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Bruno Cirillo

CORPORATE REJUVENATION THROUGH TECHNOLOGICAL SPIN-OUTS:

EVIDENCE FROM HIGH-TECH INDUSTRIES

A dissertation presented

by

Bruno Cirillo

in partial fulfillment of the requirements for the PhD in Business Administration & Management

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1. INTRODUCTION

The generation of corporate spin-outs - i.e., corporate-backed ventures formed by an employee, a team, or a unit of a parent organization - may be beneficial for the rejuvenation of the parent's inventive efforts. This notion builds on the organizational learning literature assumption that the level of knowledge developed by units or subunits in a system may influence the returns to invest in learning for the system as a whole (e.g., March 1991, Levinthal and March 1993). Understanding the role of corporate spin-outs has important theoretical and practical implications. This dissertation aims at providing an understanding that corporate spin-outs bear the costs and risks of exploration initiatives in new technological domains. Doing so, they provide the originating organization with new elements of external knowledge that may eventually sustain the rejuvenation of parent's inventive efforts.

As many scholars have highlighted, the decline of many organizations in high-tech industries - such as electronics, pharmaceuticals, semiconductors - is caused by failure to renew innovation efforts in rapid changing environments (e.g., Stopford and Baden-Fuller 1990). To be successful, or even survive, organizations need to systematically explore new technologies and also excel in established technological domains (Benner and Tushman 2003, O'Reilly and Tushman 2004). Yet, organizations consistently face an important paradox. Experimentation with pioneering technologies is less attractive than exploitation of current knowledge (Levitt and March 1988, March 1991, Levinthal and March 1993). It generates unpredictable R&D outcomes that hardly ever fit with the organization's knowledge base, and it may cannibalize the organization's core business (Chesbrough 2006).

Managing simultaneously exploitation and exploration activities generates conflicts in knowledge generating processes (March 1991), which organizations may solve by adopting dual structures and strategies (Benner and Tushman 2003, O'Reilly and Tushman 2004). By this insight, organizations often spin-out disruptive inventions into independent - loosely coupled - units (e.g., Christensen 1997, Chesbrough 2006). To avoid myopia in learning, on the other hand, they extensively search for successful exploration carried by other firms (Levinthal and March 1993, Rosenkopf and Nerkar 2001).

The literature on innovation has emphasized the role of corporate spin-outs in capturing value from promising ideas that do not fit with the parent core businesses. Hence, spin-outs have been mostly presented as strategies for capitalizing on corporate untapped technology (Chesbrough 2002) and for re-focusing corporate innovation efforts within core businesses (e.g., Chesborugh 2002, McKendrick et al 2009). Yet, substantial evidence exists that spin-outs may eventually pursue new scientific and technological developments that can also help the originating organization to capture new technological opportunities. Examples are corporate spin-outs generated by several large corporations, such as Xerox, Lucent Technologies, Thermo Electron, Unilever, Philips Electronics (e.g., Allen 1998, Chesbrough 2002, Chesbrough and Garman 2009).

In one of his remarkable inquiries on Xerox Corporation spin-outs, Chesbrough (2002) notes:

> 'The market [capitalization of spin-out ventures] reflects not only the potential that resided in Xerox's technology, but also the importance of developing processes to create new markets for that technology' . . . ' Instead of looking to them primarily for near term revenue that would be incremental to the current business, the [spin-out] could be managed as long-term options on new future markets. This would free the [spin-out] from the tyranny of supporting only the existing businesses and could provide Xerox with a platform for building future businesses.' (Chesbrough 2002: 835-836)

Notwithstanding these important insights, no large empirical study has yet provided evidence that the exploration subsequently carried out in spin-out organizations may come to the advantage of the originating firms.

To reconcile these views, this dissertation enquires corporate spin-outs as strategies meant to provide the originating firms with future technological opportunities. Building on organizational learning (e.g., March 1991, March and Levinthal 1993) this work delves into corporate spin-outs by means of understanding *(i)* whether and how spin-outs allow overcoming of inertia plaguing their parent organizations, and *(ii)* whether parent organizations are able to capture innovative R&D eventually carried out by spin-out organizations. These two issues are formalized in the following research questions: *(1) Do corporate spin-outs enable old-timers to develop explorative strategies? (2) Do corporate spin-outs loose inventor embeddedness in the collaboration network? (3) Do corporate spin-outs benefit the parent organization?*

I test hypotheses in a multi-industry research context. The dissertation is structured as follows. Chapter 2 addresses research question 1. Using longitudinal data on the patenting activity of a sample of inventors employed in Xerox Corporation and its spin-outs, it argues that mobility to spin-out enhances individuals' explorative outcomes by desocializing inventors from the established organizational codes of the parent corporation.

Chapter 3 addresses research question 2. Using data on co-inventions in 8 large US corporations and their spin-outs, it offers insight on spin-outs as loci where organizations can manage collaboration across different communities of inventors.

Chapter 4 addresses research question 3. Using longitudinal patent data on a sample of 50 corporations in global chemicals, pharmaceuticals, electronics, semiconductors, computers, and telecommunications it argues about the spin-out impact on the parent innovation performance.

Chapter 5 concludes.

Eventually, my results contribute to literature understanding of corporate spin-outs as strategic mechanisms for *(i)* breaking inertia by rejuvenating old-timers inventive efforts and fostering collaboration among different knowledge communities of a corporation, and thus *(ii)* providing technological opportunities for the rejuvenation of parent innovation efforts.

References

Allen, J. 1998. Capital markets and corporate structure: The Equity Carve-outs of Thermo Electron. *Journal Of Financial Economics* **48** 99-124.

Chesbrough, H.W. 2002. Grateful Exits and Missed Opportunities: Xerox's Management of its Technology Spin-off Organizations. *The Business History Review* 76 803-837.

Chesbrough, H.W. 2006. *Open innovation: researching a new paradigm*. Oxford University Press, USA.

Chesbrough, H.W., A.R. Garman. 2009. How Open Innovation Can Help You Cope in Lean Times. *Harvard Business Review,* December.

Christensen, C.M. 1997. The Innovator's Dilemma. Harvard Business School Press, Boston, MA.

Cohen, W.M., D.A. Levinthal. 1990. Absorptive Capacity: A New Perspective On Learning and Innovation. *Administrative Science Quarterly* **35** 128-152.

Hannan, M.T., J. Freeman. 1984. Structural inertia and organizational change. *American Sociological Review* **49** 149-164.

Levinthal, D.A., J.G. March. 1993. The Myopia of Learning. *Strategic Management Journal* **14** 95-112.

March, J.G. 1991. Exploration And Exploitation In Organizational Learning. *Organization Science* **2** 71-87.

McKendrick, D.G., Wade, J.B., J. Jaffe. 2009. A good riddance? Spin-offs and the technological performance of parent firms. *Organization Science* **20**(6) 979-992.

Nelson, R.R., R.G. Winter. 1982. *An Evolutionary Theory of Economic Change.* Harvard University Press, Cambridge, MA.

Rosenkopf, L., A. Nerkar. 2001. Beyond Local Search: Boundary-Spanning, Exploration, And Impact In The Optical Disc Industry. *Strategic Management Journal* **22**(4) 287-306.

Stopford, J.M., C. Baden-Fuller. 1990. Corporate Rejuvenation. *Journal of Management Studies* **27**(4) 399-415.

2. SPIN-OUTS AND THE REJUVENATION OF OLD-TIMERS

2.1 Introduction

Participation in a spin-out, defined as new venture founded by employees with the support of their originating organization, can revamp inventive output at the individual level. The notion builds on March's (1991) original idea of socialization as a driving force of exploitation and thus ultimately inertia. That is, members of an organization over time grow more alike and align with the prevailing organizational code, which hinders their learning. The greater the socialization rate, the faster the inertial effect (March 1991). This process is of fundamental concern for established organizations that hope to remain continuously innovative and creative. To overcome the negative effects of socialization, this study proposes spin-outs as a *desocialization* strategy that attempts to rejuvenate the innovative potential of organizational members by removing them from the constraints imposed by their organizational code.

Spin-outs have become an increasingly common strategic choice for established innovative companies, including technological venture programs established by leading organizations such as Philips Electronics' New Business Initiative, Siemens's Technology Accelerator, and Shell's Game Changer program. However, extant literature mainly imagines corporate spin-outs as mechanisms for dealing with inventions that do not fit the parent organization's core strategy (e.g., Chesbrough 2002, 2003). In this case, parent organizations actively invest and transfer assets to a new independent organization to enter a new product market (e.g., Chesbrough 2003; Franco and Filson 2006), even as the spin-outs allow the parent organization to focus on its core business by redirecting its strategic resources to established innovation processes in traditional technological fields (e.g., McKendrick et al. 2009).

We propose that the spin-out experience also can rejuvenate the explorative efforts undertaken by inventors, especially experienced ones, whom we call old-timers to indicate their relatively long tenure with the same organization. Tenure tends to be associated with a reduced likelihood that the inventors contribute to progress in technological fields other than the organization's main fields of expertise; over time, they become exploitative. This tendency reflects their dependence on past experience and the convergence toward established knowledge and search heuristics, which are embedded in an established organizational code (March 1991; Nelson and Winter 1982). We contend that moving to a spin-out organization may provide inventors with an opportunity to detach from the organizational code and receive novel stimuli, which then should increase the likelihood that they explore new technological trajectories.

With a sample of inventors employed by Xerox Corporation and its spin-outs over 1975–2008, we show that inventors who join a spin-out company demonstrate greater exploration in their inventive activity, whereas comparable inventors who remain with the originating organization do not. Furthermore, this effect is stronger for inventors with a longer tenure with the originating organization. We measure exploration as the number of claims reported in patents generated after the spin-out decision that belong to novel U.S. patent classes. That is, spin-out experience increases the mean of patent claims when inventors explore a new technological class. These results are robust to several econometric specifications that try to account for the endogeneity of the spin-out decision.

Ultimately, our findings thus enrich understanding of how established corporations can revamp the explorative activity of their inventors, as well as offer detailed theoretical and practical implications from the perspectives of corporate entrepreneurship, technology strategy, and organizational learning.

2.2 Background

As they grow, organizations tend to become inert and prefer the exploitation of old certainties to the exploration of new possibilities. Sorensen and Stuart (2000) show that a larger organizational size generally is associated with a stronger tendency to build and rely on previous innovative activities, as well as to refine and elaborate older areas of technology. More generally, Ahuja and Lampert (2001) describe how larger organizations tend to favor the familiar to the unfamiliar, the mature over the nascent, and solutions that are nearer existing knowledge and routines rather than de novo solutions.

Recent research also suggests this process is driven by a mutual positive feedback between experience and competence. Experience with a given technology leads to enhanced absorptive capacity and greater competence with it. Greater competence with a technology in turn fosters increased usage, which then again increases experience with the technology. In summary, the increased ease of learning and specific problem solving enabled by enhanced absorptive capacity and established organizational routines in known technological areas make the adoption of alternate directions of development less attractive (Cohen and Levinthal 1990; Levinthal and March 1993).

In his seminal paper, March (1991) thus proposed a model to formalize the process of mutual learning in knowledge development. In this model, firms consist of an “organizational code” of received truth, which represents their beliefs about (external) reality. Individual members modify their beliefs through their socialization into the organization by adapting to the code. The organizational code also could adapt to the beliefs of those members that offer a better representation of reality.

The organizational code thus plays a pivotal role in the learning process, in that individual beliefs do not affect other individual members directly but rather do so only by influencing the code. Improved knowledge thus results when the code mimics the beliefs of individuals and then individuals mimic the code. Yet this process implies that over time, individual members become more homogenous in their knowledge, and eventually equilibrium occurs, such that all members and the code reflect the same (not necessarily accurate) beliefs about reality. On the one hand, the resulting stable interactions allow colleagues to converge to shared understandings and experiences through their socialization (March 1991). On the other, they increase group-thinking behaviors and reduce the level of openness to the external environment (Katz and Allen 1982).

Socialization, or the process through which people learn from the organizational code, therefore reduces diversity and hinders learning, because individuals come to rely on stable, repetitive, socially accepted routines (March 1991; Nelson and Winter 1982). As a result, long-tenured members likely build new knowledge only within the organization’s existing field of expertise. Even if such knowledge building is optimal in the short term, only organizations that can balance exploration and exploitation succeed in the long run (He and Wong 2004). Accordingly, socialization-induced inertia becomes a problem to overcome.

March (1991) notes the potential utility of maintaining a certain level of variety in the organization, perhaps through personnel turnover. Turnover introduces less socialized people into the firm, increases exploration, and thus improves aggregate knowledge. The resultant gains thus come from *diversity*, not necessarily superior capabilities. Inter alia, Rosenkopf and Almeida (2003) show that mobility is associated with interfirm knowledge flows, which might support the exploration of technologically distant knowledge (Song et al. 2003).

Diverse inputs are not necessarily associated only with turnover though. For example, recent research on open innovation (e.g., Chesbrough 2003, 2006) has stressed several different mechanisms that enable established organizations to maintain and enhance connections to the external environment, obtain different knowledge, and use it routinely to generate new ideas. The idea that external knowledge helps firms avoid inertial forces is well established in prior literature. Stuart and Podolny (1996) trace the technological trajectory of the ten largest Japanese semiconductor producers between 1982 and 1992 and show that only Matsushita was able to reposition itself technologically, by moving away from local search. This repositioning seemingly was accomplished through extensive alliances with other firms, which gave Matsushita access to different technologies. Furthermore, Rosenkopf and Nerkar (2001) find that inventive efforts that do not span organizational boundaries generate lower impacts on subsequent technological evolutions.

Finally, other streams of research have emphasized how companies might overcome the tendency to build and rely on previous innovative activities by making specific investments in new initiatives. Decades ago, Burgelman (1983) highlighted the role of internal corporate venturing in revitalizing established firms’ innovative strategies; more recently Dushnitsky and Lenox (2005) have shown the contribution of corporate venture capital (CVC) investments to firm value, especially when firms explicitly pursue CVC to harness entrepreneurial inventions.

We focus on another tool available to established organizations to prevent inertia: spin-outs. We conceive of spin-outs as an instance of desocialization, which we define for this study simply as unlearning (e.g., Tsang and Zahra 2008) of previous normative expectations and roles, as are embodied into what March (1991) calls the organizational code. We thus argue that spin-outs enable old-timers to revamp their explorative activities.

2.3 From the Spin-Out Decision to Exploration

There are two main building blocks to our proposal. First, we consider how mobility affects exploration, as has been well established in prior literature. Second, we focus on the different effect of mobility through spin-outs on the explorative strategies of inventors with *different* levels of tenure with the parent organization (compared with a control group of inventors without spin-out experience). The first building block relies on literature on mobility (e.g., Trajtenberg 2005); the second builds on and extends organizational learning literature (e.g., March 1991).

Previous literature uses spin-off and spin-out mostly as synonyms. For example, Agarwal et al. (2004) define spin-outs as new ventures founded by former employees that enter the same industry and compete with the parent organization, which has no equity. Other studies define the same scenario as a spin-off (e.g., Klepper and Thompson 2007; McKendrick et al. 2009). Still other research (e.g., Chesbrough 2002, 2003) refers to either spin-outs or technology spin-offs as modes of entry into industries or technologies that are new to the parent organization.

For the purposes of this study, and following Chesbrough (2003), we define corporate spin-outs as the incorporation of a new independent organization composed of former employees, a unit, or a division of the parent organization. This definition clearly distinguishes corporate spin-outs from spin-offs. First, the parent organization voluntarily creates corporate spin-outs. Second, the parent organization invests equity in and transfers assets to this spin-out company, such that the spin-out is part of the parent organization (i.e., subsidiary or participating organization), which the parent eventually may decide to reintegrate or sell. Third, because the parent organization retains interest in the spin-out organization, it usually does not compete directly with the parent organization.

If they join the spin-out, employees change their formal affiliation (Hoisl 2007), though they do not necessarily engage in *geographic* mobility. Typically, geographic mobility does not occur when an entire unit or division is spun out and incorporated into a new, independent organization. An example is Xerox PARC, an R&D unit of Xerox Corporation that was spun out into a new and independent subsidiary (i.e., PARC Inc.) in 2002.

The relationship between mobility (organizational and/or geographical) and inventive activity is certainly not a new idea. Turnover and mobility often introduce variety into organizations (e.g., Almeida and Kogut 1999; Miller et al. 2006; Rosenkopf and Almeida 2003), and Trajtenberg (2005) shows that mobile inventors are more likely to produce highly cited inventions and patents with greater economic value (Trajtenberg 1990). Yet there could be an issue of reverse causality: Does mobility spur productivity, or are more productive inventors better able to move? Hoisl (2007) explores the simultaneous correlation between inventor mobility and patenting productivity and shows that interfirm mobility actually enhances inventors' patenting productivity, thanks to the contact they gain with different sources of knowledge. Spin-outs reinforce this effect: They free organizational members from an environment that provides very few nonredundant stimuli (March 1991) and allow them to connect with different information. Therefore, we hypothesize:

Hypothesis 1. A spin-out increases the extent of exploration by organizational members who join it.

