenant firm name, (2) the year that a patent is filed

for, and an exact match on (3) the IPC-technology class(es) at the three-digit level on both treatment and control patent, with a dummy on-park/off-park being the treatment variable.

b. Outcome variable

Forward citations are generally regarded as a metric for measuring the technological impact of patents (Breitzman & Mogee, 2002; Sampat & Ziedonis, 2004). Using forward citations and more specifically looking at the place in the distribution of forward citations received by patents, we suggest an outcome measure based on whether a patent can be considered as 'breakthrough'. In line with prior literature (Verhoeven *et al.*, 2016), for our outcome variable we use a measure of technological impact which captures whether the invention on the patent can be considered as a *breakthrough* invention, which denotes whether the invention can be considered as a "break from the past and/or a having a large impact on the future along some technological dimensions" (Verhoeven *et al.*, 2016). This measure assesses for each individual patent whether a patent family is among the two-standard deviation[4] outliers in the distribution of forward citations received by year and IPC subclass in the five years following the year the patent was filed for. Furthermore, we also use the total count of forward citations received by the tenant's patents in the five years subsequent to filing to run a robustness check.

c. Independent variables and controls

Our main variable of interest is a dummy indicating whether a patent of a tenant firm is created on-park or off-park. As explained above, we have used individual inventor addresses to determine whether a patent is on- or off-park, taking into account the distance of the inventor on the patent who lives closest to the Science Park. In our main model, we apply a range of 30 km between the science park address and the home address of the closest-living inventor.

Next, we have included a list of control variables to isolate the effect of a patent being on-park or off-park on the propensity to be a breakthrough invention. We control on four different levels, namely at the level of the region, the level of the patent, the level of the firm and the level of the science parks.

First, at the level of the region, we control for the *research intensity of the region*, by including the total number of patents filed by non-tenant firms within the same 30 km radius around the Science Park. The motivation for this control is that knowledge spillovers may not only happen due to presence on the Science Park, but may also be positively related to the research intensity of the broader region in which the Science Park is located.

As a second region-level control, we have included a set of dummies indicating the *level of urbanization* of the region the science park is located in. Data to construct this variable has been derived from the US National Center of Education Statistics (NCES). This database lists for every location where a university is located the degree of urbanization. Since all of our science parks are by construction located in a city or town where a research institution or university is located, we are able to determine for each of our science parks whether it is located in a densely populated or rural area. In total, 12 possible degrees of urbanization are provided by the data, ranging from 'Large City' to 'Rural Remote Area'. The degree of urbanization is a relevant control, since science parks that are located in densely populated areas can tap into a larger pool of highly-skilled, highly-educated workers, which might affect the likelihood of producing breakthrough inventions.

As a third variable at the level of the science park region, we create a dummy variable which indicates whether a *patent is located near a US research university*. To do so, we follow the same approach as in the creation of our variable of interest, by calculating the geographical distance between the research university and the closest-living inventor mentioned on the

patent. When this distance is below 30 km, we indicate our patent as being nearby a research university. To determine our list of research universities, we started from a long list of all US universities and colleges, and their geographical longitudes and latitudes. This data is also obtained from the US National Center of Education Statistics (US NCES). Based on this list, we have retained these universities which grant PhD degrees, and as a further restriction, we require that our research universities are R1, R2 or R3 research universities[5]. Based on these restrictions, we end up with a list of 332 research-intensive universities spread across the US, which are used as a basis for deciding if the patent is invented near a research university. In subsequent analyses, we use the distinction between the three tiers of research universities in order to observe whether our effects are driven by a certain category of research university.

Next, we introduce several control measures on the level of the patent. Specifically, we include controls for size of the inventor team, the number of applicants on the firm's patent, the number of scientific citations the patent makes (non-patent references or NPRs) as well as a measure of the originality of the patent.

As a first patent-level measure, we include *the team size of the inventors* on the patent. Prior literature suggests a direct link between the size of the inventor team and the number of forward citations received (Breitzman & Thomas, 2015). Furthermore, a larger inventor team may result in a more diverse knowledge set (Fleming & Singh, 2010), which is positively correlated to the creation of frontier-pushing inventions (Verhoeven, 2018). The size of the inventor team is measured in this study as a count of the inventors mentioned in the patent filing.

Secondly, we include a measure for the *number of applicants* on the patent, since inter-firm collaborations may provide opportunities for technological knowledge spillovers as well. Here

[5] The classification R1 ('highest research activity'), R2 ('higher research activity') or R3 ('moderate research activity') is based on the Carnegie Classification of Institutions of Higher Education. The categorization of the universities with their research activity level is also provided by the US NCES.

too, this variable assumes the format of a count of the number of applicants mentioned on the patent application.

Thirdly, we control for the number of *scientific citations* that our focal patent makes. Including a measure of NPRs made by the patent gives an indication of how firmly the patent's claims are rooted in basic science, as compared to being backed by just technological claims made in other patents (Callaert *et al.*, 2006). Prior literature suggests a positive link between the level of basic science involved and the subsequent likelihood of producing a breakthrough invention (Della Malva *et al.*, 2015).

As a last control at the level of the patent, we include a commonly-used measure for the *originality of the patent* (i.e. Trajtenberg *et al.*, 1997). Originality of a patent is calculated as the Herfindahl index score of backward citations across technology classes, being 1 minus the squared shares of citations in each technology class. This measure assumes the value zero if all backward patent citations are in the same technology class, and approaches the value one as citations are distributed over more technology classes (Trajtenberg *et al.*, 1997; Jaffe & de Rassenfosse, 2017). It is argued that patents with a larger number of technology classes in their citations to prior art have a higher originality, which means that these patents combine technological elements from different fields (Guerzoni *et al.*, 2014), which might in turn make these patents serve as an important cornerstone for subsequent inventions (Rosenberg, 1994; Fleming, 2001).

At the level of the tenant firm, we introduce two control measures which proxy for the degree of technological specialization and the degree of technological diversity in the tenant firm's patent portfolio, respectively, as well as a control for the on-park size of the tenant firm. *Technological specialization* is calculated as the share of patents in the technological portfolio that the firm has filed for in the focal technology (at IPC-3 digit level), which captures the

weight or centrality of the focal technology in the entire technology portfolio of a tenant firm. The measure for *technological diversification* is calculated here as the inverse Herfindahl index of the shares of technology classes (IPC-3 digit) in the technological portfolio of the tenant firm and grasps to what extent the tenant firm has a research agenda which is spread over different technologies. It is argued that firms with a more diverse technology portfolio are better able to recombine different technological components, and that breakthrough inventions likely originate from these sort of new recombinations (Fleming, 2001). Both technological specialization of the firm and its degree of technological diversification are calculated in a 5-year lagged time window.

We also include an indicator for *tenant firm size*. We expect larger firms with a higher number of patent applications to be more likely to have breakthrough patents. The reasoning for this is twofold: on the one side, there is a correlation between firm size and R&D budgets (Acs *et al.*, 1994), allowing larger firms to do more research. This in turn enables them to be more innovative and build a more specialized knowledge base, since they can build on prior research in their innovative projects (Kim & Kogut, 1996). A second argument is that larger firms are more diverse, operating in different product markets (Cantwell & Piscitello, 2000; Breschi *et al.*, 2003). This diverse knowledge portfolio enables larger firms to recombine more diverse knowledge sets, which benefits their likelihood to generate breakthrough inventions (Grandstrand *et al.*, 1997; Garcia-Vega, 2006). Prior literature has further highlighted the role of technologically diversified firms as a major source of innovation (Patel & Pavitt, 1997; Leten *et al.*, 2007). To proxy for tenant firm size, we use the number of on-park patents that the tenant has filed for in the 5 years preceding the filing of the focal patent.