We next turn to a discussion of how different levels of tenure in the parent organization affect the relationship between spin-out participation and individual-level exploration. Although they maintain formal links with the parent organization, spin-outs allow former members of the originating organization to interact with new counterparts and detach from the established organizational code, which creates a basis for revamped innovative activity. The spin-out first prompts organizational members to unlearn roles and expectations of appropriate behavior, which grants them the opportunity to experiment with and receive new and different stimuli. We refer to such unlearning as an instance of desocialization. Similar to Siggelkow and Levinthal (2003), who argue that organizational decentralization enhances exploration at the business unit level, we posit that spin-outs enable individual members to diverge from the established organizational code, which in turn allows them to depart from their previous trajectories and explore again.

If spin-outs enable people to receive new stimuli, they also support a desocialization process through detachment from the former organizational code, which reinforces the effect of the diverse stimuli provided by mobility and turnover. Otherwise, companies could obtain the same result simply through job rotation, for instance.

The idea of innovation through desocialization also is consistent with recent work on entrepreneurship and start-ups, which identifies the role of tenure and pre-entry experience as crucial for understanding the innovative performance of new firms. For example, Klepper (2001) finds that industry tenure is a key explanatory factor for spin-off performance. The general idea is that industry-specific relevant experience is embodied in people, and founders transfer such knowledge when they join the spin-off. Thus spin-offs from incumbent firms seem to enjoy improved performance in various industries, including automobiles (Klepper 2002), disk drives (Agarwal et al. 2004), lasers (Klepper and Sleeper 2005), and semiconductors (Balconi and Fontana

2011). Over time though, the effect of founders' embodied knowledge fades. Klepper (2001) shows that the impact of initial knowledge endowments tend to be very strong in the beginning, then decrease. This finding is consistent with the idea that over time in a new firm, socialization pressures crowd out diversity and reduce exploration.

We extend this line of reasoning on the strength of observations by Louis (1980) and March (1991) that the effects of turnover differ according to tenure in the organization. People with low turnover, such as old-timers, become well socialized in the organization, more so than newcomers. Their contribution to knowledge-generating activities thus declines; in March's terms, the slow learners (i.e., organizational members with the slowest rate of socialization) provide a relatively greater contribution in terms of new knowledge generation.

The theory underlying this argument is not knowledge obsolescence; what old-timers know can be of great utility, as literature on entrepreneurship has highlighted (e.g., Klepper 2001). Rather, the problem is that once old-timers' beliefs align completely with the organizational beliefs embodied in its code, there is no endogenous mechanism for learning. Consistent with Taylor and Greve (2006), according to whom experience may improve inventive output when inventors access new sources of knowledge, spin-outs can enable old-timers to leverage their knowledge and apply it to different contexts, even as they learn new roles and seek new logics. Experienced people even may be better than relatively junior organizational members at adapting their behaviors to novel knowledge environments, because a key distinction between expert problem solvers and novices is their ability to connect elements and build patterns, rather than describing situations in terms of specifics (e.g., Newell and Simon 1972). Accordingly, we hypothesize that spin-out experience benefits old-timers relatively more than newcomers, because they can apply their pattern-making skills to the novel situations that require them.

Hypothesis 2. The positive effect of spin-outs on the extent of exploration is stronger for old-timers than for newcomers.

2.4 Methods

2.4.1 Data

In this study, we aim to establish the effect of spin-outs on inventors' behavior. In particular, we contend that participating in spin-outs increases inventors' extent of exploration (H1), and this positive effect is stronger for old-timers (H2). To test these hypotheses, we use data pertaining to the patenting activities of a sample of inventors employed by the Xerox Corporation and its spin-outs. Xerox is a well-known example of an organization that has initiated many spin-outs in the past 30 years. Although Xerox has been widely studied (e.g., Chesbrough 2002, 2003), most investigations consider either its constraints in commercializing new technologies or the financial performance of its spin-offs. Focusing on Xerox thus facilitates the collection of reliable data about its spin-outs, while also automatically controlling for possible unobserved confounding factors at the parent level. This choice also is coherent with our theoretical framing: We are interested in understanding the extent to which desocialization, or unlearning of a specific "organizational code," enables inventors to revamp their innovative activities. Thus our sample and control group should be exposed to the same organizational code. Moreover, the theoretical point we attempt to substantiate relates to the extent of socialization and the ensuing lack of diversity (March 1991). We do not test for the outcomes of different organizational codes (i.e., more innovative vs. more conservative); Xerox itself is a highly innovative company and encourages its employees to devise new things. Thus it is meaningful to compare a sample of spun-out inventors with a sample of inventors who stayed with the originating company.

Empirically, in the computer and office equipment industry, patents constitute an effective and valuable way to appropriate returns from R&D (Arora et al. 2008), and they correlate well with new product or innovation counts (Hagedoorn and Cloodt 2003), so they provide a valid indicator of technological performance. This status is important because, as we explain subsequently, our measure of the extent of inventors' exploration is based on patent statistics.

We gathered information about spin-outs from several sources, including academic papers (Chesbrough 2003; Chesbrough and Rosenbloom 2002), teaching case studies (Chesbrough 1998), and news releases (e.g., Xerox press releases, spin-out press releases, news from Factiva). We identify corporate spin-outs according in four criteria (Chesbrough 2002):

1. A Xerox employee, unit, or division departs the parent organization and forms a new incorporated organization.
2. The organization is voluntarily released by Xerox to enter a new product market with a technology born and incubated within the parent organization.
3. The spun-out firm employs former Xerox inventors.
4. Xerox's ownership of the new independent firm varies from 0% (no equity) to 100% (wholly owned) of the spin-out's initial capital.

Eighteen companies fit these four selection criteria and have received patents from the U.S. Patent and Trademark Office (USPTO).

Table 1 about here

From among these companies, we identified a sample of inventors using the recent data set built by Lai et al. (2009). We found inventors affiliated with a Xerox spin-out by searching the patent assignees (Almeida and Kogut 1999; Hoisl 2007). From among these inventors, we then noted those who patented with Xerox prior to the spin-out initiation date. Of the 18 spun-out companies, only 8 earned patents that were applied for by former Xerox inventors. Therefore, the final sample of inventors includes 136 individuals who generated or joined a spin-out and display patenting activities both before and after this spin-out event.

To support our comparisons, we built a control sample of Xerox inventors who did *not* move to a spin-out. This sample of 226 *co-inventors* of inventors that moved to a spin-out instead continued patenting with the parent organization. We selected the co-inventors precisely because they have been exposed to a similar knowledge environment and should display similar pre–spin-out output. To account for potential differences across the two groups, we collected additional data about the inventors' ages (from http://www.birthdetails.com) and patenting behavior. In Table 2, we summarize these variables for the three samples of inventors: those who moved to a spin-out, those in the control group, and other inventors in the parent organization. The control group is largely comparable to the group of treated inventors in terms of inventive productivity, breadth of knowledge, collaborative patterns, and seniority in the parent organization.

Table 2 about here

An additional step for defining the sample pertains to the distinction between old-timers and newcomers. To ensure the robustness of results, we employ two alternative categorizations. To test H2, we define old-timers as inventors who had been working with the parent for at least five or ten years before they moved to a spin-out (for co-inventors, the measure referred to the time before his or her previous colleague moved to the spin-out). In contrast then, newcomers are inventors (co-inventors) who had been working with the parent company for at most four or nine years before moving to a spin-out (before his or her previous colleague moved to a spin-out). The timeline for inventors and organizations in the sample appears in Table 1, which shows that the sample encompasses spin-outs generated by former employees, units (e.g., more than one inventor), and divisions (e.g., Xerox PARC).

2.4.2 Measures

Dependent variable

Our dependent variable is inventors' *extent of exploration*, which we measure for each inventor as the number of claims in patents successfully applied for in a *new* patent class in a given year. The patent classes established by the USPTO identify the technological areas to which the knowledge encompassed in the patent belongs (Fleming 2002). Such a count measure is common as a measure of exploration (e.g., Banerjee and Campbell 2009; Fleming 2002). Specifically, we identify whether an inventor *i* has applied for a patent in a new patent class in year *t*. If there are multiple classes, following Benner and Waldfogel (2008), we refer to the first class listed in the patent document.

Patents feature statements that differentiate their inventions from prior art in the same technological field. The number of claims therefore defines novel features of the patented invention and thus the technological distance between the protected invention and the prior art in that technological class (Lanjouw and Schankerman 2004). In this study, we consider both the number of claims and the novelty of technological classes, because together they provide a better appraisal of the extent of inventors' exploration by revealing whether the inventor's output is new with respect to the inventor and the parent organization, as well as the extent to which the invention output is new with respect to the world.

Independent and control variables

Our main independent variable, *spin-out*, captures inventors' affiliation at any moment in time. Specifically, it takes the value of 1 if the patents awarded to inventor *i* at time *t* are assigned to a spin-out, and 0 otherwise. In our sample, 1688 patents were awarded to Xerox inventors who moved to a spin-out, and 616 of them relate to the period in which inventors were affiliated with a spin-out.

We control for several variables that might influence inventors' extent of exploration. Previous literature (e.g., Banerjee and Campbell 2009; Fleming et al. 2007; Singh and Fleming 2010) suggests that individual inventive outcome depends on collaboration patterns, patenting experience, and knowledge background. We therefore include the following covariates at the inventor and organizational levels of analysis:

- *Team size*. Measured as the mean number of inventors listed on patents awarded to inventor *i* at year *t*, it provides a proxy for direct knowledge spillovers in team projects (e.g., Fleming et al. 2007).

- *Knowledge generality*. This variable measures the dispersion of patenting activity of inventor *i* prior to year *t* in different technological fields, such that it is a proxy for the extent to which the inventor might exploit past knowledge in new inventions (Banerjee and Campbell 2009; Hall et al. 2001). It is measured as a complement to a Herfindahl index, ranging from 0 (previous experience is concentrated in a single technological class) to 1 (highest dispersion of individual experience across different technological classes).
- *Solo patents*. This variable measures the proportion of patents awarded to inventor *i* in year *t* and in which inventor *i* is the sole inventor. It proxies for the propensity for collaboration, which Fleming et al. (2007) identify as a determinant of explorative inventions.
- *Patents*. This variable measures the total number of patents applied for by inventor *i* in year *t*.
- *Total patents.* This variable refers to the total number of patents applied for by inventor *i* by year *t*. Following Banerjee and Campbell (2009), this measure captures inventor productivity and tenure in the industry.
- *Seniority*. It refers to the number of years elapsed since the first patent by inventor *i*.
- *Parent patents*. This variable accounts for the total number of patents applied for by the parent organization in year *t*. It might help capture variance in individual inventive output, due to an organizational effect and possible knowledge spillovers.
- *Parent equity*. It measures the parent's ownership in inventor *i*'s spin-out. For observations with patents assigned to the parent organization, this variable equals 1. For observations with patents assigned to a spin-out, the variable is coded from 0 to 1, according to the percentage of the spin-out's equity owned by the parent organization at its foundation (i.e., from 1 for wholly owned to 0 for no parent equity).

- *PARC*. This dummy refers to inventors employed in Xerox PARC, the only spin-out in the sample that is a former division of Xerox. Because it does not imply geographical mobility and most old-timers with more than 10 years of tenure in the parent organization were affiliated with PARC Inc., we decided to include this variable to capture possible effects due to this specific affiliation.
- *Year dummies*.

Table 3 reports the summary statistic of the main variables of interest, as well as pairwise correlations.

Table 3 about here

2.4.3 Empirical Strategy

Our basic specification estimates the following model:

$$\text{Extent of exploration}_{it} = f\,(\text{Spin-out}_{it}, X_{it}; \gamma, \beta), \qquad (1)$$

where X is a vector of control variables, and γ and β are vectors of parameters to be estimated. The dependent variable, extent of exploration, is a count variable that takes only non-negative integer values. Because it also reveals overdispersion, we use a negative binomial regression model (Cameron and Trivedi, 1998). Exploiting the panel structure of our data, we include inventor fixed effects to account for time-invariant unobserved heterogeneity across individual inventors, which might influence their inventive performance.

Estimating the effect of spin-out on inventors' extent of exploration is potentially challenging because of the endogeneity of the decision of founding or joining a spin-out. In particular, spin-outs can be generated by the most explorative inventors in the parent organization, and/or the observed impact of the spin-out may relate to work actually carried out by the inventor when he or she was still employed by the parent organization. A greater extent of exploration therefore might be simply the result of a trend already in place. We try to minimize this potential bias in several ways.

First, because a plausible concern is that the spin-out is motivated by particularly explorative research carried out in the parent organization prior to inventors' spin-out, we exclude patents applied for in the first year of the spin-out's incorporation from our analysis. Of the 4,709 total inventor-year observations, 340 relate to patents applied for by inventors in the first year of the spin-out. By excluding them, we reduce the total sample size, including both inventors who moved to a spin-out and those who remained with Xerox, to 356. Second, we perform a difference-in-differences (DD) estimation. To identify the impact of a treatment on a group, the DD estimator computes (1) the difference in outcomes before and after the treatment for the treated group (i.e., for this study, inventors who moved to spin-outs), (2) the parallel difference for the control group (i.e., co-inventors who remained with Xerox), and (3) the difference between these differences, which offers evidence of the effect of the treatment. This procedure removes biases in second-period comparisons between the treatment and control group that could result from permanent differences between those groups, as well as biases from comparisons over time in the treatment group that could be the result of trends.

Yet the DD estimates also might be biased in the case of endogeneity in the treatment (Bertrand et al. 2004). We therefore estimated another model based on matching (Imbens 2004) that assesses the effect of the spin-out event on inventors' extent of exploration. Matching estimators provide a possible solution to the fundamental problem of causal inference that arises when estimating a causal effect from nonexperimental data. Using formal notation, let Y_{i1} be the value of the outcome variable of interest (i.e., extent of exploration) when i is subject to the treatment; Y_{i0} is the value of the same variable when the unit is exposed to the control. In this study, the treatment entails moving to a spin-out, and the control units do not. The effect of spin-outs on inventor i is then $e_i = Y_{i1} – Y_{i0}$, and the "true" expected effect on the treated population (i.e., on inventors that join a spin-out) is:

$$e\,|_{T=1} = E(Y_{i1}\,|\,T_i = 1) – E(Y_{i0}\,|\,T_i = 1),$$

where T = 1 (= 0) if inventor i moved (did not move) to a spin-out. However, we cannot directly observe $E(Y_{i0} \mid T_i = 1)$; we lack counterfactual evidence of what would have happened to inventor i if he or she had not moved to a spin-out, provided inventor i actually moved. If treated and untreated inventors systematically differ (i.e., the decision to move to a spin-out is not random), then $E(Y_{i0} \mid T_i = 0)$ is a biased estimator of $E(Y_{i0} \mid T_i = 1)$ (Heckman and Navarro-Lozano 2004). Matching estimators provide a possible solution to this problem by imputing the missing outcomes Y_{i0} of treated individuals using the outcome of individuals with *similar* values of relevant pre-treatment variables or covariates that were not exposed to treatment. A variable is relevant and appropriate to the extent that it affects the probability of being subject to treatment (Imbens 2004). Different matching estimators exist; we estimate that proposed by Abadie et al. (2004).

2.5 Results

This study explores the effect of spin-outs on inventors' inventive outcomes, relative to their level of tenure in the originating organization. We hypothesize that as inventors move to spin-outs, they increase the level of exploration in their inventive activity. In Figure 1 we provide the mean number of claims in new patent classes for the treated group and the control group. There is a substantial increase in the extent of exploration by inventors who moved to a spin-out, as confirmed by a t-test ($p < .001$). We do not observe the same pattern in the control group, which indicates a stable outcome over time.

Figure 1 about here

However, the increase in the extent of exploration observed after the spin-out event may result from other factors at the individual or organizational levels. To account for these factors, we estimate Equation (1).

Table 4 about here

In Column (1) in Table 4, we report the coefficients of the negative binomial regressions with inventors' extent of exploration as the dependent variable. The positive and significant parameter estimate for the spin-out variable ($p < .05$) indicates that spin-outs enhance individual efforts in technologies that are new with respect to the individual and organizational experience, as well as with respect to the state of the art in that specific technological field. We estimate the same model with a Poisson regression and ordinary least squares (OLS; log-linear specification). The results are robust to these different specifications and provide further support for Hypothesis 1.

In Hypothesis 2, we further predict that after the spin-out event, long-tenured inventors would increase the extent of their exploration more than newcomers. Venkatraman (1989) suggests that when researchers explore the different effects of certain strategies across different contexts, they should use subgroup analysis. Therefore, we first separated the sample into two groups, according to their tenure in the parent company before the spin-out date. As we explained in the previous section, for robustness we considered two alternative cut-offs and defined, in two different specifications, old-timers as inventors with a tenure of at least five or at least ten years, whereas newcomers were those with shorter tenures. We then generated two spin-out variables, one for each group, coded as 1 when a newcomer (old-timer) moves to a spin-out, and 0 otherwise. Finally, we ran an OLS regression for both groups and computed the test for equivalence between the coefficients related to newcomers' and old-timers' spin-out (Chow 1960).

The results of these estimations in Table 5 show that the effect of the spin-out variable on individual inventiveness is positive for old-timers. In the model presented in Column (4), we differentiate old-timers and newcomers according to the five-year tenure threshold. The parameter estimates show that the effects of spin-out for old-timers are higher in magnitude than those for newcomers, and the difference (Δ =

2.694) is statistically significant. Moreover, the spin-out experience does not seem significant for newcomers with fewer than five years of tenure in the parent organization. When we differentiate old-timers and newcomers according to the ten-year tenure threshold (Column (5)), we confirm the higher magnitude effect for old-timers (Δ = 0.1911), such that only the old-timers are affected significantly by the spin-out experience ($p < .05$). However, for the ten-year threshold, the difference among groups is less significant than in the previous specification. In summary, the results provide some evidence in support of Hypothesis 2.

Table 5 about here

To ensure the robustness of our results for Hypothesis 1, we also performed several additional analyses. First, we performed a DD estimation of the impact of spin-out on the extent of individual exploration. The results in Table 6 confirm that the spin-out produces a positive and significant ($p < .05$) effect on the inventor's extent of exploration.

Table 6 about here

To obtain consistent DD estimates, both groups must reveal the same trend for the dependent variable before the treatment period. As we discussed previously, inventors in the sample are homogeneous in several of their individual characteristics and their patent productivity in the period before spin-out incorporation. Figure 2 reveals the average extent of exploration by treated inventors and the control group; they are largely comparable before the spin-out event. Moreover, the DD estimates indicate no significant difference between the treated and control groups in the pre-treatment period.

Figure 2 about here

To assess the effect of spin-outs further, we computed a matching estimator (Abadie et al. 2004), which requires two key decisions: how many comparison units to consider, and whether to match with replacement (i.e., are the same control units actually used as controls more than once?). Dehejia and Wahba (2002) discuss these issues thoroughly and suggest that matching with replacement is beneficial in terms of bias reduction, but matching without replacement could improve the precision of the estimates. By using more comparison units, we might increase the precision of the estimates, though at the cost of increased bias. Therefore for this study, we estimate a model with replacement and three comparison units. The results in Table 7 confirm the positive effect of spin-outs on inventors' extent of exploration.

Still, Abadie and Imbens (2002) warn that matching estimators might be biased in finite samples with at least one continuous variable on which to match or, in general terms, when exact matching is not possible, such that they are generally not efficient. Hirano et al. (2003) show that weighting observations for the propensity score (i.e., probability to be subject to treatment) to create balance between the treated and control units result in the semi parametric efficiency bound. We therefore estimated the effect of spin-out using an inverse probability of the treated weighted estimation. The results of these estimations, with both a negative binomial and an OLS specification, are in Columns (2) and (3) of Table 4. They again provide evidence consistent with Hypothesis 1.

Table 7 about here

2.6 Discussion and Conclusion

This study reveals that spin-outs rejuvenate old-timers' innovative strategies. Compared with a control group of similar inventors, old-timers who joined spun-out organizations patented broader ideas in novel technological classes. Hence, spin-outs increased the likelihood that these inventors would generate a significant technological development in a field that is new, compared with their prior experience. Moreover, our findings indicate that the spin-out effect was stronger for those with a long tenure in the originating organization.

We have argued that this evidence indicates that spin-outs act as a desocialization mechanism that allows inventors with a long tenure in the same organization to diverge from past behavior. In line with March’s (1991) intuition about the impact of socialization rates on invention outcomes, our argument builds on two complementary explanations. First, spin-outs expose inventors to new sources of diverse knowledge and provide them with new stimuli to engage in explorative behaviors. Second, though old-timers might be expert decision makers, they are oversocialized in the organizational environment and aligned with the organization’s established search heuristics (i.e., organizational code). Yet after the spin-out, these old-timers’ superior experience favors their ability to exploit new stimuli, so they are likely to generate highly explorative strategies. Experience may provide an opportunity to produce significant technological progress in new fields if old-timers can increase the range and variety of external stimuli they receive. Spin-outs also provide old-timers simultaneously with the chance to break away from their oversocialization with the parent organization’s code and gain exposure to new sources of knowledge through low social integration (e.g., Morrison 2002) with acquaintances that have expertise in different technological areas (e.g., Ahuja 2000).

Although we did our best to support our theoretical claims empirically, we acknowledge that we cannot rule out alternative explanations conclusively. First, the increase in the extent of exploration might be driven endogenously by the spin-out decision, because by definition spin-outs are devoted to entering new product markets with ideas largely explored by the parent organization. In this respect, we note that only a minority of Xerox spin-outs produced patents after their incorporation. Thus, though spin-outs serve as means to enter new product markets, they do not necessarily imply explorative activity or, to be more precise, any R&D activity that necessarily leads to patent applications. Second, we tried to correct for the endogeneity of the spin-out decision, both through our variable construction, which excluded patents applied for in the first year of spin-out incorporation, and econometrically, by using various specifications. Nonetheless, we realize that in our non-experimental context, we cannot indisputably prove causality.

At the same time, we lack direct evidence that desocialization is the actual process that leads to the observed effects of spin-outs. Although we cannot directly observe desocialization, we outline two additional empirical results (summarized here for conciseness) that indirectly support our theoretical argument. First, if spin-outs desocialize inventors due to the combined effects of desocialization and mobility, similar (but weaker) results should be produced by a sole inventor's mobility within the parent organization. Internal mobility then should enable old timers to gain access to novel sources of ideas, though within the bounds set by the organization code. Therefore, we coded inventors' mobility within Xerox using patent data regarding the inventor's location (Lai et al. 2009) and estimated the impact of intra-organizational mobility on the extent of exploration through a negative binomial regression. These results show that intra-organizational mobility has a positive and significant effect on the extent of exploration by the inventor (consistent with the idea that intra-organizational mobility enables inventors to access novel sources of ideas). However, if we regress our dependent variable on both intra-organizational mobility and spin-out, the effect of the former is no longer significantly different from zero. Inter-organizational mobility through spin-out therefore appears related to desocialization from the established organizational code, which in turn is related to the greater effect on the extent of exploration shown by spin-out participation, compared with intra-organizational (i.e., intra-code) mobility. Figure 3 shows linear predictions for these results.

Figure 3 about here

Second, in line with March's (1991) argument about the relationship between socialization and organizational learning, we argue that desocialization might be proxied for by the extent to which inventors decrease self-citations to Xerox's patents, after they spin out. We thus estimated the effect of spin-out on the proportion of backward self-citations (to Xerox patents) using a fractional logistic regression (Papke and Wooldridge 2008). Table 8 shows this result. After they spin out, inventors reduce the proportion of their citations to their parent's patents, which we interpret as evidence that spin-outs desocialize them from the parent's organizational learning processes.

Table 8 about here

Beyond these results, our comparison of newcomers and old-timers shows that the latter exhibit a stronger positive effect of spin-outs, which is consistent with our theoretical explanation. If the simple exposure to new colleagues or different organizational incentives (e.g., due to the smaller size of the new organization) were responsible for increased exploration, this effect should not be any stronger for old-timers.

Even with these caveats, this study provides significant implications for extant literature. First, whereas previous literature (e.g., Chesbrough 2002, 2003) has analyzed spin-outs mainly as organizational choices driven by *previous* explorative efforts, whose results could not be exploited by the parent organization, we show that spin-outs can continue the pursuit of original patterns and revamp inventors' (especially old-timers') explorative behavior. Thus spin-outs are not only caused by exploration in product markets but may bring about exploration in novel technological fields by desocializing old-timers who previously belonged to the parent organization. We contribute to corporate entrepreneurship literature by suggesting spin-outs as another organizational tool to foster organizational search and exploration.

Our findings also relate to traditional literature on ambidexterity (e.g., Benner and Tushman 2003, O'Reilly and Tushman 2004), which suggests that novel technologies should be developed and engineered in structurally independent units, only loosely coupled with the existing management hierarchy. This literature stream has not presented large-sample results though, and to a large extent, it has not explored the *ex post* effects of this organizational choice.

The relationship between spin-outs and inventive activity also is relevant for research into the organizational determinants of technological performance.

Motivated by early contributions by Schumpeter (1934, 1942), a vast body of empirical work considers the determinants of firms’ propensity to produce innovative ideas. Yet we know little about the determinants of the quality and value of such inventions (Fleming 2002). Although producing new ideas and knowledge is a necessary condition to sustain superior performance, it is not sufficient: Not all inventions are equally useful and valuable (Gambardella et al. 2008). In this study, we provide evidence that spin-outs are associated with an increase in the claims of patents produced by inventors who move to a new organization. The number of claims defines the novel features of the invention and thus the technological distance between the protected invention and the prior art; claims also constitute very good indicators of inventions’ economic value (Lanjouw and Schankerman 2004) and quality. Prior literature examining the drivers of the quality of inventions has stressed the importance of the resources available in the inventive process, and in particular the diversity of knowledge inputs available to inventors (e.g., Fleming 2001). However, it also notes the need for organizational incentives (e.g., Zenger 1994). Consistent with Kapoor and Lim (2007), we show that knowledge and incentive-based perspectives complement each other as explanations of technological performance. Not only do spin-outs increase the possibility that inventors receive new stimuli, but through desocialization, they also allow these inventors to interpret the stimuli through new lenses, unlike those suggested by the organizational code. Thus, we contribute to entrepreneurship literature that has identified founders’ embodied knowledge as a leading determinant of the superior innovative performance of spin-offs from industry incumbents (e.g., Balconi and Fontana 2011; Klepper and Sleeper 2005; Klepper and Thompson 2007). Founders bring with them relevant, industry-specific knowledge, but their desocialization enables them to reinterpret it and enrich it in novel ways—hence the superior innovative performance of spin-offs founded by inventors with long tenures in industry incumbents that appears in many studies.

Furthermore, unlike prior studies, this study examines a different mechanism, desocialization, that might underlie the increase in explorative behavior. We thus contribute to organizational learning literature and provide an empirical test of one of March's (1991) key arguments. It is clear that exploitation and exploration should be balanced to achieve superior organizational performance (He and Wong 2004), but we still know relatively little about the actual mechanisms for stimulating exploration.

Our results also make a clear contribution to managerial practice. Rapid technological change and short product lifecycles have made continuous innovation critical to sustainable competitive advantage. From the perspective of a practicing manager, explaining a mechanism that allows old-timers to overcome inertia and increase their propensity to explore new technological paths is of great importance, especially considering the associated economic stakes. To provide a more complete picture of the economic outcomes of spin-outs, further studies should investigate the extent to which the parent organization can capture the value potentially created by the exploration of spin-out firms, as well as the factors that influence this process.

Much remains to be done to explain one of the most fundamental issues of strategy research - the drivers of organizational and individual change - yet with this study we believe we have contributed to the development of a stronger, more explicit link between empirical research on mobility and theoretical research on organizational learning and innovation.

References

Abadie, A., Drukker, D., Herr, J. L., G. Imbens. 2004. Implementing matching estimators for average treatment effects in Stata. *Stata Journal* **4**(3) 290-311.

Abadie, A., G. Imbens. 2002. Simple and bias-corrected matching estimators for average treatment effects. NBER technical working paper no. 283.

Agarwal, R., Echambadi, R., Franco, A.M., M.B. Sarkar. 2004. Knowledge Transfer Through Inheritance: Spin-Out Generation, Development And Survival. *Academy of Management Journal* **47** 501-522.

Ahuja, G. 2000. The duality of collaboration: Inducement and opportunities in the formation of interfirm linkages. *Strategic Management Journal* **21**(3) 317-343.

Ahuja, G., C.M. Lampert. 2001. Entrepreneurship in the large corporation: a longitudinal study of how established firms create breakthrough inventions. *Strategic Management Journal* **22**(6-7) 521-543.

Almeida, P., B. Kogut. 1999. Localization of knowledge and the mobility of engineers in regional networks. *Management Science* **45**(1) 905-917.

Arora, A., Ceccagnoli, M., W. Cohen. 2008. R&D and the patent premium. *International Journal of Industrial Organization* **26**(5) 1153-1179.

Balconi, M., R. Fontana. 2011. Entry and innovation. An analysis of the fabless semiconductor business. *Small Business Economics* **36** 1-20.

Banerjee, P.M., B.A. Campbell. 2009. Inventor bricolage and firm technology research and development. *R&D Management* **39**(5) 473-487.

Benner, M., J. Waldfogel. 2008. Close to you? Bias and precision in patent-based measures of technological proximity. *Research Policy* **37**(9) 1556-1567.

Benner, M., M.L. Tushman. 2003. Exploitation, exploration, and process management: the productivity dilemma revised. *Academy of Management Review* **28**(2) 238-256.

Bertrand, M., Duflo, E., S. Mullainathan. 2004. How much do we trust differences-in-differences estimates? *Quarterly Journal of Economics* **119**(1) 249-275.

Burgelman, R.A. 1983. A process model of internal corporate venturing in the diversified major firm. *Administrative Science Quarterly* **28**(12) 223-244.

Cameron, C., P.K. Trivedi. 1998. *Regression Analysis of Count Data*. Econometric Society Monograph No.30, Cambridge University Press.

Chesbrough, H.W. 1998. Inxight: Incubating a Xerox Technology Spinout. Harvard Business School, December 17, 1998.

Chesbrough, H.W. 2002. Making sense of corporate venture capital. *Harvard Business Review* **80**(3) 90-99.

Chesbrough, H.W. 2003. The governance and performance of Xerox's technology spin-off companies. *Research Policy* **32**(3) 403-421.

Chesbrough, H.W. 2006. *Open innovation: researching a new paradigm*. Oxford University Press, USA.

Chesbrough, H.W., R. S. Rosenbloom. 2002. The role of the business model in capturing value from innovation: evidence from Xerox Corporation's technology spin-off companies. *Industrial and Corporate Change* **11**(3) 529-555.

Chow, G. C. 1960. Tests of equality between sets of coefficients in two linear regressions. *Econometrica* **28**(3) 591-605.

Cohen, W.M., D.A. Levinthal. 1990. Absorptive Capacity: A New Perspective On Learning and Innovation. *Administrative Science Quarterly* **35** 128-152.

Dehejia, R.H., S. Wahba. 2002. Propensity score-matching methods for nonexperimental causal studies. *The Review of Economic and Statistics* **84**(1) 151-161.

Fleming, L. 2001. Recombinant uncertainty in technological search. *Management Science* **47**(1) 117-132.

Fleming, L. 2002. Finding the organizational sources of technological breakthroughs: the story of Hewlett-Packard's thermal ink-jet. *Industrial and Corporate Change* **11**(5) 1059-1084.

Fleming, L., Mingo, S., D. Chen. 2007. Collaborative brokerage, generative creativity, and creative success. *Administrative Science Quarterly* **52**(3) 443-475.

Franco, A.M., D. Filson. 2006. Spin-outs: knowledge diffusion through employee mobility. *RAND Journal of Economics* **37**(4) 841-860.

Gambardella, A., D. Harhoff, B. Verspagen. 2008. The value of European patents. *European Management Review* **5**(2) 69-84.

Hagedoorn, J., M. Cloodt. 2003. Measuring innovative performance: Is there an advantage in using multiple indicators? *Research Policy* **32**(8) 1365-1379.

Hall, B.H., Jaffe, A.B., M. Trajtenberg. 2001. The NBER patent citation data file: lessons, insights and methodological tools. NBER working paper no. 8498.

He, Z.L., P.K. Wong. 2004. Exploration vs. exploitation: an empirical test of the ambidexterity hypothesis. *Organization Science* **15**(4) 481-494.

Heckman, J., S. Navarro-Lozano. 2004. Using matching, instrumental variables, and control functions to estimate economic choice models. *The Review of Economics and Statistics* **86**(1) 30-57.

Hirano, K., Imbens, G., G. Ridder. 2003. Efficient estimation of average treatment effects using the estimated propensity score. *Econometrica* **71**(4) 1161–1189.

Imbens, G. 2004. Nonparametric estimation of average treatment effects under exogeneity: a review. *The Review of Economics and Statistics* **86**(1) 4-29.

Kapoor, R., K. Lim. 2007. The impact of acquisitions on the productivity of inventors at semiconductor firms: a synthesis of knowledge-based and incentive-based perspectives. *Academy of Management Journal* **50**(5) 1133-1155.

Katz, R., T.J. Allen. 1982. Investigating the not invented here (NIH) syndrome: a look at the performance, tenure, and communication patterns of 50 R&D project groups. *R&D Management* **12**(1) 7-20.

Klepper, S. 2001. Employee startups in high-tech industries. *Industrial and Corporate Change* **10**(3) 639-674.

Klepper, S. 2002. The capabilities of new firms and the evolution of the US automobile industry. *Industrial and Corporate Change* **11**(4) 645-666.

Klepper, S., P. Thompson. 2007. Spin-offs in high-tech industries: motives and consequences. F. Malerba, S. Brusoni, eds. *Perspectives on Innovation*. Cambridge University Press, Cambridge.