Fifth, we include a measure for the tenant firm's *track record of producing breakthrough patents*. The idea behind this measure is that tenant firms which have a proven track record of producing inventions with a high technological impact have a higher likelihood of subsequently

generating new inventions which are highly impactful in terms of forward citations. This effect can for instance be driven by the fact that these firms have gained more expertise in experimenting with novel and emerging technologies in which they previously lacked experience (Ahuja & Lampert, 2001), and have become more efficient in integrating new technological elements into their already existing set of knowledge. Our measure for the tenant firm's track record of generating breakthrough inventions is calculated as the number of breakthrough inventions (measured by the same standards as our dependent variable) that the firm has generated both on-park and off-park in the 5 years preceding the application year of the focal patent.

A last category of control variables included in our models are a set of science park-related measures. Specifically, we include measures for the age of the science park, the extent of diversity of technologies in the science park, and the number of tenants which have patented in the same IPC-class as our focal tenant, which indicates the degree of specialization within the science park.

As a first science park-level control, we have included a dynamic measure for the age of each science park at the year of the patent filing, arguing that the maturity of a science park may play a role in the propensity of tenant firms generating breakthrough inventions on-park. As a science park becomes more mature, its management may develop its capabilities to stimulate university-firm spillovers as well as inter-firm spillovers between tenant firms.

A second and third science park-level control we include in our models are on the one hand, the degree of specialization of the science park, which is proxied by the number of tenants on the science park that have patented in the same IPC[6]-code(s) as the focal tenant within the previous 5 years. On the other hand, we take into account the degree of diversification of the

[6] Measured at the IPC-3digit level.

science park, which is calculated as the Herfindahl Index of the shares of technology classes in which tenants on the focal science park have filed patents in within the 5 years preceding the application of the focal patent. The motivation for inclusion of these two variables is that the degree of specialization of the science park captures Marshall-type externalities, while the degree of diversification of the science park captures externalities of the Jacobs-type. Marshall type-externalities are externalities which occur between firms within the same industry (Marshall, 1920; Glaeser *et al.*, 1992; Helmers, 2017), while Jacobs-type externalities occur between firms across different industries (Jacobs, 1969). A broader set of technology classes in the patent applications of tenant firms in a science park fosters the establishment of links and spillovers with co-tenants in different industries, which in turn may enhance the diversity of the technology portfolio of the focal tenant on the science park. On the other hand, a higher number of same-IPC tenants would lead to a higher degree of specialization.

Next to adding confounders on the level of the patent, the tenant firm, the science park and the region, we include a technology domain dummy which for each patent controls for the technology domain in which the patent is classified. For this purpose, we use the ISI-OST-INPI (Fraunhofer) classification, which comprises 35 technology classes and is based on a concordance with the IPC technology classification (Schmoch, 2008). In order to control for time-invariant unobservable traits, we furthermore include a set of application year-dummies.

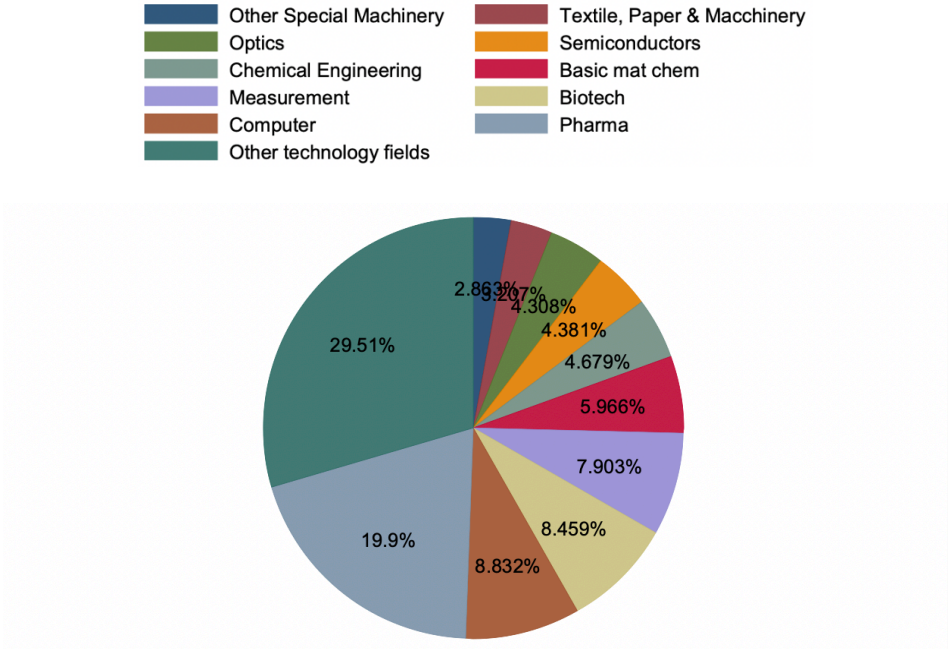
4.4 Results

4.4.1 Descriptive statistics

In total, data on 548 patenting tenant firms was collected, spread over 60 US Science Parks. The 548 patenting tenants held a total of 205,614 US patents, out of which 9,116 (around 4%) are created on-park. Looking at the distribution of the on-park patents over 35 ISI-OST-INPI technology classes (Figure 1), we observe that the Pharma and Biotech, Computer and

Measurement, and Basic Materials Chemistry classes are well represented in the sample. Together, these technology classes make up for over 50% of the on-park patents in our sample. We have aggregated the technology categories that are minor in the sense that they amount for less than 2% of on-park patents in a category called 'Other technology fields'.

Figure 4.1: Distribution of on-park patents over technology domains (based on the ISI-OST-INPI (Fraunhofer) Classification, comprising 35 technology classes and based on a concordance with the IPC technology classification (Schmoch, 2008).



After applying an exact matching procedure on tenant firm, application year and IPC-technology field, we obtain a sample of 3,846 on-park patents by 212 patenting tenants on 24 different science parks, which are matched to similar patents by the same tenant that are created off-park, resulting in a total sample of 7,692 patents. Table 4.1 presents the descriptive statistics for our main variables. We see that on-park patents are almost twice as likely to be a breakthrough patent as compared to off-park patents. Another observation is that the number of inventors on a patent is significantly higher when a patent is generated on a science park, while science park patents on average also involve significantly more applicants on a patent. Furthermore, we see that on-park patents cite significantly more often to basic research (as

proxied for by the number of NPRs) as compared to off-park patents. Interestingly, we observe that the originality measure for off-park patents is significantly higher than for on-park patents (.44 versus .42). Hence, on-park patents do not necessarily outperform off-park patents in all possible dimensions.

Table 4.1: Descriptive statistics

	FULL SAMPLE			ON-PARK PATENTS			OFF-PARK PATENTS			DIFFERENCE
Variable	**Obs**	**Mean**	**St. Dev.**	**Obs**	**Mean**	**Std. Dev.**	**Obs**	**Mean**	**Std. Dev.**	**Pr(|T| >|t|)**
Breakthrough 2 St.Dev.	7.692	0,07	0,25	3846	0,08	0,27	3846	0,05	0,22	-0,03***
Team size	7.692	2,85	2,38	3846	3,10	2,64	3846	2,59	2,06	-0,51***
Number of Applicants	7.692	1,55	1,89	3846	1,61	2,07	3846	1,49	1,68	-0,12**
Number of NPRs	7.692	6,85	16,24	3846	7,59	17,04	3846	6,11	15,36	-1,47***
Breakthrough Track Record	7.692	81,78	68,44	3846	81,78	68,44	3846	81,78	68,44	0,00
Originality (IPC-3)	7.692	0,44	0,24	3846	0,43	0,25	3846	0,45	0,23	0,02***
Firm Size On-Park	7.692	1499,73	1374,31	3846	1499,73	1374,40	3846	1499,73	1374,40	0,00
Tenant Diversification	7.692	0,97	0,06	3846	0,97	0,06	3846	0,97	0,06	0,00
Tenant Specialization	7.692	0,24	0,23	3846	0,24	0,23	3846	0,24	0,23	0,00
Number Off-Park patents	7.692	252749,10	147016,20	3846	252742,00	147034,00	3846	252756,20	147017,60	14.17
University Nearby	7.692	0,81	0,39	3846	1	0,08	3846	0,63	0,48	-0,35***
Science Park Age	7.692	36,55	15,76	3846	36,55	15,77				
Science Park Specialization	7.692	0,97	0,07	3846	0,97	0,07				
Science Park Diversification	7.692	0,12	0,12	3846	0,12	0,12				

4.4.2 Multivariate analyses

Results of our baseline regressions are presented in Table 4.2. In column (1), we present a probit model in which we include control variables only, while in column (2) we add our variable of interest, the patent being on- or off-park as measured by a 30km radius around the Science Park. The dependent variable in our models is a measure indicating if a patent is among the 2-standard deviation outliers of number of forward citations received in a five-year time window. As displayed in Model 2, our probit model expects patents that are created on-park to have a substantially higher impact, as measured by being an outlier in the number of forward citations received within a 5-year time window following the application of the patent. From an postestimation analysis of the average marginal effects, we see that being developed on-park increases a patent's likelihood of being a breakthrough patent by 1.6%.

Furthermore, we observe that our included patent characteristics are all significant drivers in the propensity of a patent to be a breakthrough patent, although the effect of firm size is surprisingly a negative one. Furthermore, we observe that the degree of specialization of the firm is positively correlated to the likelihood of generating a breakthrough invention.

In Model 3, we add a control which indicates whether the patent has been developed in the vicinity of a research university. We include this measure indicating whether the patent is generated nearby a research university to further explore the mechanisms behind science park presence. To determine whether a patent is generated in the vicinity of a research university, we adopt the distance threshold we also use to determine whether a patent is generated on-park. Thus, patents which have been invented in a 30km radius surrounding a research university are considered as a patent invented near a university.

Table 4.2: Results of multivariate regression analyses

MODEL	**(1)**	**(2)**	**(3)**	**(4)**
REGRESSION METHOD	PROBIT	PROBIT	PROBIT	PROBIT
TIME FRAME	30Y	30Y	30Y	30Y
DEPENDENT	BREAKTHROUGH 2 ST.DEV.	BREAKTHROUGH 2 ST.DEV.	BREAKTHROUGH 2 ST.DEV.	BREAKTHROUGH 2 ST.DEV.
ON-PARK 30KM		0.236***	0.143*	0.145**
		(0.050)	(0.056)	(0.056)
UNIVERSITY NEARBY			0.282***	0.287***
			(0.084)	(0.085)
SCIENCE PARK AGE				0.012*
				(0.006)
SP DIVERSIFICATION				0.008
				(0.967)
SP SPECIALIZATION				-0.632
				(0.373)
TEAM SIZE	0.060***	0.053***	0.052***	0.052***
	(0.011)	(0.011)	(0.011)	(0.011)
NUMBER OF APPLICANTS	0.059***	0.060***	0.063***	0.062***
	(0.012)	(0.012)	(0.012)	(0.012)
NUMBER OF NPRs	0.009***	0.009***	0.009***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
BREAKTHROUGH TRACK RECORD	0.010***	0.010***	0.010***	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)
ORIGINALITY IPC-3	0.378**	0.388**	0.377**	0.378**
	(0.122)	(0.123)	(0.123)	(0.123)
TENANT FIRM SIZE ON-PARK	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
TENANT DIVERSIFICATION	0.420	0.441	0.444	0.659
	(0.565)	(0.568)	(0.568)	(1.249)
TENANT SPECIALIZATION	0.316*	0.322*	0.296	0.417*
	(0.160)	(0.161)	(0.161)	(0.181)
NUMBER OFF-PARK PATENTS	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-3.146***	-3.274***	-3.461***	-4.118***
	(0.562)	(0.565)	(0.569)	(0.636)
YEAR DUMMIES	YES	YES	YES	YES
TECHNOLOGY DOMAIN DUMMIES	YES	YES	YES	YES
REGION DUMMIES	YES	YES	YES	YES
N	7,624	7,624	7,624	7,624
Pseudo R-squared	0.13	0.14	0.14	0.14

* $p<0.05$; ** $p<0.01$; *** $p<0.001$
Robust standard errors in parentheses

This ‘university nearby’ dummy includes Tier 1 (R1), Tier 2 (R2) and Tier (3) research universities. We observe that the patent being developed in the vicinity of a research university highly correlates with the likelihood of generating a breakthrough patent, with an estimated marginal effect of 3.1%. The science parks dummy coefficient lowers as compared to model 2. Hence, research university presence could be considered as one important mechanism through which science park presence influences the generation of breakthough inventions.

Furthermore, we observe that in this model, patent-level confounders remain important drivers for a firm to generate a breakthrough invention, with inventor team size and number of applicants on the patent both leading to a marginal increase of about 0.1% on the propensity of generating a breakthrough patent, while the originality of a patent is a strong driver, contributing to a marginal increase of 4.9%. The marginal effect of a patent being on-park on the likelihood of generating a breakthrough patent is 1.6%.

In Model 4, controls on the level of the Science Park are included. For off-park patents, no science park controls could be calculated, which is why these observations assume value zero for these observations. We observe a positive significant effect of the age of the science park on the propensity to create a breakthrough patent, with a one-year increase in the age of the science park leading to a 0.1% increase in the propensity of a patent being a breakthrough patent. However, both the degree of diversification of the science park patents, which is a Herfindahl Index of the shares of patents applied for by the science park tenants, and the degree of specialization of the science park, which is measured by the share of tenants patenting in the same IPC-class as the focal patent, do not seem to significantly drive the likelihood of generating a breakthrough patent. This could suggest the absence of a Jacobs’ externalities-type effect within the setting of a science park, which would mean that diversity across industries among the tenants in a science park benefits the likelihood for tenants to create breakthrough inventions. Furthermore, the model also suggests the absence of a Marshall-type

effect, which would mean that a higher degree of technological specialization on the science park benefits the likelihood of generating breakthrough inventions[1,2].

4.4.3 Supplementary analyses and robustness checks

We have performed a number of supplementary analyses and robustness checks, which are reported in Tables 4.3, 4.4 and 4.5 (Models 5 to 12).

Models 5 through 7 explore the contributing effect of the patent being invented close to a research university. The Carnegie classification of higher education institutions classifies US universities in different tiers, based on research output parameters. Hence, research universities are classified in three segments of research activities ('Highest'(R1), 'higher' (R2) and 'moderate' (R3) research activity). The results suggest that a strong contribution of being generated close to a top-tier university on the propensity of the patent being a breakthrough patent. However, being generated in the vicinity of a top-tier university cannibalizes on the strength of the on-park effect. When taking 'higher'- and 'moderate'-tier universities into account, we observe that the effect of being generated close to a research university is no longer significant[3].