Klepper, S., S. Sleeper. 2005. Entry by spinoffs. *Management Science* **51**(8) 1291-

1306.

Lai, R., D’Amour, A., L. Fleming. 2009. The careers and co-authorship networks of U.S. patent-holders, since 1975. http://hdl.handle.net/1902.1/12367 UNF:5:daJuoNgCZlcYY8RqU+/j2Q== Harvard Business School, Harvard Institute for Quantitative Social Science [Distributor] V3 [Version].

Lanjouw, J.O., M. Schankerman. 2004. Patent quality and research productivity: measuring innovation with multiple indicators. *Economic Journal* **114**(495) 441-465.

Levinthal, D.A., J.G. March. 1993. The Myopia of Learning. *Strategic Management Journal* **14** 95-112.

Louis, M.R. 1980. Surprise and sense making: what newcomers experience in entering unfamiliar organizational settings. *Administrative Science Quarterly* **25**(2) 226-251.

March, J.G. 1991. Exploration And Exploitation In Organizational Learning. *Organization Science* **2** 71-87.

McKendrick, D.G., Wade, J.B., J. Jaffe. 2009. A good riddance? Spin-offs and the technological performance of parent firms. *Organization Science* **20**(6) 979-992.

Miller, K.D., Zhao, M., R.J. Cantalone. 2006. Adding interpersonal learning and tacit knowledge to March’s exploration-exploitation model. *Academy Management Journal* **49**(4) 709-722.

Morrison, E.W. 2002. Newcomers’ relationships: The role of social network ties during socialization. *Academy of Management Journal* **45**(6) 1149-1160.

Nelson, R.R., R.G. Winter. 1982. *An Evolutionary Theory of Economic Change.* Harvard University Press, Cambridge, MA.

Newell, A., H. A. Simon. 1972. *Human Problem Solving*. Prentice Hall, Englewood Cliffs, NJ.

O’Reilly, C., M.L. Tushman. 2004. The ambidextrous organization. *Harvard Business Review* **84**(4) 74-81.

Papke, L.E., M. Wooldridge 2008. Panel data methods for fractional response variables with an application to test pass rates. *Journal of Economics* **145**(1-2) 121-133.

Rosenkopf, L., A. Nerkar. 2001. Beyond Local Search: Boundary-Spanning, Exploration, And Impact In The Optical Disc Industry. *Strategic Management Journal* **22**(4) 287-306.

Rosenkopf, L., P. Almeida. 2003. Overcoming local search through alliances and mobility. *Management Science* **49**(6) 751-766.

Schumpeter, J.A. 1934. *The Theory of Economic Development*. Harvard University Press, Cambridge, MA.

Schumpeter, J.A. 1942. *Capitalism, Socialism and Democracy*. Harvard University Press, Cambridge, MA.

Siggelkow, N., D. A. Levinthal. 2003. Temporarily divide to conquer: centralized, decentralized, and reintegrated organizational approaches to exploration and adaptation. *Organization Science* **14**(6) 650-669.

Singh, J., L. Fleming. 2010. Lone inventors as sources of technological breakthroughs: Myth or reality? *Management Science* **56**(1) 41-56.

Song, J., Almeida, P., G. Wu. 2003. Learning-by-hiring: when is mobility more likely to facilitate interfirm knowledge transfer? *Management Science* **49**(4) 351-365.

Sorensen, J.B., T.E. Stuart. 2000. Aging, obsolescence, and organizational innovation. *Administrative Science Quarterly* **45**(1) 81-112.

Stuart, T.E., J.M. Podolny. 1996. Local Search And The Evolution Of Technological Capabilities. *Strategic Management Journal* **S17** 21-38.

Taylor, A., H.R. Greve. 2006. Superman or the fantastic four? Knowledge combination and experience in innovative teams. *Academy of Management Journal* **49**(4) 723-740.

Trajtenberg, M. 1990. A penny for your quotes: patent citations and the value of innovations. *RAND Journal of Economics* **21**(1) 172-187.

Trajtenberg, M. 2005. Recombinant ideas: the mobility of inventors and the productivity in research. *Proceedings of 2005 CEPR Conference*, Munich.

Tsang, E.W.K., S. A. Zahra. 2008. Organizational unlearning. *Human Rel.* **61**(10) 1435-1462.

Venkatraman, N. 1989. The concept of fit in strategy research: toward verbal and statistical correspondence. *Academy of Management Review* **14**(3) 423-444.

Zenger, T.R. 1994. Explaining organizational diseconomies of scale in R&D: agency problems and the allocation of engineering talent, ideas, and effort by firm size. *Management Science* **40**(6) 708-729.

TABLE 1. Xerox: Spin-Outs and Old-Timers in the sample[a]

Spin-outs with assigned patents, 1975–2008	Spin-out year	Inventors with patents in both parent and spin-out	Inventors with tenure > 5 years	Inventors with tenure > 10 years
3COM Co.	1979	0	0	0
Optimem	1980	0	0	0
Sunrise Systems Inc.	1982	0	0	0
Filenet Co.	1982	0	0	0
Komag Inc.	1983	0	0	0
SDL Inc.	**1983**	**3**	**3**	**0**
Synoptis Comm. Inc.	1985	0	0	0
Microlytics Inc.	**1985**	**1**	**0**	**0**
AMTX Inc.	**1988**	**1**	**1**	**0**
ParcPlace Systems	1988	0	0	0
Documentum Inc.	1990	0	0	0
Semaphore Comm.	1990	0	0	0
Placeware Inc.	**1996**	**3**	**2**	**1**
InXight Inc.	**1996**	**2**	**2**	**0**
DpiX LLC	**1996**	**5**	**4**	**3**
Gyricon Media Inc.	2000	0	0	0
ContentGuard Inc.	**2000**	**15**	**9**	**6**
PARC Inc.	**2002**	**106**	**69**	**51**
No. of inventors in spin-outs		136	90	61
No. of co-inventors in parent		226	179	123
No. of patents granted to both		5,377	4,865	4,051

[a]Bold indicates that the sample includes both spin-outs and inventors

TABLE 2. Xerox Inventors' Characteristics by Groups, Pre-Spin-Out

Variable	Mean	SD	Min	Max
Age				
Treated group	42.48	8.32	18	68
Control group	44.62	10.18	20	83
Age at first patent				
Treated group	35.98	6.19	18	58
Control group	35.78	7.52	20	61
Mean number of team				
Treated group	2.60	2.60	0	17.28
Control group	2.56	2.60	0	21
Knowledge generality				
Treated group	0.68	0.35	0	1
Control group	0.61	0.36	0	1
Patents by individuals per year				
Treated group	1.99	2.50	0	20
Control group	1.83	2.53	0	21

TABLE 3. Descriptive statistics and correlations[a]

	Variable	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10
1	*Extent of exploration*	1.48	6.80	0	105										
2	*Spin-out*	0.10	0.30	0	1	.09									
3	*Team size*	2.57	2.57	0	21	.06	.11								
4	*Knowledge generality*	0.63	0.36	0	1	.05	.14	.16							
5	*Solo patent*	0.02	0.11	0	1	.06	-.01	-.08	-.11						
6	*Patents in focal year*	1.88	2.53	0	21	.21	.08	.44	.17	.02					
7	*Total patents*	16.37	20.08	1	158	.13	.13	.23	.21	-.10	.43				
8	*Seniority*	9.08	6.5	1	32	.02	.02	.09	.31	-.15	.10	.59			
9	*Parent patents*	1660	1504	0	4,130	.10	.08	.67	.22	.00	.53	.28	.12		
10	*Parent ownership*	0.99	0.04	0.3	1	-.06	-.27	-.08	-.02	-.01	-.02	.01	.03	-.06	
11	*PARC dummy*	0.22	0.41	0	1	.00	.38	.02	.10	.00	.02	-.05	-.12	.07	.05

[a] N = 4,709. All correlations above |.03| are significant at the .05 level.

TABLE 4. Fixed Effects Panel Regressions on Inventors' Extent of Exploration[a]

DV: *Inventors' Extent of Exploration*	*Negative Binomial*		**DV:** *Ln(Inventors' Extent of Exploration)*	*OLS*
		(weighted)		(weighted)
	(1)	*(2)*		*(3)*
Independent variable				
Spin-out	0.51* (.23)	0.92* (.44)		0.26** (.09)
Controls				
Team size	0.01 (.03)	-0.01 (.06)		-0.02* (.00)
Knowledge generality	1.14*** (.26)	1.23* (.55)		0.10 (.06)
Solo patents	3.13*** (.33)	2.98*** (.67)		0.83*** (.23)
Patents in focal year	0.13*** (.01)	0.11** (.03)		0.04*** (.01)
Total patents	0.00* (.00)	0.00 (.00)		-0.00 (.00)
Seniority	0.03 (.02)	0.00 (.05)		0.01 (.01)
Parent patents	0.00* (.00)	0.00 (.00)		0.00** (.00)
Parent ownership	1.16 (1.50)	1.95 (3.16)		-0.03 (.51)
PARC dummy	-0.01 (.22)	0.08 (.43)		*dropped*
Year dummies	*included*	*included*		*included*
Constant	-6.60*** (1.52)	-7.12* (3.20)		0.05 (.60)
Log likelihood	-1,484.9	-381.7	F	4.80***
Wald chi^2	222.4***	55.5***	R2 (between)	0.1346
n (w/o 1st year)	2,482	2,135		3,744
Number of groups	165	145		303

*** p<0.001, ** p<0.01, * p<0.05

[a] Standard errors in parentheses.

TABLE 5. Difference between Newcomers and Old-Timers[a]

DV: *Ln(Inventors' Extent of Exploration)*	*OLS*		***Chow tests***
Independent variables	*(4)*	*(5)*	
Old-timer5 (1 if tenure≥5 years; 0 otherwise)	*dropped*		Tenure threshold: 5 years
Spinout (newcomer5)	-0.07 (.09)		β(Spinout old-timer5) - β(Spinout newcomer5) = 2.694
Spinout (old-timer5)	0.19* (.08)		H_0: β(Spinout old-timer5) - β(Spinout newcomer5) = 0
Old-timer10 (1 if tenure≥10 years; 0 otherwise)		*dropped*	chi2 = 4.61 Prob > chi2 = 0.0318
Spinout (newcomer10)		0.04 (.08)	
Spinout (old-timer10)		0.23* (.11)	
Controls		*included*	Tenure threshold: 10 years
PARC dummy	*dropped*	*dropped*	β(Spinout old-timer10) - β(Spinout newcomer10) = 0.1911
Year dummies	*included*	*included*	H_0: β(Spinout old-timer10) - β(Spinout newcomer10) = 0
Constant	0.55 (0.51)	0.45 (0.51)	chi2 = 1.96 Prob > chi2 = 0.1620
F	5.13***	5.12***	
R^2 (between)	0.1875	0.1841	
n	4,369	4,369	
Number of groups	356	356	

*** p<0.001, ** p<0.01, * p<0.05

[a] Robust standard errors in parentheses.

TABLE 6. Difference-in-Difference on Inventors' Extent of Exploration[a]

DV: *Ln(Inventors' Extent of Exploration)*	*OLS*
Independent variables	*(6)*
Group (1 for treated group; 0 for control group)	*dropped*
Treatment period (1 for post-spinout; 0 for pre-spinout	-0.04 (.07)
Group X Treatment period	0.17* (.07)
Controls	*included*
PARC dummy	*dropped*
Years dummy	*included*
Constant	0.46 (.50)
F	4.77***
R^2 (between)	0.1652
n	4,050
number of groups	356

*** p<0.001, ** p<0.01, * p<0.05

[a] Fixed Effects, Robust standard errors in parentheses

TABLE 7. Average Treatment Effect on the Mean Extent of Exploration

Matching estimator: Average Treatment Effect for the Treated (ATT)

Weighting matrix: inverse variance

Dependent variable: Mean number of "claims in new USpc classes" in the 3 years after the incorporation of spin-outs

	Coeff.	Std. Err.	Z	p
Sample average treatment effect (SATT)	1.75*	0.79	2.21	0.027
Number of inventors	294			
Number of matches	3			

Matching variables: inventor's age at first patent; number of team members; individual portfolio generality; patents in the focal year; inventor's seniority in the parent organization; firm's patents per year; parent's ownership; PARC dummy

* p<0.05

TABLE 8. Fractional Logit Regression on Inventors' Proportion of Xerox-Citations[a]

DV: *Proportion of self-citations (i.e., backward citations to Xerox patents)*	*GLM*
	(7)
Independent variable	
Spin-out	-0.5676* (.251)
Controls	
Team size	0.1013*** (0.03)
Knowledge generality	0.0166 (.173)
Solo patents	-1.2449*** (.608)
Patents in focal year	0.0464** (.017)
Total patents	0.0038* (.002)
Seniority	0.0099 (.022)
Parent patents	0.0001* (.000)
Parent ownership	102.023*** (2.596)
PARC dummy	0.0362 (.150)
Year dummies	*included*
Constant	-105.4*** (2.594)
Log likelihood	-321.2
Akaike Information Criterion	0.219
n	3,066
Number of groups	362

*** p<0.001, ** p<0.01, * p<0.05

[a] Standard errors in parentheses.

FIGURE 1. T-Test of Group Means Pre- and Post-Spin-Out

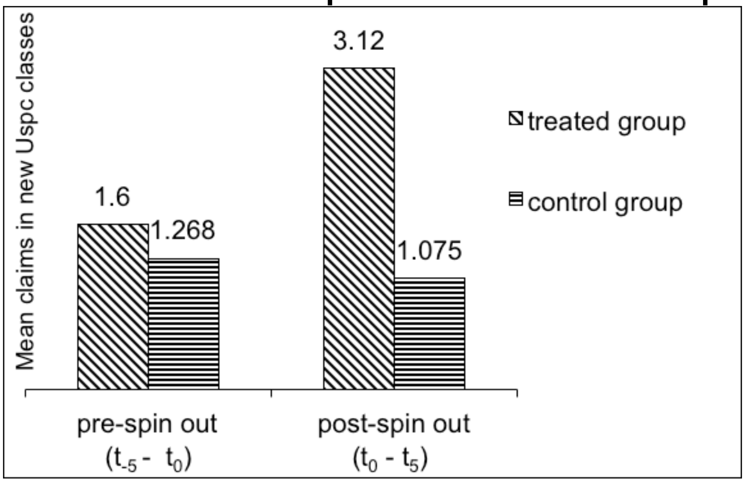


FIGURE 2. Group Mean Trend of Inventors' Extent of Exploration

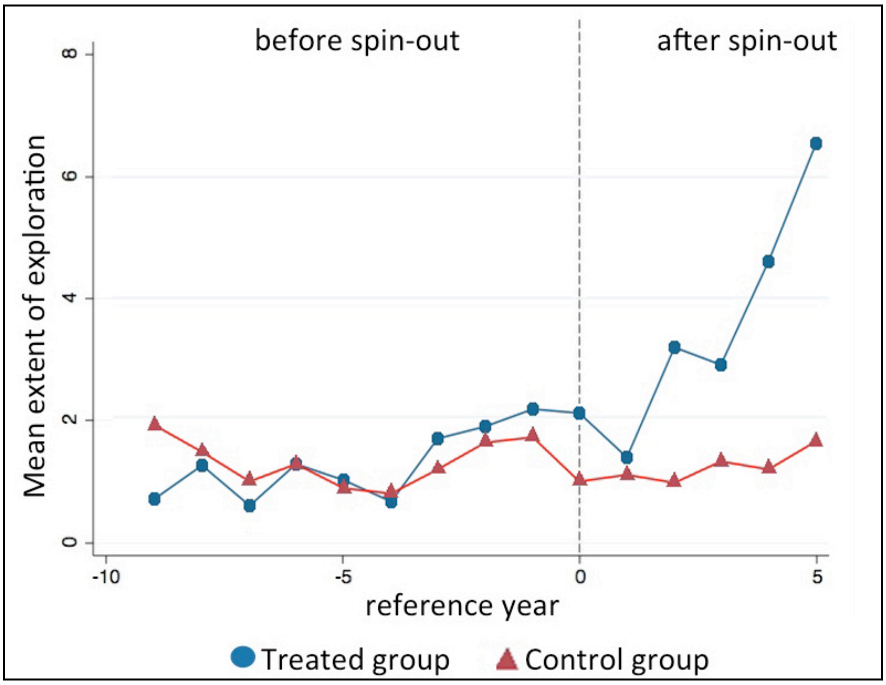
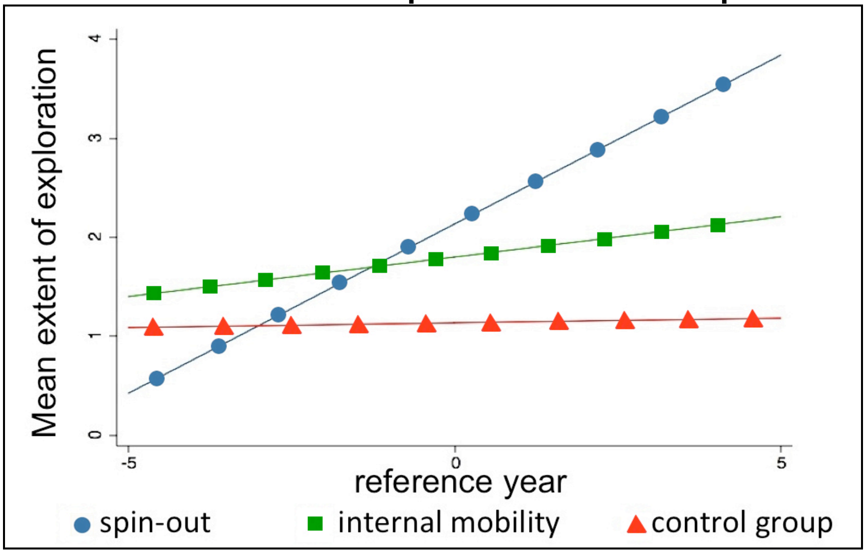


FIGURE 3. Combined effects of Spin-out and Intra-corporation mobility



3. LINKING COMMUNITIES OF INVENTORS

3.1 Introduction

In 1996, Inxight inc. spun out from Xerox Corporation as a parent-backed venture with the aim to product-market Xerox's visualization and linguistic technologies (Chesbrough 1998). These 'state-of-the-art' technologies were developed independently by two teams of scientists employed over the past 20 years in Xerox Corporation. Although Xerox had longed recognized an important value in the complementarities between the two technologies, it had never been able to embed them into valuable commercial applications though an internal business. As Chesbrough (1998) reports, in Xerox the two research teams were focused on investigating the next generation of either visualization or linguistic technology. Eventually, the spin-out of both projects into a new independent firm proved to be a suitable solution for exploiting important complementarities among the two technologies for commercial ends (Chesbrough 1998).