[1] As a robustness check (table not reported here), we have interacted our on-park variable with the technology domain dummies, to explore whether being on a science park is more advantageous within certain technologies. Results of the regression analysis including the interaction terms between our on-park variable and the technology dummies yielded a significant (negative) interaction for the technology domain BASIC MATERIALS CHEMISTRY, while the main effect of being developed on-park on the likelihood of an invention being a breakthrough invention is no longer significant. For the other technology domains, no significant interactions with being generated on-park have been found.

[2] As a further robustness check, I have left out firms with only very recent inventors. I have excluded observations where the earliest year of patenting in the area is very recent (as a cut-off, I took "2010 – 3 years"). This applies to only 5 unique tenants (GWC Technologies; Halo Monitoring; Radius Health; Siemens PLM Software; Synapse Wireless). In the regression analysis, we observed no change of the effects as compared to the main analysis in which these 5 firms are included.

[3] As a robustness check, we have tried interacting proximity to a top-tier university (R1) with the degree of science park diversification and specialization. We found no evidence for any of these interaction effects.

Table 4.3: Results of multivariate regression analyses

MODEL	**(5)**	**(6)**	**(7)**
REGRESSION METHOD	PROBIT	PROBIT	PROBIT
TIME FRAME	30Y	30Y	30Y
DEPENDENT	BREAKTHROUGH 2 ST.DEV.	BREAKTHROUGH 2 ST.DEV.	BREAKTHROUGH 2 ST.DEV.
ON-PARK 30KM	0.135*	0.248***	0.239***
	(0.058)	(0.050)	(0.050)
UNIVERSITY NEARBY - R1	0.240***		
	(0.071)		
UNIVERSITY NEARBY - R2		-0.145	
		(0.074)	
UNIVERSITY NEARBY - R3			0.026
			(0.063)
SCIENCE PARK AGE	0.010	0.009	0.012
	(0.006)	(0.006)	(0.006)
SP DIVERSIFICATION	-0.089	-0.064	-0.025
	(0.959)	(0.971)	(0.966)
SP SPECIALIZATION	-0.634	-0.610	-0.685
	(0.373)	(0.376)	(0.373)
TEAM SIZE	0.051***	0.054***	0.053***
	(0.011)	(0.011)	(0.011)
NUMBER OF APPLICANTS	0.061***	0.059***	0.059***
	(0.012)	(0.012)	(0.012)
NUMBER OF NPRs	0.008***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)
BREAKTHROUGH TRACK RECORD	0.009***	0.009***	0.009***
	(0.002)	(0.002)	(0.002)
ORIGINALITY IPC-3	0.385**	0.388**	0.389**
	(0.123)	(0.123)	(0.123)
TENANT FIRM SIZE ON-PARK	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
TENANT DIVERSIFICATION	0.766	0.755	0.701
	(1.242)	(1.250)	(1.246)
TENANT SPECIALIZATION	0.421*	0.446*	0.454*
	(0.181)	(0.180)	(0.180)
NUMBER OFF-PARK PATENTS	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Constant	-3.972***	-3.817***	-3.913***
	(0.633)	(0.633)	(0.632)
YEAR DUMMIES	YES	YES	YES
TECHNOLOGY DOMAIN DUMMIES	YES	YES	YES
URBANIZATION DUMMIES	YES	YES	YES
N	7,624	7,624	7,624
Pseudo R-squared	0.14	0.14	0.14

* $p<0.05$; ** $p<0.01$; *** $p<0.001$
Robust standard errors in parentheses

Table 4.4: Results of multivariate regression analyses

MODEL	**(8)**	**(9)**	**(10)**
REGRESSION METHOD	NEG BIN	PROBIT	PROBIT
TIME FRAME	30Y	30Y	15Y
DEPENDENT	FW. CIT. 5Y	BREAKTHROUGH 5 ST. DEV.	BREAKTHROUGH 2 ST. DEV.
ON-PARK 30KM	0.087**	0.065	0.218**
	(0.028)	(0.106)	(0.075)
UNIVERSITY NEARBY	0.183***	0.212	0.190
	(0.037)	(0.159)	(0.106)
SCIENCE PARK AGE	0.011***	0.010	0.010
	(0.003)	(0.011)	(0.008)
SP DIVERSIFICATION	-0.366	-1.774	1.919
	(0.506)	(1.416)	(2.016)
SP SPECIALIZATION	-0.074	0.569	-0.098
	(0.166)	(0.687)	(0.427)
TEAM SIZE	0.052***	0.038*	0.045***
	(0.007)	(0.019)	(0.013)
NUMBER OF APPLICANTS	0.054***	0.047*	0.069***
	(0.009)	(0.019)	(0.014)
NUMBER OF NPRs	0.008***	0.008***	0.008***
	(0.001)	(0.002)	(0.001)
BREAKTHROUGH TRACK RECORD	0.011***	0.010**	0.013***
	(0.001)	(0.003)	(0.002)
ORIGINALITY IPC-3	0.136*	1.170***	0.730***
	(0.057)	(0.280)	(0.173)
TENANT FIRM SIZE ON-PARK	-0.000***	-0.000**	-0.001***
	(0.000)	(0.000)	(0.000)
TENANT DIVERSIFICATION	-0.013	3.766	-1.103
	(0.655)	(2.168)	(2.231)
TENANT SPECIALIZATION	0.033	0.678*	0.407
	(0.092)	(0.329)	(0.213)
NUMBER OFF-PARK PATENTS	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Constant	0.634	-6.337***	-4.090***
	(1.013)	(1.345)	(0.743)
lnalpha	-0.054**		
	(0.019)		
YEAR DUMMIES	YES	YES	YES
TECHNOLOGY DOMAIN DUMMIES	YES	YES	YES
URBANIZATION DUMMIES	YES	YES	YES
N	7,692	7,454	5,072
Pseudo R-squared	0.05	0.21	0.20

* $p<0.05$; ** $p<0.01$; *** $p<0.001$
Robust standard errors in parentheses

Model 8 explores the effect of a patent being generated on a different outcome variable. Here, we look at the effect on the total number of forward citations received in a 5-year time window. Since our outcome variable is a non-negative count variable, we opt for a negative binomial regression for this analysis. We observe that when taking into account the total number of forward citations a patent receives, there is a significant positive influence of being generated on-park on the number of forward citations received in the subsequent 5 years. Furthermore, being generated in the vicinity of a research university has a strong positive correlation with our outcome variable.

In Model 9, an alternative and more restrictive measure of a patent being a breakthrough patent is taken into account. Under this assumption, a patent is considered 'breakthrough' if it is a 5-standard deviation outlier in the distribution of forward citations received in the five years following its filing. Interestingly, we observe that when adopting this more restrictive measure, the effect of being located on a science park on the impact the patent generates is not significant anymore. A possible explanation for this finding is that this 5-standard deviation outcome measure might be too restrictive for our sample which is limited in size compared to the universe of patents.

In Model 10, we check whether our assumed on-park effect holds when considering only the most recent 15 years of our time period. The reason why we look at this time period, is that our list of tenants is based on a snapshot of 2018. By looking at the last 15 years (1995-2010), we might get a closer approximation to the current situation. Considering these years, we see that being created on-park is still a strong predictor of being a patent which is among the 2-standard deviation outliers in the number of received forward citations. Interestingly, we do not observe a significant positive effect of being near a research university when looking at the last 15 years.