Unlike previous studies, we think that this story is indicative that corporate spin-outs may act as strategies to get access to talents from diverse 'knowledge communities' and, therefore, encourage these researchers to establish cross-disciplinary collaborations.

We build on the notion of R&D units of large corporations as sets of 'knowledge communities' (e.g., Cowan et al. 2000, Amin and Cohendet 2004). Knowledge communities define sets of cohesive research collaborations around specific knowledge domains (Amin and Cohendet 2004). They bring together researchers with similar purposes by stimulating reciprocal learning and, hence, converging their interests and specialties (Merton 1972). As different approaches posit (e.g., Gulati and Singh 1998, Cohendet et al. 2004, Rosenkopf and Padula 2008), cohesiveness in collaboration networks emerges by means to reduce collaboration hazards. It enhances creativity, synergies in individual efforts (Amin and Cohendet 2004), and individuals' ability to seize opportunities (Leonard-Barton 1995). However, cohesiveness also reinforces individual embeddedness in past research collaborations and it likely brings inertia (e.g., Granovetter 1985). Since communities are important vehicles for the generation, accumulation, and distribution of knowledge in the organization (Amin and Cohendet 2004), the issue of inventors' embeddedness (e.g., Granovetter 1985) into communities is of fundamental importance for the corporation balance in exploitation and exploration. How to overcome the problems of inventors' embeddedness in communities, therefore?

The literature on innovation discusses a wide range of strategies – such as alliances, mergers and acquisitions, corporate venture capital - that organizations extensively use to overcome inertia and local search (e.g., Stuart and Podolny 1996, Rosenkopf and Almeida 2003). Although we cannot offer a comparative analysis of these strategies, we believe that corporate spin-outs may be a unique strategy for bridging existing communities of an organization. We propose that spin-outs enable the creation of common purposes, generate common codes, jargon, and languages which are necessary to enhancing communication across communities (e.g., Amin and Cohendet 2004) and, hence, overcome inventor embeddedness in a focal knowledge community.

We enquire this issue by using longitudinal data on the patenting activity of a sample of inventors employed in 8 US large corporations and their spin-outs in chemicals, semiconductors, and computers. We show that inventors who experience spin-out increase the likelihood of collaborating with inventors who belong to other communities, whereas a control group of inventors who remains in the parent organization do so at a lower rate. Moreover, this effect is stronger for inventors who occupy a central position in the former collaboration network, which we interpret as evidence that the spin-out experience releases individuals' embeddedness in the focal community.

Eventually, our results shed a light on corporate spin-outs as a feasible strategy through which corporations may sponsor loose organizational structures that enable the generation of a common knowledge architecture across communities specialized in different knowledge domains (e.g., Amin and Cohendet 2004, Thompson 2005).

3.2 Theory and Hypotheses

3.2.1 Inventor communities in large organizations

In this work we build on the notion of R&D departments in large corporations as sets of 'knowledge communities' (e.g., Cowan et al. 2000, Amin and Cohendet 2004), i.e., sets of cohesive collaboration networks that produce knowledge in specific domains.

Knowledge communities are the locus where knowledge is created, transferred and practiced (Liedtka 2000, Amin and Cohendet 2004). They do not necessarily correspond to the structure of organizational hierarchies, and more likely refer to small informal groups (e.g., Cowan et al. 2000) whose boundaries are not clear or explicit (Cohendet et al. 2004). Unlike formal structures, knowledge transfers in communities according on voluntary acts rather than hierarchical imperatives. Communities provide a knowledgeable research audience, stimulate intellectual dialogue and, hence, encourage collaborations in cohesive pattern of research (Upham et al. 2010).

In the pursuit of a common purpose, researchers in a community work jointly by sharing knowledge and making their interest and specialties gradually converge (Merton 1972). Repeated collaborations favor the establishment of common values, culture of action, social norms and codes[1], which make knowledge circulate more easily among community members (Amin and Cohendet 2004). Involvement in tight collaboration and cooperation stimulates a technical dialogue in specific knowledge domains (e.g., Upham et al. 2010) and it leads to cohesive pattern of research in specialized areas (e.g., Upham et al. 2010).

[1] The literature on organizational learning (e.g., March 1991) refers to codes as sets of norms, procedures and beliefs in knowledge activities that are shared by individuals in the organization. Although this literature makes no explicit reference to firms as sets of heterogeneous communities, one of its underlying assumptions is that organizations may hold several heterogeneous 'sub-codes'.

3.2.2 The emergence of communities as cohesive collaboration structures

The literature on knowledge networks provides comprehensive accounts on how cohesiveness emerges in collaboration networks (e.g., Barabasi et al. 2001, Girvan and Newman 2002, Newman 2006). It argues on the tendency of diverse kind of networks (e.g., firms R&D collaborations, scientists co-invention networks, academic co-authoring networks) to evolve over time into dense clusters of collaborations.

Collaborations serve to the general mean of transferring information, knowledge, competencies, and they expose partners (i.e., either individuals or firms) to costs and risks of opportunistic behaviors (e.g., Gulati and Singh 1998). The clustering property common to most networks is a natural response to the need of reducing such costs and risks. It is achieved through cohesive collaboration structures, which help building efficiency, trust and reliability. In studies on inter-firm strategic alliances (e.g., Rosenkopf and Padula 2008, Gulati 1995) cohesiveness is mostly referred to as the extent to which two partners share the same third parties. Cohesiveness is an indicator of reliability (Rosenkopf and Padula 2008). As such, it is an important predictor of new collaboration generation (Gulati 1995). Sharing the same partners provides a valuable channel for collecting information about potential new partners, thus increasing the likelihood of generating new collaborations with former partners. As a consequence, collaborations evolve by means of reciprocal trust and partners' reliability (e.g., Shan et al. 1994, Podolny and Stuart 1995, Gulati 1995), and they are necessarily grounded in personal relationships, social capital, past dyadic interactions (Hite, 1999; Hite and Hesterly 2001). In a study of inter-firm collaborations in the chemical industry, Ahuja (2000) argue on such collaboration stability as a consequence of firms' positional, relational, and structural embeddedness in the established network of collaborations. First, positional embeddedness (i.e., centrality) provides informational benefits that favor stability in existing collaborations (Polidoro et al. 2011). According to Polidoro et al. (2011), although central individuals will have superior knowledge about alters, they will tend to select partners with similar structural positions. Second, since past collaborations provide reliable information about existing partners, the latter become more trustable than other potential partners (e.g., Uzzi 1997). Finally, high cohesive networks promote social monitoring, which reduces the hazards of collaboration dissolutions (e.g., Polidoro et al. 2011).

The tendency of collaboration networks to cluster in cohesive, stable relations is also stressed in the literature on knowledge communities. Repeated interactions within a community provide economic benefits by reducing opportunistic behaviors in knowledge sharing, and it allows the establishment of shared norms and reputation, which reduce moral hazard (Cohendet et al. 2004).

In sum, since cohesive networks reduce collaboration hazards, new collaborations are more likely embedded in previously established collaborations (Hite and Hesterly 2001). In line with this logic, establishing repeated collaborations within a community sustains a culture for the generation and distribution of ideas (Upham et al. 2010), it enhances synergies in individual efforts and creative outcomes (Amin and Cohendet 2004) and it reinforces individuals' ability to seize opportunities (Leonard-Barton 1995).

Although cohesiveness is widely recognized as sources for innovation in knowledge communities (Amin and Cohendet 2004), another consequence of the clustering property is also the emergence of embeddedness in the collaboration structure. Because of different historical patterns of interactions, different communities possess and produce heterogeneous knowledge (Fang et al. 2010). Knowledge communities have the prerequisites to develop idiosyncratic capabilities and routines, unique language and meanings, which may contribute to reduce knowledge sharing with other communities (e.g., Upham et al. 2010). Difficulties in knowledge sharing mainly reside in language differences (Bechky 2003), and incompatible codes and routines (Carlile 2004). Moreover, the commitment to specific goals likely leads to unique codes of received truth, which reduces individual exposure to new external stimuli and focuses innovation efforts within specific knowledge domains (Whitley 2000, Lambiotte and Panzarasa 2009). As a consequence, cohesiveness hinders inter-community learning and likely cause communities to isolate in an organization. In this respect, the market for a knowledge community is primarily the community itself (Upham et al. 2010). The emergence of such inertial forces to inter-community learning embeds individuals, i.e., new collaborations are more likely formed with former collaborators who belong to the same focal community. Individual embeddedness in communities may bring inertia and constraints to exploration of new technological domains, which organizations need to take into account in the purpose of balancing exploration and exploitation.

Communities are important vehicles for the generation, accumulation, and distribution of knowledge in the organization (Amin and Cohendet 2004). Accordingly, the issue of how to overcome inventors' embeddedness (e.g., Granovetter 1985) into communities is of fundamental importance for organizations.

3.2.3 Sharing knowledge across communities

As Amin and Cohendet (2004) posit, the governance of the firm for maintaining a varied selection environment for innovation "*becomes an act of integrating aspects of management by design with aspects of management by communities*" (p.122). Communities are often complementary in terms of their contribution to the organizational innovation processes. Preserving communities heterogeneity and promoting inter-community learning provide significant contribution to innovation performance (e.g., Brown and Duguid 1991). Then, enquiring how collaborations span across communities is of fundamental importance for understanding how heterogeneous knowledge and radical ideas are recombined in innovation processes (e.g., Fang et al. 2010).

The literature on organizational knowledge provides several considerations on how firms may share knowledge across boundaries (e.g., Bechky 2003, Thompson 2005, Kellogg et al. 2006). For example, effective communication across communities can be achieved through the construction of shared commitments (Kelloggs et al. 2006), the development of a common language (e.g., Nonaka 1994, Carlile 2004), the transformation of local understandings and meanings (e.g., Clark 1996), or the use of various boundary-spanning roles (e.g., Granovetter 1973, Burt 1992).

According to Cohendet et al. (2004), the exchange of knowledge between different knowledge communities can be influenced by arrangement in organizational structures that convey changes in organizing principles and individual socialization**.** Organizational arrangements can intervene at different levels. First, Nonaka (1994) stresses the importance of self-organizing teams in high-tech organizations. Self-organizing teams are social contexts where individuals from different functional departments or knowledge backgrounds can establish a field of interaction (Nonaka 1994). Second, Cohendet and Simon (2007) suggest that hybrid forms of project management, which combine decentralized platforms and a specific management of space, can favor across-community informal interactions. Likewise, the literature on 'organizational scaffolding' (e.g., Orlikowski 2000, 2006) suggests that organizations may manage material (i.e., codes, language, norms) and cultural dimensions of knowledge (i.e., physical objects, structures, spatial contexts and technological artifacts) through the established of temporary decentralized R&D structures. They support distributed cognition through, for example, realignment in researchers relationships (Orlikowski 2006).

In sum, the frequency and quality of interactions between communities may be improved through spatial arrangements (e.g., physical co-location of researchers who belong to different communities), and coordination of individual actions or beliefs to overcome the lack of common codes, jargon, and languages in inter-communities collaborations.

3.2.4 Spin-outs and management of knowledge across communities

The argument of this work is that spin-outs may offer a valuable strategy to enhance communication among different knowledge communities in a corporation. A first argument relate to the role of spin-out for corporate explorative innovation. Spin-outs incentivize entrepreneurial initiative within the corporation (e.g., Block and Macmillan 1993) and facilitate new search processes based on expanding the search space beyond local knowledge constraints (e.g., Chesbrough 2003). The provision of autonomy to research units is widely recognized as an important way to foster the generation of innovative discontinuities. It provides some degree of isolation that encourages explorations of diverse technological domains (e.g., Siggelkow and Levinthal 2003, Fang et al. 2010), which are usually achieved by developing links with distant participants active at the leading edge of the scientific and technological world (Cohen and Levinthal 1990, Rosenkopf and Padula 2008). Accordingly, autonomy promotes interchanges across different learning communities (Brown and Duguid 1991) and it releases individuals from existing organizational paradigms, thus allowing the pursuit of new technological possibilities (Fang et al. 2010).

A second argument is that spin-outs configure as an organizational innovation and they likely create new social connections between people (e.g., Obstfeld, 2005). Not only spin-outs co-locate talented researchers who were previously employed in different teams or units of the parent corporation (Chesbrough 2003), so also do they hire knowledgeable individuals from the industry and provide researchers with a new organizational environment. Accordingly, they offer the opportunity to create cognitive proximity between different communities.

As a consequence, spin-outs may facilitate learning across communities through the emergence of new shared languages, jargons and codes, where parent organizations would fail because of constraints imposed by higher hierarchical imperatives. Important evidence is highlighted by a case study on Xerox's spin-out InXight, where Chesbrough (1998) reports:

> 'One of the biggest surprises is how different the cultures within the spin-outs are from the typical Xerox culture' … 'In these spin-outs, the culture is to set up the charter and ground rules' … 'Corporate help is something you generally want to avoid' (Andrew Garman, former vice president of Xerox New Enterprises, in Chesbrough 1998: 3)

In line with March's (1991) theoretical argument on the role of turnover on organizational learning, spin-outs may act as a strategy for disrupting the organizational code, which individuals are aligned to. As a consequence, spin-outs may offer an opportunity to establish common knowledge architecture across different cultures to establish interactions in the pursuit of cross-disciplinary R&D goals (e.g., Amin and Cohendet 2004).

Therefore, we hypothesize that:

Hypothesis 1. A spin-out increases the likelihood of collaborations across communities by organizational members who join it.

3.2.5 The role of centrality

As the literature on social network makes clear, not all individuals in a network will show the same probability of engaging in new collaborations. According to Barabasi and Albert (1999), the probability that an individual will develop new collaborations is proportional to the number of collaborations she already has, i.e., individual centrality in the collaboration network.

The role of centrality on the generation of new collaborations is not straightforward. Literature highlights two sets of research findings. On the one hand, centrality is commonly associated with embeddedness in the network. New collaborations are likely based on prominence and homophily (Zuckerman and Philips 2001), which make central individuals willing to search for similar (known) others.

On the other hand, literature highlights that centrality helps in getting access to any other part of the network. First, since centrality derives from the patterns of overall connections among inventors in the network, central inventors hold greater information about the rest of the network. They hold important information on where external knowledge resides and who can exploit it. Hence, central inventors will reach other inventors in the network more easily than peripheral inventors (Nerkar and Paruchuri 2005). Second, central inventors will be more visible than any other inventor in the network, both in-between and across communities. The number of previous collaborations correlates with attractiveness of a potential partner as seen from distant others, and it favors the formation of collaborations that span the boundaries of communities in a network (e.g., Tsai and Ghoshal 1998). Third, network centrality is generally associated to a high position in a status hierarchy, which is correlated with a high degree of control on resources (Ibarra 1993, Burt 1982). Since central individuals usually hold a high status in the network, they will be less risk adverse than peripheral individual in searching for new collaborations with other communities (e.g., Zuckerman and Philips 2001). On the contrary, peripheral individuals will be more prone to gain status in their local community, hence they will likely collaborate with individuals they can trust and avoid new collaborations with unknown outsiders.