Table 4.5: Results of multivariate regression analyses in presence of 'anchor' firm on science park

MODEL	**(11) Anchor firm on SP**	**(12) No anchor firm on SP**
REGRESSION METHOD	PROBIT	PROBIT
TIME FRAME	30Y	30Y
DEPENDENT	BREAKTHROUGH 2 ST.DEV.	BREAKTHROUGH 2 ST.DEV.
ON-PARK 30KM	0.227***	-0.065
	(0.068)	(0.111)
UNIVERSITY NEARBY	0.331**	0.192
	(0.105)	(0.158)
SCIENCE PARK AGE	0.011	0.025
	(0.009)	(0.017)
SP DIVERSIFICATION	0.699	-1.167
	(1.436)	(1.520)
SP SPECIALIZATION	-0.589	-0.440
	(0.567)	(0.789)
TEAM SIZE	0.064***	0.019
	(0.013)	(0.023)
NUMBER OF APPLICANTS	0.065***	0.060*
	(0.015)	(0.024)
NUMBER OF NPRs	0.008***	0.009**
	(0.002)	(0.003)
BREAKTHROUGH TRACK RECORD	0.008***	0.020***
	(0.002)	(0.006)
ORIGINALITY IPC-3	0.476**	0.197
	(0.147)	(0.254)
TENANT FIRM SIZE ON-PARK	-0.000***	-0.001*
	(0.000)	(0.001)
TENANT DIVERSIFICATION	0.233	0.477
	(1.811)	(1.948)
TENANT SPECIALIZATION	0.467*	-0.013
	(0.206)	(0.560)
NUMBER OFF-PARK PATENTS	-0.000	-0.000
	(0.000)	(0.000)
Constant	-4.416***	-3.096*
	(0.876)	(1.268)
YEAR DUMMIES	YES	YES
TECHNOLOGY DOMAIN DUMMIES	YES	YES
URBANIZATION DUMMIES	YES	YES
N	5,710	1,717
Pseudo R-squared	0.16	0.17

* $p<0.05$; ** $p<0.01$; *** $p<0.001$
Robust standard errors in parentheses

Lastly, Models 11 and 12 present split-sample findings under the presence of an anchor tenant on the science park. In line with Agrawal & Cockburn (2003), we define an 'anchor tenant' as "a highly R&D-intense firm, which may reflect significant externalities upon smaller

innovative firms in its vicinity, through its participation in local markets for technology". By being around and interacting with an anchor tenant, smaller firms may benefit from knowledge spillovers and specialized inputs from the larger anchor firm, which may in turn have a positive impact on the tenant's propensity to generate breakthrough inventions. In this study, an anchor tenant is defined as a firm which is above average in on-park firm size across our sample. Hence, as can be derived from Table 4.1, we assume that an anchor tenant is a tenant which has applied for more that 1499 patents on-park in the last five years before the focal year.[4] Models 11 and 12 show that patents generated on science parks that host an anchor tenant indeed seem to have a higher likelihood to generate breakthrough inventions. Moreover, from the number of observations in the split samples, we can see that the majority of patents in our sample indeed seem to be generated in science parks where an anchor tenant is present. In case no anchor tenant is present on the science park, we in turn witness that tenants have no significantly higher likelihood of generating breakthrough inventions.

4.5 Conclusion

This study sheds light on whether science park presence leads to an increased likelihood to create inventions with a substantial technological impact. To measure technological impact, we have adopted a measure of breakthrough invention, which assesses whether a patent is among the two-standard deviation outliers in number of forward citations received within a 5-year time window following the filing of the patent. By studying this question, we contribute to the stream of literature by adopting a quality-oriented measure, whereas prior studies rather looked to innovative performance from a 'quantity' point of view. Furthermore, this study takes

[4] The choice for an above-mean firm size across the sample is an arbitrary cut-off point, especially when taking into account that science parks differ in terms of the size of the tenants they host at their science park. For this reason, we have applied several other cut-off points as a sensitivity check. These other cut-off points (500, 1000) yielded similar results, although less pronounced as the number of non-anchor firms decreases due to a looser threshold for defining a firm as an anchor tenant.

into account all US Science Parks, as identified by the UNESCO list of science parks, for an extensive period stretching from 1980 to 2010.

Our results suggest that patents which are created on a science park indeed seem to have a more substantial technological impact, as compared to patents which are created off-park. In our analyses, we control for patent-, science park- and region-level characteristics, as well as for time-, firm-, and technology-invariant unobservable traits, by adopting a matching approach which matched each on-park patent to an off-park patent with the same characteristics for firm, application year and technology class(es) mentioned on the patents. Furthermore, we find that the propensity of generating breakthrough inventions is stronger when inventions are made close to a top-tier university, defined by the level of research activity of the institution, indicating that nearby presence to a research university is an important mechanism through which science park presence affects the generation of breakthrough inventions. Lastly, we find that the presence of large R&D-intensive 'anchor tenants' on a science park, who may generate externalities that smaller innovative firms benefit from, play a significant role in the propensity of generating a breakthrough invention.

This study has several limitations, which open avenues for further research. A first limitation is in the nature of our dataset. We use inventor-level disambiguated data (Li *et al.*, 2014) for the period 1980 to 2010. However, the listing of tenant firms based on the science parks in our sample is a snapshot of February 2018. A disadvantage here is that we are not able to track movements in tenement over years, nor that we can expand our dataset to the year that we registered tenants on our science parks. To cope with this issue, we have looked into a subset of the most recent 15 years for which we have inventor-level data, in order to check whether our results remain robust under this situation. A second limitation, which we want to address in a future version of this paper, is in the refinement of several of our control variables. For instance, in the current models, we include a count variable for the number of applicants

mentioned on a patent. However, it would be beneficial to disentangle these applicants, to identify in a clearer way the effect of a science park. In the current set-up, we are not able to track patterns like whether the patent is co-applied for by for instance two tenant firms, or if there is a co-application with a research university in the neighborhood of the science park. Disentangling would help here to isolate the science park effect more clearly.

Thirdly, we want to argue that the increase in forward citations a science park patent receives may also be partly the result of gaining a higher visibility due to locating on a science park. For instance, R&D activities undertaken by firms that are active on a science park may be higher on the radar of other R&D-intensive firms, due to the link with the science park and its perceived "science"-label. While we believe this visibility may operate at the firm level rather than at the patent level, and our research design accounts for that by comparing on- and off-park patents of a single firm, this may offer an alternative explanation for the increase in forward citations and we encourage future research to further tease out this effect.

A fourth limitation of our paper lies in the measurement of the tenant's exposure to basic research, which we consider as one of the main goals that science parks should facilitate. In our set-up, we have tried to approximate for exposure to basic research by including controls for the vicinity of a university or a research institution, and by disentangling these universities into different tiers based on their level of research activity. However, we acknowledge that this approach remains imperfect.

A fifth limitation in our study is that we only make use of counts of non-patent references (NPR), as provided by PATSTAT. In future research, it would be interesting if these NPRs could be further disentangled. By disentangling, we would be able to discriminate between 'basic' and 'applied' NPRs, which would provide a closer proxy for the patent's rootedness in basic science.

Lastly, R&D projects are not assigned to a firm's subsidiary on a random basis. This means that our on-park variable is endogenous due to a selection issue. In our paper, we have tried to deal with this endogeneity issue by an exact matching approach on observable patent-level traits (IPC 3-digit technology class). Furthermore, in the empirical set-up of this study, we do not control for the science parks' selection processes of tenants. Selecting which firms may enter the science park is a process typically undertaken by park management, and also this selection process is arguably not random. For instance, park management may have a preference for selecting firms which whose R&D agenda is at the frontier of their field. Therefore, we must acknowledge that there remain unobservable traits which might have an influence on the propensity of being located on a science park which we do not capture in our current models.

4.6 References

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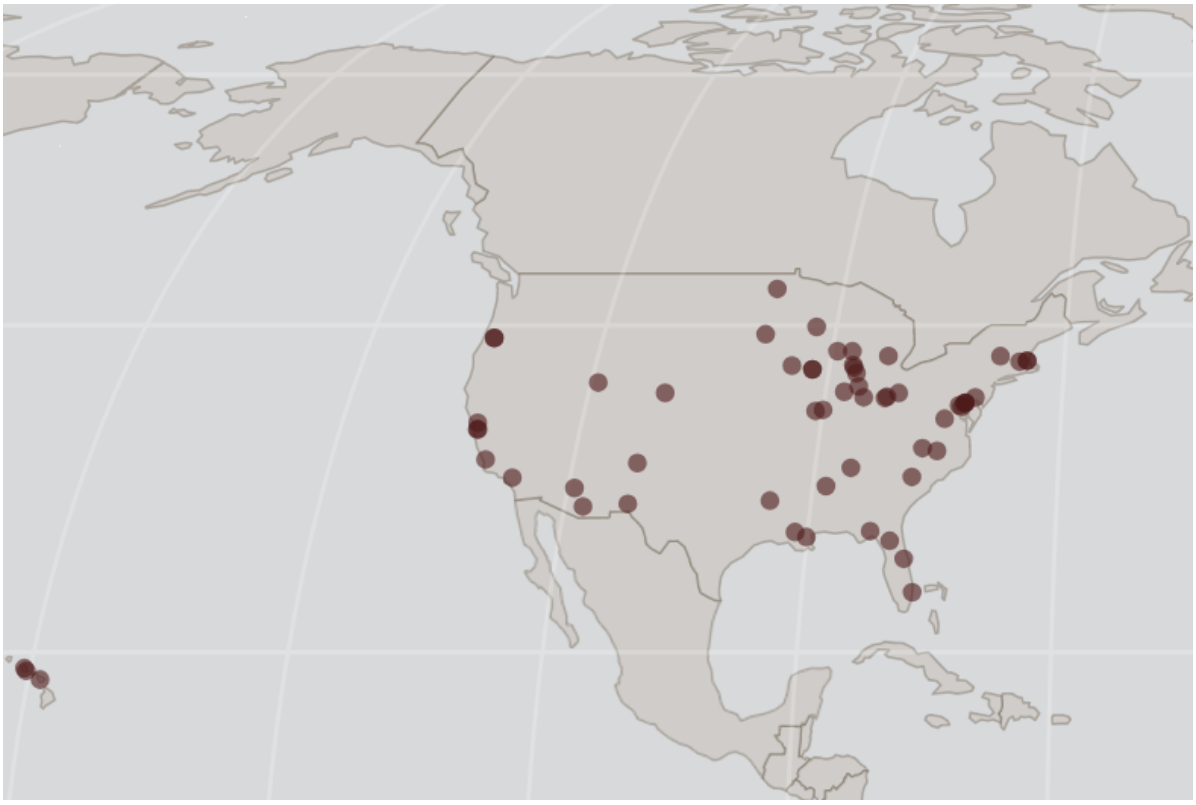
4.7 Appendices

Appendix 4.1: List of US Science Parks in sample

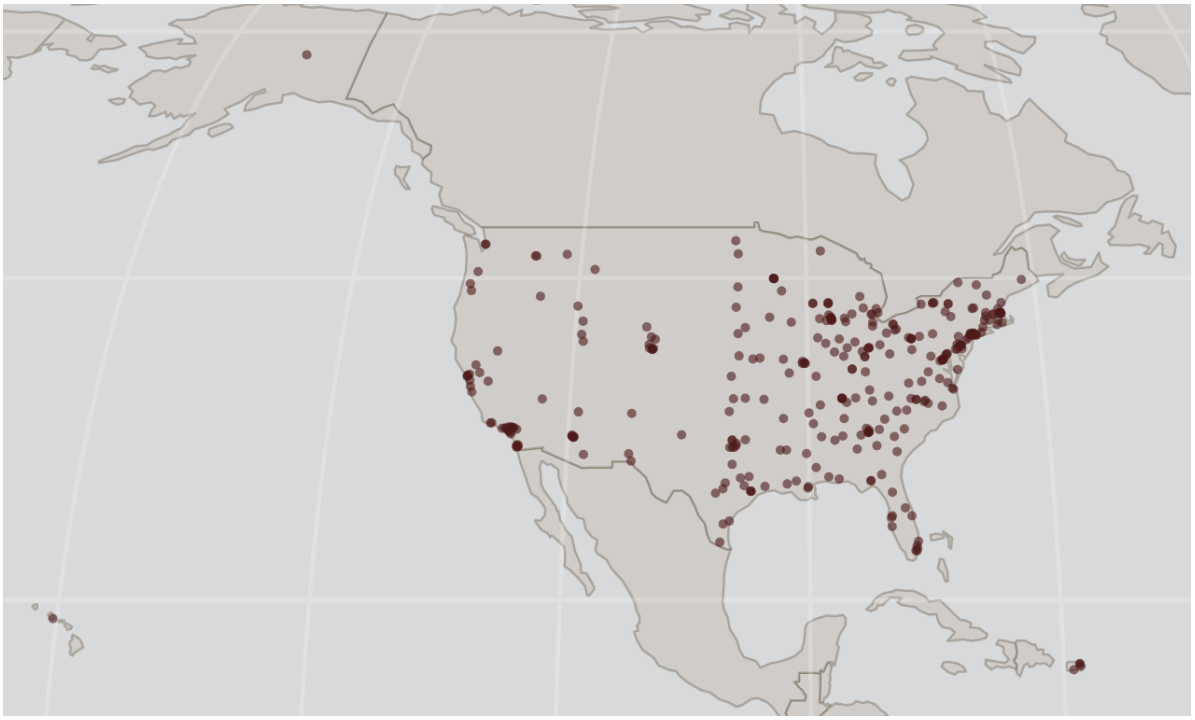
	Science Park	State	City
1.	Arizona State University Research Park	AZ	Tempe
2.	Arrowhead Business and Research Park	NM	Las Cruces
3.	BioSquare at Boston University	MA	Boston
4.	BioVentures Center (University of Iowa)	IA	Coralville
5.	Biomedical Research Park, Louisiana	LA	Shreveport
6.	California Institute for Quantitative Biosciences	CA	Berkeley
7.	California Polytechnic State University Technology Park	CA	San Luis Obipso
8.	Carolina Research Park	SC	Columbia
9.	Central Florida Research Park	FL	Orlando
10.	Cummings Research Park, Alabama	AL	Huntsville
11.	Delaware Technology Park, Delaware	DE	Newark
12.	Florida Atlantic University Research Park	FL	Boca Raton
13.	High Technology Development Corporation (HTDC)	HI	Honolulu
14.	Innovation Park Tallahassee, Florida	FL	Tallahassee
15.	Innovation Park at Penn State, Pennsylvania	PA	State College
16.	Innovation Village Research Park at Cal Poly Pomona	CA	Pomona
17.	Iowa State University Research Park, Iowa	IA	Ames
18.	Johns Hopkins University Montgomery County Campus	MD	Rockville
19.	LSU Innovation Park	LA	Baton Rouge
20.	LabCentral	MA	Cambridge
21.	Miami Valley Research Park, Kettering	OH	Kettering
22.	Mililani Technology Park	HI	Mililani
23.	Milwaukee County Research Park, Wisconsin	WI	Milwaukee
24.	Missouri Research Park, Missouri	MO	Boone Township
25.	Mound Advanced Technology Center	OH	Miamisburg
26.	NASA Research Park, California	CA	Moffett Field
27.	Oakdale Research Park, University of Iowa	IA	Coralville
28.	Piedmont Triad Research Park, North Carolina	NC	Winston-Salem
29.	Progress Corporate Park	FL	Gainesville
30.	Purdue Reseach Park of West Lafayette	IN	West Lafayette
31.	Purdue Research Park of Indianapolis	IN	Indianapolis
32.	Purdue Research Park of Northwest Indiana	IN	Crown Point
33.	Rensselaer Technology Park, New York	NY	North Greenbush
34.	Research Triangle Park North Carolina	NC	Research Triangle
35.	Riverfront Research Park, Oregon	OR	Eugene
36.	Riverfront Research Park, University of Oregon	OR	Eugene
37.	Sandia Science and Technology Park, New Mexico	NM	Albuquerque
38.	Science & Technology Campus Corporation	OH	Columbus
39.	Science & Technology Park at Johns Hopkins	MD	Baltimore
40.	South Dakota State University Innovation Campus Research Science Technology Park	SD	Brookings
41.	Stanford Research Park	CA	Palo Alto
42.	Stout Technology Park	WI	Menomonie
43.	Thad Cochran Research, Technology and Economic Development Park, MSU	MS	Starkville
44.	The Illinois Science & Technology Park	IL	Skokie
45.	University Corporate Research Park	MI	Lansing
46.	University Research Park Wisconsin-Madison	WI	Madison