The impact of the different forces in place is difficult to be disentangled. Although the two perspectives on centrality provide different rationale, we think that the two interact in providing an explanation for the generation of collaborations across communities. If we combine the ability of central individuals to disseminate knowledge quicker than peripheral inventors and their higher likelihood of being selected from others, then centrality likely plays an important role when organizations engage in exploration, where inventors would be expected to seek for partners who possess heterogeneous knowledge (e.g., Ahuja 2000). Indeed, as research on small-worlds predicts (e.g., Watts 1999, Fleming et al. 2007), combining embeddedness in a community with a high propensity to generate collaborations across communities can provide the best solution in terms of information diffusion and learning (e.g., Schilling and Phelps 2007).

In this respect, we think that inventor centrality will have a twofold impact on the spin-out effect. On the one hand, central individuals who move to spin-outs can participate to build up a new organization code (e.g., March 1991), which will help them remove constraints imposed by embeddedness in former socialization practices. Since they suffer of higher embeddedness than individuals who occupy a peripheral position in the community, the spin-out will impact central individuals to a higher extent than peripheral individuals who join spin-outs. On the other hand, among all individuals who move from the parent corporation to spin-outs, central individuals will be more attractive as seen from outsiders such as, for example, new hires in spin-out organizations.

Accordingly, we expect that:

Hypothesis 2. The likelihood that a spin-out positively affects the generation of future collaborations across communities increases with inventor's present network centrality.

3.3 Method

3.3.1 Data

We test our hypotheses on a longitudinal data set on patents successfully applied by a sample of inventors employed in 8 US Corporations and their 25 spin-outs incorporated in the US. Starting from Fortune 100 corporations in chemicals, semiconductors, and computer industries we looked for corporate spin-outs incorporated from 1979 to 2006 gathering information from news (source: Factiva), corporation press releases, and spin-out firms press releases. We identify corporate spin-outs according to four criteria:

1. An employee, unit, or division departs from a US parent firm to establish a new firm (spin-out) in the US.
2. The spin-out is voluntarily released by the parent in order to product-market technologies originally incubated within the parent firm.
3. The spin-out employs at least one inventor who was previously employed in the parent firm.
4. Parent's ownership varies from 0% (no equity) to 100% (wholly owned) of the spin-out's initial capital. Conditional on criteria 1-3, in case of no equity we consider the new firm as a spin-out if the parent stipulates agreements for the future licensing or transfer of technologies developed by the spin-out. We exclude cases of spin-out as divestiture.

For the 8 corporations, 25 spin-outs fit these four selection criteria and have received patents from the U.S. Patent and Trademark Office (USPTO). Using the patent data set developed by Lai et al. (2009) we identified inventors affiliated to a spin-out by looking at patent assignees record (Almeida and Kogut 1999; Hoisl 2007). From among these inventors, we then extracted those who successfully applied at least 2 patents[2] when they were employed in the parent organization (in a five-year window prior to mobility to a spin-out), and at least 2 patents when they were employed in a spin-out (in a five-year window subsequent to mobility to the spin-out). The final sample includes 609 individuals who moved to a spin-out and display at least two patents both before and two patents after this spin-out event. We refer to this as "treated group".

To support our comparisons, we built also a "control group" of comparable inventors affiliated to parent organizations and who did *not* move to a spin-out. We selected a sample of 415 *co-inventors* of inventors who moved to a spin-out and who display at least two patents before and two patents after a spin-out event.

3.3.2 Measures

Dependent variable

In order to measure whether a focal patent *j* connects inventor *i* to a different communities we refer to Clauset et al. (2004) algorithm for detecting community structure in the network of collaborations. Following the authors, we use a 'modularity' approach and measure the density of collaborations inside a community as compared to collaborations between communities. Community structures are detected using patent data applied in a five-year window prior to the focal observation year[3].

The dependent variable, *New Community*$_{itj}$ *(dummy)*, is coded as a 1 if inventor *i* connects to a different community of inventors through patent *j* successfully applied for in year *t*. It is coded as a 0 otherwise.

[2] Observing two patents is a necessary condition for reducing inventor's affiliation bias (see Hoisl 2007) and for obtaining longitudinal data on the structure of inventors' collaboration network.
[3] Five-year windows may be suitable for studying firms in high-tech industries that generally engage in long-term innovation projects. For a detailed explanation of how we detect communities see the appendix.

In order to control for the robustness of results we also use a continuous specification of the same variable, *New Community*$_{itj}$ *([0,1])*, which is the proportion of co-inventors in patent *j* who belong to other communities than inventor *i* 's.

Independent variables

S*pin-out*. Our main independent variable is a dummy that captures whether inventor *i*'s is affiliated to a spin-out. Following previous studies (e.g., Almeida and Kogut 1999) we refer to patent assignee as a proxy for inventor's affiliation. Moreover, in order to correctly estimate inventor affiliation to a spin-out we follow Hoisl (2007) and control for the applicant sequence of each inventor in order to classify changes in assignee name as "move to a spin-out" vs "no move to a spin-out". This allows us to reduce the bias of a misspecification in inventor's affiliation in cases where patents are applied by the parent after the inventor departure to a spin-out. Specifically, the variable *spin-out* is coded as a 1 if patent *j* successfully applied by inventor *i* is assigned to a spin-out and a mobility event[4] has occurred, and 0 otherwise.

Centrality. We use normalized degree centrality, i.e., the number of co-inventors that inventor *i* has divided by the total number of inventors in inventor *i*'s component.. For each inventor-patent observation we coded inventor *i*'s network centrality as inventor's normalized degree centrality in her network of co-inventions in a five-year window prior to patent application date (i.e., from *t-5* to *t-1*).

Control Variables

We control for several variables that might influence the formation of ties across communities. We therefore include the following covariates at the inventor and organizational levels of analysis:

- *Knowledge generality.* It measures technological dispersion of inventor *i*'s patenting activity prior to year *t,* and refers to the extent to which the inventor

[4] When the applicant sequence of inventor *i* shows mobility from parent to spin-out, we code a mobility event in the application year of the first patent assigned to spin-out in the sequence.

exploits past knowledge (Banerjee and Campbell 2009, Hall et al. 2001). It is the complement to one of a Herfindahl index, and it ranges from 0 (concentration of previous experience in a single technological class) to 1 (highest dispersion). Inventor's experience in diverse technological classes may reduce inventor's propensity to develop ties across communities by means of sourcing diverse knowledge.

- *Tenure.* It refers to the total number of years inventor *i*'s has spent in the organization where she is affiliated at time *t* (either parent or spin-out). It is measured as the number of years elapsed from inventor *i*'s first patent observed in the focal organization.
- *Seniority.* It is a measure of experience and it refers to the total number of years elapsed from the very first patent successfully applied by inventor *i* at USPTO.
- *Exploration.* This variable measures the extent to which inventor *i* explores new technological fields in year *t*. It counts the number of patents successfully applied by inventor *i* at year *t* in a technological class (USPC) that is new with respect to previous inventor's records. One of the main concerns that might bias our results is that the motivation for generating ties across communities may be driven by a corporate mandate to explore new technologies. We include this control variable in order to capture the inventor's likelihood to develop ties across communities that is due to the spin-out strategic aim of exploring new technological domains[5].
- *Technological expertise.* For technological classes inventor *i* has successfully applied for at year *t*, the variable measures the mean number of patents previously awarded to inventor *i* in those same technological classes.
- *Co-inventors.* It reports the mean number of inventors *i*'s co-inventors in patents successfully applied for at year *t.*
- *Patents.* At year *t*, it is a count of patents successfully applied for by inventor *i* until year *t*.

[5] Data shows that the number of explorative patents per inventor (i.e., patents that are awarded in a USPC class new for the inventor) is almost equally distributed between groups of inventors (i.e., treated and control) and periods (i.e., before and after spin-out events).

- *Community size*. At year *t*, the variable counts the total number of inventors in inventor *i*'s community with reference to patents successfully applied in a five-year window from t-5 to t-1. We include this control to capture variance that is due to a size effect. For example, inventors in small communities may have a higher propensity of searching for cross-community ties.
- *Parent ownership.* At year *t*, the variable reports the proportion of spin-out equity owned by parent.
- *Spin-out size.* At year *t*, it reports the number of inventors who moved from parent to inventor *i* 's spin-out.
- *Corporation, and individual dummies.* We include dummies for inventors with the aim to capture variance that is due to individual unobserved characteristics. Likewise, we control for inventors' affiliation to the originating (parent) organization.
- *Geography (California dummy).* Since more than 70% of patents in our sample are assigned to organizations and inventors who are based in California, we include this dummy as a control for geography.
- *Spin-out incorporation year* and *application year* dummies.

3.3.3 Analysis

We adopted a lagged structure for our regression model which takes into account that some of the variables (e.g., centrality) where measured over 5-year moving windows. Our final dataset includes 17,919 observations that are unique for inventor-patent combinations on a sample of 11,949 patents[6].

Table 9 reports the descriptive statistics and the correlations between variables.

Table 9 about here
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[6] Of these patents, 5,020 are assigned to our treated group, of which 2,590 to spin-outs. The total number of inventor-patent observations in spin-outs is 4,146.

3.4 Results

The purpose of this study is to show that inventors who experience spin-out increase the likelihood of generating ties across communities of inventors, while a control group of inventors who stay in parent corporations does so to a lower extent. Moreover, we hypothesize that the combined effect of inventor centrality in the collaboration network and the spin-out experience positively impacts on the likelihood of generating ties across communities.

To start with, we compute t-tests on group means for our dependent variable before and after spin-out events. As figure 4 shows, while the control group is not affected by any spin-out event, the treated group is positively affected by moving to spin-outs. Furthermore, results on the t-tests (not reported here) are significant for both *(i)* the difference in the means pre and post spin-out of the treated group, *(ii)* the difference in the means post spin-out among treated and control group. On the contrary, the t-test reports no significant difference in the means for the treated and the control groups in the period pre spin-out events.

Figure 4 about here

To estimate the effect of spin-out we use a logistic regression model with standard errors adjusted for inventors. Column (1) in table 10 reports results for hypothesis 1. The significant positive coefficient ($p < .001$) on spin-out demonstrates that the spin-out experience increases inventor's the likelihood of forming ties across communities of inventors.

Table 10 about here

The positive and significant coefficient for spin-out is also confirmed when we use a different specification for our dependent variable. Column (3) in table 11 shows results of a fractional logistic estimation on the proportion of co-inventors in the focal patent who belongs to other communities than inventor *i*'s. Inventor's participation to a spin-out is confirmed to have a positive and significant effect ($p < .001$) on the formation of ties across communities.

Table 11 about here

As regard hypothesis 2, in Column (2) in table 10 adding inventor's centrality and the interaction term between spin-out and centrality provide some intuition that when inventors occupy a central position in their collaboration network and they experience spin-out their likelihood of generating ties across communities would be considerably improved. However, since we use a nonlinear model the coefficient for the interaction term is not representative for the real magnitude of the effect on our dependent variable, nor is its significance correctly specified (Norton et al. 2004, Greene 2010). In our logit model, the interaction effect represents the change in the predicted probability that *New Community* = 1 for a change in both *Spin-out* and *Centrality*. Referring to Norton et al. (2004), the interaction effect is the discrete difference (with respect to *Spin-out*) of the single derivative (with respect to *Centrality*), i.e., for *New Community* as a nonlinear function F(*u*) of the index of independent variables:

$$\frac{\Delta \frac{\partial F(u)}{\partial Centrality}}{\Delta Spinout} = \frac{\Delta \{(\beta_1 + \beta_{12} Spinout)\, f(u)\}}{\Delta Spinout}$$
$$= (\beta_1 + \beta_{12}) f\{(\beta_1 + \beta_{12}) Centrality + \beta_2 + X\beta\} - \beta_1 f(\beta_1 Centrality + X\beta)$$

In order to obtain a correct estimation of the marginal effect of a change of our two interacted variables we run the *Stata* code *INTEFF* developed by Ai and Norton (2003) on the same variable list of our logit model. Since our model contains only one interaction term, the use of this code is a good alternative to simulation-based approaches (e.g., Zelner 2009). Table 5 reports the corrected mean interaction effects, standard errors and *t* statistics for estimated partial effects. Results confirm that the mean interaction effect on *New Community* is positive and significant ($z > 2.58$).

Table 12 about here

Although the interaction effect significantly varies across observations between the minimum and maximum values reported in table 12, the plot of all interaction effects on the predicted probability of *New Community* (figure 5) shows that the corrected marginal effects are positive for all individuals. Moreover, if we look at the plot of the *z*-statistics for all interaction effects on the predicted probability of *New Community* (figure 6) nearly all interaction effects are statistically significant. Results support hypothesis 2.

Figure 5 about here

Figure 6 about here

Finally, Greene (2010) suggests that graphical representations are the most valid informative supplement for analyzing interactions. Figure 7 shows a linear plot of the effect of *Centrality* on the prediction of *New Community* conditional on *Spin-out* with confidence intervals set at 95% level. In the figure, the lover curve represents the impact of *Centrality* on *New Community* in case of *Spin-out* equal 0 (i.e., when inventors are employed in parents). The upper curve is for the case of *Spin-out* equal 1 (i.e., when inventors are employed in spin-outs).

Figure 7 highlights two important considerations. First, the upward shift of the curve in case of *Spin-out* equal 1 confirms that there is a significant impact of spin-out on the likelihood of generating ties across communities. It supports hypothesis 1. Second, the magnitude of the impact of *Centrality* on *New Community* significantly changes contingently on *Spin-out*. The graph reports a positive difference in the slope of the two lines, which can be interpreted as evidence of a positive action effect. The graph brings also important considerations on the mechanisms that might explain the interaction effect. Indeed, it is important to notice that in the impact of centrality on tie generation is negative in the case of *Spin-out* equal 0, in case of

Spin-out equal 1 centrality apparently does not have any impact on out dependent variable. We consider this as evidence that central inventors are the ones with higher embeddedness in the focal community. Spin-out likely releases inventors from the constraints imposed by socialization and endogenous network properties and, because of their higher constraints, central inventors will gain higher benefits from spinning out the parent corporation than peripheral individuals. Finally, the absence of an effect of centrality on the likelihood of ties across communities when inventors are affiliated to a spin-out may be an evidence that centrality plays a stronger role in embedding inventors than making them more likely to be connected to other communities.

In conclusion, figure 7 supports our hypothesis 2 that the inventor centrality in the community positively moderates the impact of the spin-out experience on our dependent variable by flattening individual propensity in the case of low to medium levels of centrality, and increasing the propensity of individuals with a high level of centrality.

Figure 7 about here

3.5 Robustness Checks

A possible concern on the robustness of our results might come from a possible sample selection bias, i.e., individuals who decide or are selected to join a spin-out may be those with the highest propensity to generate collaboration ties across clusters. In order to reduce this bias we run additional analysis by (1) weighting observations in out dataset on the inversed predicted probability of joining a spin-out and by (2) matching the outcome of individuals in the treated group with those in the control group.

First, for each inventor-patent observation we predict inventors' probability of joining a spin-out through a probit regression model on all covariates, where the dependent variable coded as a 1 if in year *t* the focal inventor moved to a spin-out, 0 otherwise. Then we use the inverse of this prediction for weighting observations in our main logit model to test the spin-out impact on the likelihood of generating ties across communities. We do so in order to account for possible selection bias and reduce the spin-out effect proportionally to the bias. Column (5) in table 13 shows results of a logistic regression model with Stata sampling weights option, i.e., weights as the inverse of the probability that the single observation is included because of the sampling design. Results confirm the positive and significant ($p < .05$) main effect of *Spin-out* on *New Community*, which we interpret as an evidence that even controlling for individual propensity to join a spin-out individuals who experience spin-out increase their likelihood to generate ties across communities more than a control group of inventors who stay in parent corporations.

Table 13 about here

Second, we use difference-in-differences (DID) model to estimate the main effect of *Spin-out* on *New Community* comparing our "treated" group with a "control" group of comparable inventors[7]. DID estimator allows identifying the impact of a treatment (i.e., affiliation to a spin-out) on a group of treated individuals (i.e., inventors who move to spin-outs) as compared to a control group of untreated individuals (i.e., inventors who stay in parents) by comparing group outcomes before and after the treatment. It computes (i) the difference in outcome before and after the treatment for the treated group; (ii) the same difference for the control group; (iii) the difference in the differences at points (i) and (ii). This estimation helps reducing a possible bias in the post-treatment comparisons between treated and control group that could be the result of either a sample selection or trends.

Table 14 shows results of a DID logit regression model on the impact of the treatment on our dependent variable *New Community*. Results report no significant evidence of a sample selection bias (i.e., the coefficient of the group dummy *treated* is statistically not significant), nor of a trend effect on *New Community* (i.e., the

[7] We include observations for the control also in our main model (i.e., Column (1) to (5)) that is displayed in tables 9, 10, 11 and 12.

coefficient of the group dummy *period* is statistically not significant). The interaction term for the DID estimation reports a positive and significant coefficient. Although we refer to an interaction effect in a nonlinear model, several approaches (e.g., Athey and Imbens 2002) have argued that DID in nonlinear models provide unbiased estimation, which let us conclude that results support hypothesis 1.