47.	University Technology Park at IIT, Illinois	IL	Chicago
48.	University of Arizona Science and Technology Park, Arizona	AZ	Tucson
49.	University of Colorado Research Park	CO	Boulder
50.	University of Illinois Urbana Champaign Research Park	IL	Champaign
51.	University of Minnesota Valley Technology Park, Minnesota	MN	Crookston
52.	University of New Orleans Research and Technology Park, Louisiana	LA	New Orleans
53.	University of Utah Research Park, Utah	UT	Salt Lake City
54.	University of Virginia Research Park, Virginia	VA	Deerwood
55.	Utah University - Innovation Campus	UT	Logan
56.	Virginia Bio Technology Research Park, Virginia	VA	Richmond
57.	Virginia Tech Corporate Research Centre, Virginia	VA	Blacksburg
58.	WMU Technology & Research Park	MI	Kalamazoo
59.	Wake Forest Innovation Quarter	NC	Winston-Salem
60.	bwtech @ UMBC Research and Technology Park, Maryland	MD	Baltimore

Appendix 4.2: Geographical distribution of Science Parks across the US *(n=60)*



Appendix 4.3: Geographical distribution of research universities *(n=332)*



Chapter 5
General Conclusions

5.1 Concluding remarks

In today's fast-paced and rapidly changing R&D environment, external collaborations play an increasingly central role in firm innovation management and performance (West & Bogers, 2014). Searching and finding new combinations of knowledge and technology which are commercially exploitable is a key aspect of the innovation process (Nelson & Winter, 1982; Stuart & Podolny, 1996; Fleming & Sorenson; 2004; Laursen, 2012), and firms whose aim is to be successful innovators are required to work with and source in knowledge components from actors outside their own organization (Shan *et al.*, 1994; Rosenkopf & Nerkar, 2001). In this Ph.D. dissertation, we have focused on two important channels through which firms can search for and source in knowledge outside of their organizational boundaries. On the one hand, we argue that this sourcing process can be achieved through activity on the markets for technology. These markets for technology allow firms to search, evaluate and integrate external technology into the existing knowledge structures of a firm's R&D activities, and hence facilitate knowledge recombinations which allow them to generate novel technology (Fleming, 2001; Hargadon & Sutton, 1997, Laursen & Salter, 2006). On the other hand, R&D-intensive firms can source in external knowledge through the development of industry-science links. Prior literature has shown strong correlations between a firm's involvement in basic research and their innovative performance (Gambardella, 1992; Arora *et al.*, 2015; Fabrizio, 2009). Furthermore, basic research institutions (such as universities) seem to play an important role in the innovation efforts of firms (Bozeman, 2000; Salter & Martin, 2001; Cohen *et al.*, 2002), given that these institutions diffuse basic knowledge which spills over into the R&D programs

of technology-intensive firms (Mansfield & Lee, 1996). Therefore, we argued in this dissertation that channels bridging science and industry players can play a crucial role in firms' innovation strategies. In this dissertation, our final essay looked at the role of science parks as one of such bridging vehicles. Science parks fulfill this bridging role by bringing together R&D-intensive companies in a spatial cluster and are generally closely related to a research university. The innovative performance effects of science park-based firms have been highlighted already in prior literature (i.e. Löfsten & Lindelöf, 2002; Squicciarini, 2009). However, in this dissertation, we have extended this view on innovative performance by assessing the value of being located on a science park by looking at qualitative measures regarding inventions created on a science park.

In general, the findings of this dissertation support prior research on the beneficial role of connecting with external collaborators, and more precisely, stress the learning mechanisms established through accessing markets for technology links or strengthening industry-science links through locating on a science park.

Essay 1

Chapter one signals that licensors benefit from the interaction with a licensee, following a license agreement. This interaction between licensor and licensee is inherent to many license agreements, since licensing contracts often include an arrangement through which a licensor not only permits the right to use the licensed technology, but furthermore offers a guidance track to the licensee in order to permit effective transfer of the licensed technology (Leone *et al.*, 2016). These interactions between scientists at the licensor and licensee firm provide a channel for knowledge flowbacks from licensee to licensor and establishes a 'reverse learning' effect. Through this reverse learning mechanism, the licensor may become aware of novel applications of the out-licensed technology or new ways to recombine knowledge elements of

the licensee with their own existing pool of knowledge. This chapter furthers the idea of licensing-out, in the sense that it extends the practice of licensing-out beyond a pure revenue effect but shows that apart from financial benefits, licensors may also reap technology learning effects from a licensing deal. While the implementation of guidance trajectories as a complement to a mere grant to use technology requires an additional effort from the licensor firm, we argue that a managerial take-away from our findings is that these 'technical assistance clauses' that licensees request actually offer learning opportunities to the licensor that go beyond a mere contractual obligation that a licensor might see as a burden it has to comply with.

Essay 2

The second chapter of this dissertation focused on corporate venture capital (CVC) investments as tools for entering new-to-the-firm technology domains. By making a CVC investment in a venture company, an investor acquires a minority equity stake in that venture and, by doing so, gains exposure to the R&D developments in that venture. We argue in this chapter that exploring and building competencies in new technology domains is quintessential for firms to survive in turbulent business environments, and that CVC investments – from an organizational learning point of view - can be used by investors as a means of exploring and learning about new technologies. Through CVC investments in ventures with an expertise in technology domains that are unfamiliar to the investor firm, they can initiate a process of acquiring, assimilating, translating and exploiting the venture's knowledge which is necessary for the investor to build up competencies in that domain. Therefore, the main research question which we addressed in this chapter was whether prior CVC investments in ventures with expertise in new-to-the-investor technology domains increased the likelihood of the investor subsequently becoming active (i.e. starting to patent) in these new technology domains. Our findings suggest

that prior CVC investments in a new technology domain are positively correlated to an investor's likelihood of entering and building up competencies in that technology domain. Additionally, we argue in this chapter that the relation between prior CVC investments in a technology domain and the subsequent likelihood of becoming active in that domain may be moderated by the investee's perceived quality (measured by the number of forward citations the investee's patents receive), the number of CVC co-investors in an investment syndicate and the degree of technological relatedness of the venture's technology with the current technology portfolio of the investor firm. Our findings suggest that that prior CVC investments in a new technology domain are positively and statistically significantly associated with the investor firm's likelihood to enter and build up competencies in that domain. By exploring the conditions under which CVC investments lead to an increased likelihood of subsequent entry, we have found that, while the technological quality of the venture and the numbers of co-investors in a investment syndicate do not seem to be significant moderators, a firm's likelihood to enter a new technology domain increases when the ventured technology is more closely related to the firm's existing knowledge portfolio. In this chapter, we aimed to contribute to the stream of literature on technological entry by exploring the intersection with the research on corporate venturing, i.e. by studying the the relationship between making CVC investments in unfamiliar domains and the subsequent likelihood to become active in that domain. Furthermore, we contribute to the stream of literature on CVC investments in two ways. First, we extend the established association between CVC investments and the innovative performance of the investor by applying this association to the process of entering in new technology domains. We observe that CVC investors not only identify investment opportunities, but moreover are able to are able to translate knowledge components acquired from their ventures to their own organizational context, and by doing so, are able to leverage this knowledge (Brown & Duguid, 1991). Secondly, this study deepens our understanding of

the circumstances under which CVC investments may foster an increased likelihood to enter new technology domains, by looking at several interactions which moderate the relationship between CVC investments and technological entry.

Essay 3

The third chapter of this dissertation studies the effect of being located on a science park on the likelihood of generating breakthrough inventions. Multiple studies have associated science park presence with an increased innovative output (Löfsten & Lindelöf, 2002; Squicciarini, 2009; Siegel *et al.*, 2003; Lamperti *et al.*, 2015). However, the available body of prior literatures evaluates innovative output in terms of quantity-oriented measures, such patenting propensity. Yet, the effect of being located on a science park on the quality of the inventions generated on-park remained an open question. Furthermore, the way in which science park presence is associated with generating inventions with a high technological impact (breakthrough inventions) has remained underexposed. However, science parks are generally closely related to research institutions, and therefore provide tenant firms with easy access to basic research. For this reason, we presume that science parks might be a fertile ground for tenants to generate inventions with a higher impact, since prior literature (i.e. Della Malva *et al.,* 2015) suggests a positive relationship between access to basic science and generating impactful inventions. In this chapter, we have tried to address these gaps in the literature. We do that by studying whether on-park generated inventions have a higher likelihood of becoming breakthrough inventions as compared to off-park inventions belonging to the same technology domain, by the same company, in the same year. The results of this study suggest that inventions which are generated on a science park have indeed a higher likelihood of being inventions with a high technological impact, measured as three-standard deviation outliers in the distribution of forward citations, as compared to off-park patents with

the same set of characteristics. Furthermore, we find a stronger positive effect when inventions are made in the geographic vicinity of top-tier universities, suggesting an effect of the quality of basic research spill-overs on the invention's expected technological impact. Finally, this study finds that the presence of large, R&D-intensive 'anchor tenants', that have the ability to generate externalities from which smaller innovative firms can benefit in their R&D process, play a significant role in an on-park invention's likelihood of becoming a breakthrough patent. This chapter furthers the idea of science parks as catalysers for the innovative output of on-park firms. It does that adopting a quality-oriented lens on firms' innovative outputs, where prior literature only took into account quantity-oriented measures. Furthermore, this study makes a contribution to the stream of literature on radical or breakthrough inventions. While prior literature has shown a positive association between a firm's involvement in basic research and breakthrough inventions (i.e. Della Malva *et al.*, 2015), this study builds on these insights by looking at one mechanism through which R&D-intensive firms can increase their exposure to basic research in their aim of generating inventions with a high technological impact.

5.2 Limitations and future research avenues

While this dissertation provides valuable insights on organizational learning through licensing and CVC investments, and on science parks as catalysers for radical innovations, these studies inevitably have their limitations that may inspire fruitful avenues for further research. A first limitation that is applicable for all three studies, is that it would have been highly useful to possess more detailed information on staffing in the sample firms' scientific departments. While we attribute learning mechanisms to interactions between scientists in the context of a licensing agreement, or to the acquisition-, assimilation- and translation-process in the context of CVC investments, it would have been very interesting to control for movements of inventors. A significant body of literature stresses the importance of inventor mobility as a learning

mechanism affecting the innovative performance of firms (i.e. Arrow, 1962; Levin *et al.*, 1987; Almeida & Kogut, 1999; Cassiman & Veugelers, 2006; Palomeras & Melero, 2010). For instance, a study by Di Lorenzo & Van de Vrande (2019) highlights the importance of inventor mobility as a complement to CVC investments in order to increase the efficiency of knowledge flows between investor firm and the venture. This insight is corroborated by Kim & Steensma (2017), who find that incumbent firms are particularly poised to benefit from knowledge spilling in from new ventures that employ individuals previously employed by the focal incumbent firm. In an analogous way, it would be interesting to observe in what way learning effects from licensing-out are affected by the licensor (often smaller players in the biopharma industry) hiring away talented scientists at the (often larger) licensees they license-out their technology to. Likewise, when firms enter a science park, the allocation of researchers to the firm's subsidiary on the science park is arguably not random. Firms may be likely to allocate their most promising researchers to science parks. A study by Zucker & Darby (2007) shows in this respect that these so-called star scientists have a tendency to move from areas with relatively few peers in order to concentrate into prominent geographical areas in their domain. Also, since science parks are in most cases closely related to research institutions, there might be a mechanism of hiring away talented basic researchers from these institutions, which may affect the likelihood of the firm generating breakthrough patents in these science-intensive clusters that science parks are. For these reasons, I believe that a promising research avenue could be to track these movements and see in what way this phenomenon affects the findings of all three studies in present dissertation. A second limitation, which is mostly applicable to the first two essays in this dissertation, is that – by design – the focus of these studies is on the pharma and biotech industries. While these industries have a high degree of research intensity, it would be useful to see to what extent these learning mechanisms from licensing-out and making CVC investments into ventures hold for different industries. Third, and closely related

to the second limitation, our focus in the first two studies is on the most R&D-intensive players within the biopharma industry. Therefore, one could argue that the findings of these studies on the learning mechanisms stemming from licensing-out and making CVC investments only reflect the cases of these largest players in the industry. A consequence of this focus on the largest R&D-spenders may be that the findings of these chapters only provide limited generalizability towards smaller (biotech) firms, who may lack the internal resources to assimilate and translate (i.e. absorb) external knowledge components to their own organizations.

Lastly, although we believe that our findings advance the understanding of learning through interaction by tapping into the markets for technology or by fostering industry-science links through clustering in science parks, and thereby highlighting previously unexplored relationships, it should be noted that the empirical evidence provided in all three of our essays do not allow us to draw any particular causal claims. Therefore, we acknowledge the need to causally explore the relationships advanced in this dissertation in future research.

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