Table 14 about here

3.6 Discussion and conclusion

This study provides evidence that corporate spin-outs foster inventors' collaborations across different communities, and that this effect is stronger for individuals who occupy a central position in the local community. We have argued that this is evidence that corporate spin-outs facilitate the development of a common knowledge architecture (e.g., Amin and Cohendet 2004) across different communities of inventors. Our claim is based on the idea that spin-outs release inventors from embeddedness in the norms and collaboration rules that are established in the corporation. First, by causing a disruption in the established organizational norms and rules of collaborations, spin-outs loose structural constraints, and individuals can more easily build new beliefs, jargons, and codes to allow cross community communication. Because of high socialization in the community, inventors who occupy a central position are highly embedded in their collaboration network. Once such constrains are loosened, they gain the highest benefit from spinning out from the parent organization. Eventually, we interpret this as evidence that corporate spin-outs loose inventor's embeddedness in the local collaboration network and facilitate access to novel and heterogeneous knowledge recipients.

Although we did our best in order to empirically support our claims and rule out alternative explanations, we acknowledge that several limitations weaken our theoretical contribution. First, the generation of collaborations across communities may be the result of a corporate mandate to generate cross-community collaborations. However, it cannot explain our result on the role of centrality. Indeed, a corporate mandate may provide inventors with a strong incentive to engage in cross-communities collaborations, but it would not be clear why these incentives would produce different results according to inventors' centrality. Would that be the case, we should expect no difference between central and peripheral inventors. Moreover, we purposely designed our study in order to reduce this bias. First, we included in the dataset all patents granted up to a 5-year window after the spin-out event. Doing so, we account for the possibility that inventors start new projects, other than the ones related to a corporate mandate. Second, we control in all regression models for the extent to which inventors explore new technological classes. Third, in another regression model we drop all observations in the first spin-out year. The very first patents, which may relate to projects incubated in parents and then applied by spin-out organizations. Results (not reported here for conciseness) confirm our hypotheses.

A second possible bias in our study relate to self-selection. Inventors who move to spin-outs may be those with the higher propensity to act as brokers across communities. In this respect, we did our best to take into account this bias by testing the robustness of our results through weighted regression models and DID.

Third, inventors who move to spin-out may be more likely to generate collaborations with new communities because of a purposely intent to change their domain of expertise as a carrier choice. Again, the design of our study may rule out this explanation. Our argument is that, although the individual decision to join a spin-out may be either voluntary or imposed by the parent corporation, spin-out events are more likely 'collective' mobility events rather than individual career choices. The distribution of inventors in our sample supports this logic (e.g., see descriptive statistics for the *Spin-out size* variable in table 1). Moreover, most of the spin-outs in our sample are former units or divisions of the parent corporation rather than entrepreneurial firms.

Finally, the use of patent data potentially limits the validity of our study. On the one hand, we were only able to include in our study spin-outs that are innovative (by means of producing patents). On the other hand, we could identify only inventors who are listed in patent records and who are productive both before and after the spin-out event.

In spite of such limitations, this study provides significant implications for extant literature and managerial practice. To our knowledge, this is the first large study that enquires corporate spin-outs using longitudinal data on a multiple-industry research context. Delving into the micro processes that inform the organization of research and development activities, our study highlights that corporate spin-outs may be conducive to multi-domain technological explorations. This results complements and extend literature focused on the relevance of organizational contexts enabling innovation – e.g., Nonaka, 1994 – as it identifies the spin-outs' *loosening effect* on inventors' embeddedness. Although we acknowledge that we have not fully captured all dimensions of this effect, we submit that our study constitutes a first step towards a better understanding of innovation contexts.

Our results also contribute to the growing literature on communities (e.g., Amin and Cohendet 2004) by suggesting that spin-outs are a valuable organizational arrangement for linking different epistemic communities. Although we do not offer evidence of the underlying mechanisms, we show that corporate spin-outs increase inventor likelihood of co-inventing with inventors in different communities. No

Finally, we also make a clear contribution to managerial practice. In line with organization literature on knowledge communities (e.g., Amin and Cohendet 2004, Brown and Duguit 1991) we provide support to Thompson's argument (2005) that organizations can foster communicative interaction across knowledge communities. Indeed, we show that by spinning out teams, units or divisions, corporations can create organizational contexts to enable research communities to better interact to each other and engage in multi-domain R&D projects.

3.7 Appendix: Detection of community structure

This appendix illustrates the methodology adopted in this work in order to detect communities of inventors within corporations. Given a collaboration network, such as the network of co-invention, communities can be loosely defined as subsets (or clusters) of nodes such that (i) within each community there are many edges among nodes (i.e., the density of within-community links is high), but (ii) between communities there are fewer edges (i.e., the density of between-community links is lower). In other words, there must be more edges 'inside' the community than edges linking the community with the rest of the graph (Newman 2004). The recent advances in the science of networks have produced several methods to uncover communities in large graphs. Fortunato (2010) provides an exhaustive survey of the broad range of concepts and approaches in this field. In general, a problem that is common to the various methods is that they are computationally very demanding, especially when the size of the network becomes large. For this reason, several clustering techniques have been elaborated with the purpose of uncovering the community structure of large networks in a reasonable amount of time. Broadly speaking, the existing techniques adopts the concept of *modularity*, originally proposed by Newman and Girvan (2004), as their starting point.

This notion captures the essence of the problem of detecting network communities and its intuition can be summarized as follows. Given an arbitrary partition of the network into k subsets (or communities) of nodes, one can define a k x k symmetric matrix **e** where the elements e_{ij} represent the fraction of all edges in the network that link nodes in community i to nodes in community j. Then, the sum of any row (or column) of **e** – i.e., $a_i = \sum_j e_{ij}$ – represents the fraction of all edges connected to nodes in the community i. Likewise, the sum of the elements of **e** on the main diagonal – i.e., $\sum_i e_{ii}$ – is the fraction of all edges that link nodes in the same community. For a random network, which intuitively is not expected to exhibit a community structure, the expected fraction of intra-community links are equal to $a_i a_i$,, namely, the probability that an edge starts at a node in i times the probability that the same edge ends at a node in *i*. The modularity index is then defined as the difference between the fraction of edges that fall within communities and the expected value of the same quantity if edges were randomly distributed without regard for the community structure, namely:

$$Q = \sum_i (e_{ii} - a_i^2)$$

For a network without a community structure, the value of *Q* is equal to zero. Similarly, it is straightforward that the value of *Q* of the whole network, taken as a single community, is equal to zero. On the other hand, values different from zero indicate deviation from randomness. In particular, larger positive values of *Q* suggest the existence of a significant community structure. If a high value of modularity corresponds to a good partition of nodes into communities, the partition that yields the maximum value of *Q* should be the optimal one. Unfortunately, computing the optimal value of *Q* is nearly impossible, due to the extreme complexity of the problem and the time it would take. Yet, several clustering algorithms have been proposed recently, which are able to find fairly good approximations. In particular, we implemented in this work the “greedy” algorithm proposed by Clauset et al. (2004). This algorithm falls in the class of hierarchical agglomerative clustering methods. In brief, it starts from a state in which each node is the sole member of one of *n* communities and it repeatedly join communities together in pairs, choosing at each step the join that results in the greatest increase of *Q* (Newman 2004).

The progress of the algorithm can be represented as a dendrogram and cuts through this dendrogram at different points of the process give partitions of the network into a larger or smaller number of communities. The cut yielding the maximum value of *Q* is taken to represent the partition of network into communities. The code of the algorithm can be freely downloaded from http://www.cs.unm.edu/~aaron/research/fastmodularity.htm. For the calculations reported in this work, we adopted the algorithm as implemented in the igraph library (http://cneurocvs.rmki.kfki.hu/igraph/).

References

Ahuja, G. 2000. The duality of collaboration: Inducement and opportunities in the formation of interfirm linkages. *Strategic Management Journal* **21**(3) 317-343.

Ai, C. R., C. Norton. 2003. Interaction terms in logit and probit models. *Economics Letters* **80**(1) 123-129.

Aldrich, H. E., P. H. Kim. 2007. Small worlds, infinite possibilities? How social networks affect entrepreneurial team formation and search. *Strategic Entrepreneurship Journal* **1** 147-165.

Almeida, P., B. Kogut. 1997. The exploration of technological diversity and the demographic localization of innovation. *Small Business Economics* **9** 21-31.

Almeida, P., B. Kogut. 1999. Localization of knowledge and the mobility of engineers in regional networks. *Management Science* **45**(1) 905-917.

Amin, A., P. Cohendet. 2004. *Architectures of Knowledge*. Oxford University Press, New York, NY.

Athey, S., G. W. Imbens. 2002. Identification and inference in nonlinear difference-in-differences models. NBER Technical Working Paper no. 280.

Banerjee, P. M., B. A. Campbell. 2009. Inventor bricolage and firm technology research and development. *R&D Management* **39**(5) 473-487.

Barabasi, A. L., Jeong, H., Néda, Z., Ravasz, E., Schubert, A., T. Vicsek. 2001. Evolution of the social network of scientific collaborations. *Physica A: Statistical Mechanics and its Implications* **311**(3-4) 590-614.

Barabasi, A. L., R. Albert. 1999. Emergence of scaling in random networks. *Science* **286** 509-512.

Baum, J.A., T.Calabrese, B. S. Silverman. 2000. Don't go it alone: Alliance network composition and startups' performance in Canadian biotechnology. *Strategic Management Journal* **21** 267-294.

Bechky, B.A. 2003. Sharing meaning across occupational communities: The transformation of understanding on a production floor. *Organization Science* **14**(3) 312-330.

Beckman, C. M., D. Phillips, P. Haunschild. 2004. Friends or strangers? Firm-specific uncertainty, market uncertainty, and network partner selection. *Organization Science* **15**(3) 259-275.

Block, Z., I. Macmillan. 1993. *Corporate Venturing.* Cambridge, MA: Harvard Business School Press.

Breschi, S., F. Lissoni. 2005. Knowledge Networks from Patent Data. Handbook of Quantitative Science and Technology Research. H. Moed, W. Glänzel and U. Schmoch, Springer Netherlands**:** 613-643.

Brown, J.S., P. Duguit. 1991. Organizational Learning and Communities of Practice: Toward a Unified View of Working, Learning and Innovation. *Organization Science* **2**(1) 40-57.

Burt, R.S. 1992. *Structural Holes: The Social Structure of Competition*. Harvard University Press, Cambridge, MA.

Carlile, P. R. 2004. Transferring, translating, and transforming: An integrative framework for managing knowledge across boundaries. *Organization Science* **15**(5) 555-568.

Chesbrough, H. W. 1998. Inxight: Incubating a Xerox Technology Spinout. Harvard Business School, December 17, 1998.

Chesbrough, H. W. 2003. The governance and performance of Xerox's technology spin-off companies. *Research Policy* **32**(3) 403-421.

Christensen, C. 1997. *The innovator's dilemma: When new technologies cause great firms to fail.* Harvard Business School Press, Cambridge, MA.

Clark, H. 1996. Using Language. Cambridge University Press, Cambridge, U.K.

Clauset, A., Newman, M.E.J., C. Moore. 2004. Finding community structure in very large networks. *Physical Review E* **70**(6) 066111.

Cohen, W. M., D. Levinthal. 1990. Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly* **35**(1) 128-152.

Cohendet, P., Creplet, F., Diani, M., Dupouet, O., E. Schenk. 2004. Matching Communities and Hierarchies within the Firm. *Journal of Management and Governance* **8** 27-48.

Cohendet, P., L. Simon. 2007. Playing across the playground: Paradoxes of knowledge creation in the videogame firm. *Journal of Organizational Behavior* **28** 587-605.

Cowan, R., David, P.A., D. Foray. 2000. The Explicit Economics of Knowledge Codification and Tacitness. *Industrial and Corporate Change* **9**(2) 211-253.

Fang, C., Lee, J., M. A. Schilling. 2010. Balancing exploration and exploitation through structural design: The isolation of subgroups and organizational learning. *Organization Science* **21**(1) 625-642.

Fleming, L., K. Frenken. 2006. The evolution of inventor networks in the Silicon Valley and Boston Regions. Papers in Evolutionary Economic Geography # 06.09.

Fleming, L., Mingo, S., D. Chen. 2007. Collaborative brokerage, generative creativity, and creative success. *Administrative Science Quarterly* **52**(3) 443-475.

Fortunato, S. 2010. Community detection in graphs. *Physics Reports* **486**(3-5) 75-174.

Girvan, M., M. E. J. Newman. 2002. Community structure in social and biological networks. *Proceedings of the National Academy of Sciences of The United States of America* **99**(12) 7821-7826.

Granovetter, M. 1973. The strenght of weak ties. *American Journal of Sociology* **78** 1360-1380.

Granovetter, M. 1985. Economic Action and Social Structure: The Problem of Embeddedness. *American Journal of Sociology* **91(**3) 481-510.

Granovetter, M. 1992. Problems of explanation in economic sociology. In *Networks and Organizations: Structure, Form and Action,* Nohiria, N., R. Eccles (eds) 25-56. Harvard Business School Press: Boston, MA.

Greene, W. 2010. Testing hypotheses about interaction terms in nonlinear models. *Economic Letters* **107** 291-296.

Gulati, R. 1995. Familiarity breeds trust? The implications of repeated ties on contractual choice in alliances. *Academy of Management Journal* **38**(1) 85-112.

Gulati, R., H. Singh. 1998. The architecture of cooperation: Managing coordination uncertainty and interdependence in strategic alliances. *Administrative Science Quarterly* **43**(4) 781-814.

Gulati, R., M. Gargiulo. 1999. Where do interorganizational networks come from? *American Journal of Sociology* **104**(5) 1439-1493.

Hall, B.H., Jaffe, A.B., M. Trajtenberg. 2001. The NBER patent citation data file: lessons, insights and methodological tools. NBER working paper no. 8498.

Hansen, M.T. 1999. The search-transfer problem: The role of weak ties in sharing knowledge across organization subunit. *Administrative Science Quarterly* **44**(1) 82-111.

Hite, J.M. 1999. Embedded network ties in emerging entrepreneurial firms: patterns, processes and paths. Doctoral dissertation. University of Utah, Salt Lake City, UT.

Hite, J.M., W.S. Hesterly. 2001. The evolution of firm networks: From emergence to early growth of the firm. *Strategic Management Journal* **22** 275-286.

Hoisl, K. 2007. Tracing mobile inventors - The causality between inventor mobility and inventor productivity. *Research Policy* **36**(5) 619-636.

Ibarra, H. 1993. Network centrality, power, and innovation involvement: Determinants of technical and administrative roles. *Academy of Management Journal* **36**(3) 471–501.

Kellogg K., Orlikowski, W.J., J. Yates. 2006. Life in the Trading Zone: Structuring Coordination across Boundaries in Post-Bureaucratic Organizations. *Organization Science* **17**(1) 22-44.

Koka, B. R., Madhavan, R., J. E. Prescott. 2000. The evolution of interfirm networks: Environmental effects on patterns of network change. *Academy of Management Review* **31**(3) 721-737.

Lai, R., D'Amour, A., L. Fleming. 2009. The careers and co-authorship networks of U.S. patent-holders, since 1975. http://hdl.handle.net/1902.1/12367 UNF:5:daJuoNgCZlcYY8RqU+/j2Q== Harvard Business School, Harvard Institute for Quantitative Social Science [Distributor] V3 [Version].

Lambiotte, R., P. Panzarasa. 2009. Communities, knowledge creation, and information diffusion. *Journal of Infometrics* **3** 180-190.

Leonard-Barton, D. 1995. *Wellsprings of Knowledge: Building and Sustaining the Sources of Innovation*. Harvard Business School Press, Boston, MA.

Liedtka, J. 2000. Linking competitive advantage with communities of practice. In *Knowledge and Communities,* E. Lesser, M. A. Fontaine, J. A. Slusher (Eds.) 133–150. Butterworth Heinemann, Boston, MA.

March, J. G. 2004. Parochialism in the evolution of a research community: The case of organization studies. *Management and Organization Review* **1**(1) 5-22.

McKendrick, D. G., Wade, J. B., J. Jaffe. 2009. A Good Riddance? Spin-Offs and the technological performance of parent firms. *Organization Science* **20**(6) 979-992.

Merton, R. K. 1972. The sociology of science. University of Chicago Press, Chicago, IL.

Miller, K. D., Zhao, M., R. J. Cantalone. 2006. Adding interpersonal learning and tacit knowledge to March's exploration-exploitation model. *Academy Management Journal* **49**(4) 709-722.

Nerkar, A., S. Paruchuri. 2005. Evolution of R&D Capabilities: The Role of Knowledge Networks Within a Firm. *Management Science* **51** 771-785.

Newman, M. 2004. Detecting community structure in networks. *The European Physical Journal B - Condensed Matter and Complex Systems* **38**(2) 321-330.

Newman, M.E.J. 2004. Fast algorithm for detecting community structure in networks. *Physical Review E* **69**(6) 066133.

Newman, M.E.J. 2006. Modularity and community structure in networks. *Proceedings of the National Academy of Sciences of The United States of America* **103**(23) 8577-8582.

Newman, M.E.J., M. Girvan. 2004. Finding and evaluating community structure in networks. *Physical Review E* **69**(2) 026113.

Nonaka, I. 1994. A Dynamic Theory of Organizational Knowledge Creation. *Organization Science* **5**(1) 14-37.

Nonaka, I., H. Takeuchi. 1995, *The Knowledge Creating Company: how Japanese companies create the dynamics of innovation,* Oxford University Press, New York, NY.

Norton, E. C., Wang, H., C. Ai. 2004. Computing interaction effects and standard errors in logit and probit models. *The Stata Journal* **4**(2) 154-167.

Obstfeld, D. 2005. Social networks, the tertius lungens orientation, and involvement in innovation. *Administrative Science Quarterly* **50** 100-130.

Orlikowski, W.J. 2000. Using technology and constituting structures: A practice lens for studying technology in organizations. *Organization Science* **11**(4) 404-428.

Orlikowski, W.J. 2006. Material knowing: the scaffolding of human knowledgeability. *European Journal of Information Systems* **15** 460-466.

Podolny, J. M., T. E. Stuart. 1995. A role-based ecology of technological change. *American Journal of Sociology* **100**(5) 1224-1260.

Polidoro, F., Ahuja, G., W. Mitchell. 2011. When the social structure overshadows competitive incentives: The effects of network embeddedness on joint venture dissolution. *Academy of Management Journal* **54**(1) 203-223.

Portes, A., J. Sensenbrenner. 1993. Embeddedness and migration: Notes on the social determinants of economic social action. *American Journal of Sociology* **98** 1320-1350.

Reagans, R., B. McEvily. 2003. Network structure and knowledge transfer: The effect of cohesion and range. *Administrative Science Quarterly* **48** 240-267.

Rosenkopf, L., P. Almeida. 2003. Overcoming local search through alliances and mobility. *Management Science* **49**(6) 751-766.

Rosenkopf, L., G. Padula. 2008. Investigating the microstructure of network evolution: Alliance formation in the mobile communications industry. *Organization Science* **19**(5) 669-687.

Schilling, M., C. Phelps. 2007. Interfirm collaboration networks: The impact of large-scale network structure on firm innovation. *Management Science* **53**(7) 1113-1127.

Shan, W., G. Walker, B. Kogut. 1994. Interfirm cooperation and startup innovation in the biotechnology industry. *Strategic Management Journal* **15**(5) 387-394.

Siggelkow, N., D. A. Levinthal. 2003. Temporarily divide to conquer: centralized, decentralized, and reintegrated organizational approaches to exploration and adaptation. *Organization Science* **14**(6) 650-669.

Thompson, M. 2005. Structural and epistemic parameters in communities of practice. *Organization Science* **16**(2) 151-164.

Tsai, W., S. Ghoshal. 1998. Social capital and value creation: The role of intrafirm networks. *Academy of Management Journal* **41**(4) 464-476.

Upham, S.P., Rosenkopf, L., L.H. Ungar. 2010. Innovating knowledge communities. An analysis of group collaboration and competition in science and technology. *Scientometrics* **83** 525-554.

Uzzi, B. 1997. Social structure and competition in interfirm networks: The paradox of embeddedness. *Administrative Science Quarterly* **42**(1) 35-67.

Van Maanen, J., E.H. Schein. 1979. Toward a theory of organizational socialization. In *Research in Organizational Behavior*, B.M. Staw (Eds.) **1** 209-264.

Watts, D. J. 1999. Networks, dynamics and the small world phenomenon. *American Journal of Sociology* **105**(2) 493-527.

Whitley, R. 2000. *The intellectual and social organization of the sciences.* Oxford University Press, New York, NY.

Williamson, O. E. 1993. Calculativeness, trust, and economic organization. *Journal of Law and Economics* **36** 453-586.

Zaheer, A., G. Soda. 2009. Network evolution: The origins of Structural holes. *Administrative Science Quarterly* **54**(1) 1-31.

Zelner, B. A. 2009. Using simulation to interpret results from logit, probit, and other nonlinear models. *Strategic Management Journal* **30** 1335-1348.

Zhang, Y., H. Li. 2010. Innovation search of new ventures in a technology cluster: The role of ties with service intermediaries. *Strategic Management Journal* **31** 88-109.

Zuckerman, E., D. Philips. 2001. Middle status conformity: Theoretical restatement and empirical demonstration in two markets. *American Journal of Sociology* **107** 379-429.

TABLE 9. Descriptive statistics and correlations[a]

	Variable	Mean	SD	Min	Max	y1	y2	x1	x2	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10
y1	*New Community (dummy)*	0.35	0.48	0	1														
y2	*New Community ([0,1])*	0.29	0.41	0	1	.89													
x1	*Spin-out (dummy)*	0.21	0.41	0	1	.08	.10												
x2	*Centrality (normdegree)*	0.57	0.72	0	7.58	-.06	-.14	-.14											
c1	*Knowledge generality*	0.69	0.29	0	1	.08	.09	.17	-.07										
c2	*Tenure*	4.13	4.12	0	28	.04	.00	-.07	.20	.14									
c3	*Seniority*	8.23	6.26	0	30	.13	.09	.21	.01	.26	.44								
c4	*Exploration*	0.57	1.49	0	20	.16	.12	.06	-.12	-.00	-.02	.01							
c5	*Experience*	11.87	22.38	0	203	-.08	-.13	-.13	.56	-.17	.14	.02	-.20						
c6	*Co-inventors*	2.78	2.40	0	31	.31	.09	-.03	.12	-.04	.00	-.00	.25	.01					
c7	*Cumulative patents*	33.13	38.63	0	290	-.12	-.16	-.14	.64	-.08	.22	.12	-.13	.76	-.01				
c8	*Network size*	288.76	413.19	1	2,882	.19	.08	-.08	.06	.08	.15	.27	.04	.07	.25	.13			
c9	*Parent ownership*	0.85	0.33	0	1	-.08	-.12	-.90	.18	-.15	.07	-.20	-.03	.13	.07	.17	.13		
c10	*Spinout size*	45.14	105.61	1	321	.06	.12	.76	-.19	.17	-.05	.18	.04	-.14	-.09	-.16	-.13	-.85	
c11	*California (dummy)*	0.71	0.45	0	1	-.08	-.06	.16	.20	-.12	-.06	-.18	-.09	.13	-.11	.11	-.29	-.12	.25

[a] N = 17,919. All coefficients above |.02| are significant at $p < .001$

TABLE 10. Logistic regressions on across-community collaborations [a]

DV: *New community* (0/1)	*Logistic regression (1)*		*(2)*	
Independent variable				
Spin-out	0.943***	(.135)	0.662***	(.152)
Centrality (normdegree)			-0.282***	(.042)
Spin-out X Centrality			0.296***	(.066)
Controls				
Knowledge generality	0.156*	(.073)	0.157*	(.073)
Tenure	0.010*	(.004)	0.012**	(.004)
Seniority	0.028***	(.003)	0.028***	(.003)
Exploration	0.097***	(.013)	0.096***	(.013)
Experience	-0.001	(.001)	-0.001	(.001)
Co-inventors	0.286***	(.009)	0.294***	(.009)
Patents	-0.004***	(.000)	-0.002*	(.000)
Community size	0.000***	(.000)	0.000***	(.000)
Parent ownership	0.742***	(.201)	0.568**	(.206)
Spin-out size	0.000	(.000)	0.000	(.000)
Spin-out year dummies	*Included*		*Included*	
Application year dummies	*Included*		*Included*	
Corporation dummies	*Included*		*Included*	
Individual dummies	*Included*		*Included*	
California dummy	-0.758***	(.095)	-0.683***	(.096)
Constant	-2.105***	(.578)	-1.869**	(.579)
Log likelihood	-10,218.7		-10,193.8	
LR chi2	3,270.01***		3,319.84***	
n	17,919		17,919	
Pseudo R^2	0.1379		0.1400	

*** p<0.001, ** p<0.01, * p<0.05

[a]Standard errors (in parentheses) adjusted for clustering on inventors

TABLE 11. Fractional logistic regressions on across-community collaborations [a]

DV: *New Community ([0, 1])*	*Generalized linear model*			
	(3)		*(4)*	
Independent variable				
Spin-out	0.921***	(.222)	0.697**	(.255)
Centrality (normdegree)			-0.300**	(.102)
Spin-out X Centrality			0.265**	(.101)
Controls				
Knowledge generality	0.124	(.100)	0.122	(.099)
Tenure	-0.000	(.008)	0.001	(.008)
Seniority	0.012*	(.006)	0.012	(.006)
Exploration	0.074***	(.012)	0.073***	(.012)
Experience	-0.004	(.002)	-0.003	(.002)
Co-inventors	0.051***	(.010)	0.057***	(.010)
Patents	-0.005**	(.001)	-0.002	(.001)
Community size	0.000***	(.000)	0.000***	(.000)
Parent ownership	0.964***	(.333)	0.824*	(.348)
Spin-out size	0.001	(.000)	0.001	(.000)
Spin-out year dummies	*Included*		*Included*	
Application year dummies	*Included*		*Included*	
Corporation dummies	*Included*		*Included*	
Individual dummies	*Included*		*Included*	
California dummy	-0.927***	(.189)	-0.868***	(.198)
Constant	-1.891**	(.653)	-1.672*	(.654)
Log pseudolikelihood	-8,663.9		-8,643.3	
Akaike Information Criterion	1.086		1.084	
n	16,072		16,072	
Number of individuals	991		991	

*** p<0.001, ** p<0.01, * p<0.05

[a]Standard errors (in parentheses) errors adjusted for clustering on inventors

TABLE 12. Corrected interaction effects by *INTEFF Stata* command

	Mean	SD	Min	Max
Interaction effect	0.0549	0.0156	0.0001	0.0732
Standard error	.014	.002	.000	.031
z-statistic	3.85	0.99	0.61	6.82

TABLE 13. Logistic weighted regressions on across-community collaborations [a, b]

DV: *New Community (0/1)*	*Logistic Regression (5)*	
Independent variable		
Spin-out	1.309***	(.264)
Centrality (normdegree)	-0.178*	(.081)
Spin-out X Centrality	0.259**	(.089)
Controls		
Knowledge generality	-0.085	(.159)
Tenure	0.016	(.010)
Seniority	-1.038**	(.413)
Exploration	0.077***	(.022)
Experience	-0.006***	(.001)
Co-inventors	0.340***	(.016)
Patents	0.003*	(.001)
Community size	0.001***	(.000)
Parent ownership	1.779***	(.357)
Spin-out size	0.001*	(.000)
Spin-out year dummies	*Included*	
Application year dummies	*Included*	
Corporation dummies	*Included*	
Individual dummies	*Included*	
California dummy	-0.928*	(.163)
Constant	-0.239	(2.087)
Log likelihood	-4,158.07	
n	16,087	
Number of individuals	990	
Pseudo R^2	0.2292	

*** p<0.001, ** p<0.01, * p<0.05
[a] Sampling weights [pweight *Stata* option code]
[b] Robust standard errors

TABLE 14. Diff-in-diff estimation on across-community collaborations [a]

DV: *New Community (0/1)*	*Logistic*	
	(6)	
Independent variable		
Treated group	-1.224	(1.888)
Period	0.139	(.081)
Treated X Period (Diff-in-diff)	0.314**	(.115)
Controls		
Knowledge generality	0.176	(.126)
Tenure	-0.009	(.008)
Seniority	-1.518*	(.034)
Exploration	0.144***	(.015)
Experience	-0.006***	(.001)
Co-inventors	0.352***	(.011)
Patents	0.001	(.001)
Community size	0.001***	(.000)
Parent ownership	0.366	(.061)
Spin-out size	0.001*	(.000)
Spin-out year dummies	*Included*	
Application year dummies	*Included*	
Corporation dummies	*Included*	
Individual dummies	*Included*	
California dummy	-0.614***	(.112)
Constant	0.764	(1.884)
Log likelihood	-8,840.12	
n	17,336	
LR chi2	5,236.95***	
Pseudo R^2	0.2285	

*** p<0.001, ** p<0.01, * p<0.05

[a] Standard errors adjusted for clustering on inventors.

FIGURE 4. T-Test on group means of the likelihood of formation of ties across communities pre and post the spinout event

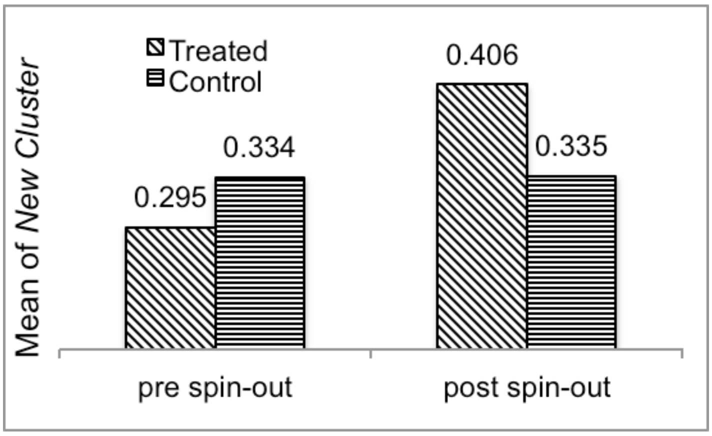


FIGURE 5. Distribution of corrected interaction effects

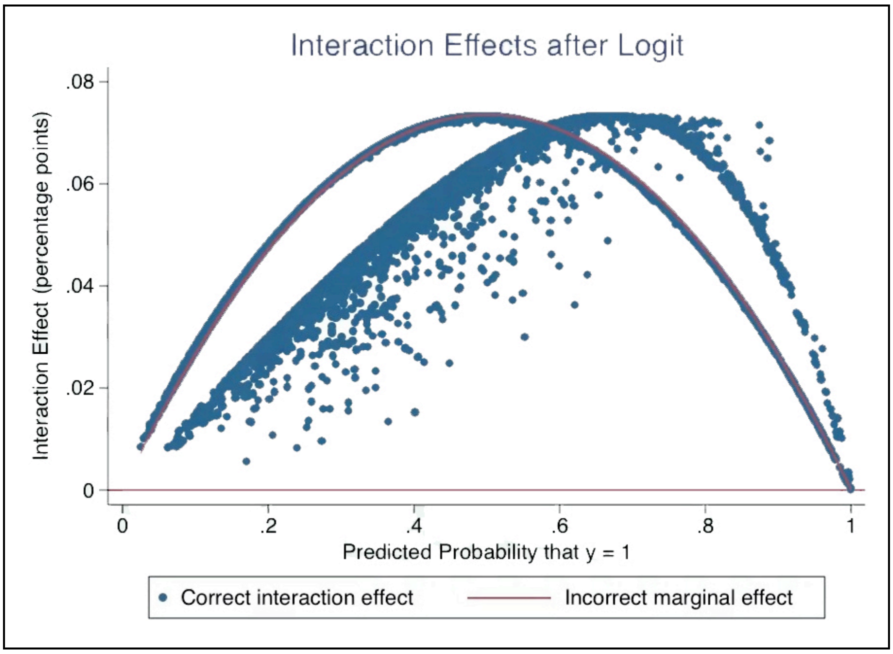


FIGURE 6. Distribution of *z*-statistic on interaction effects

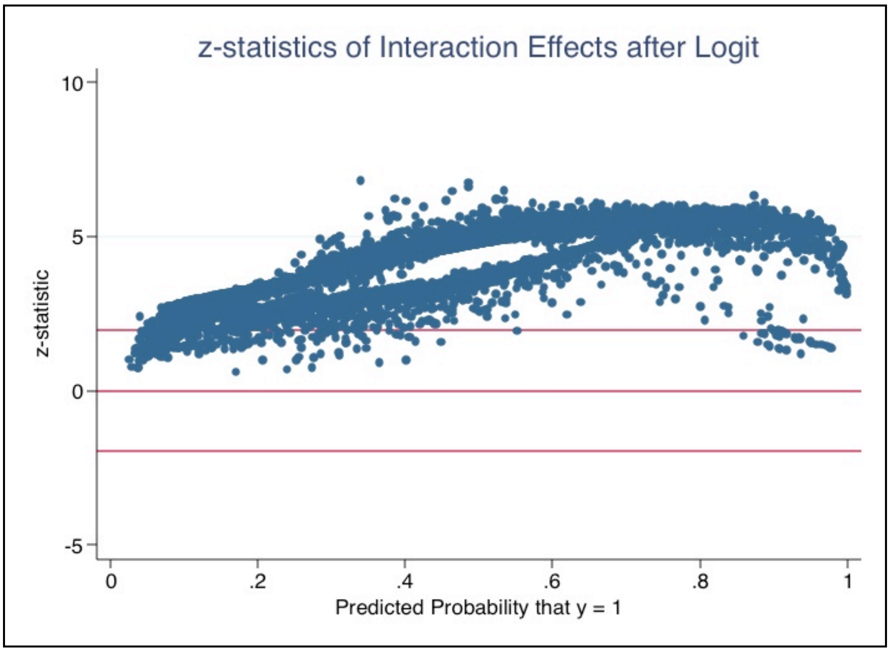
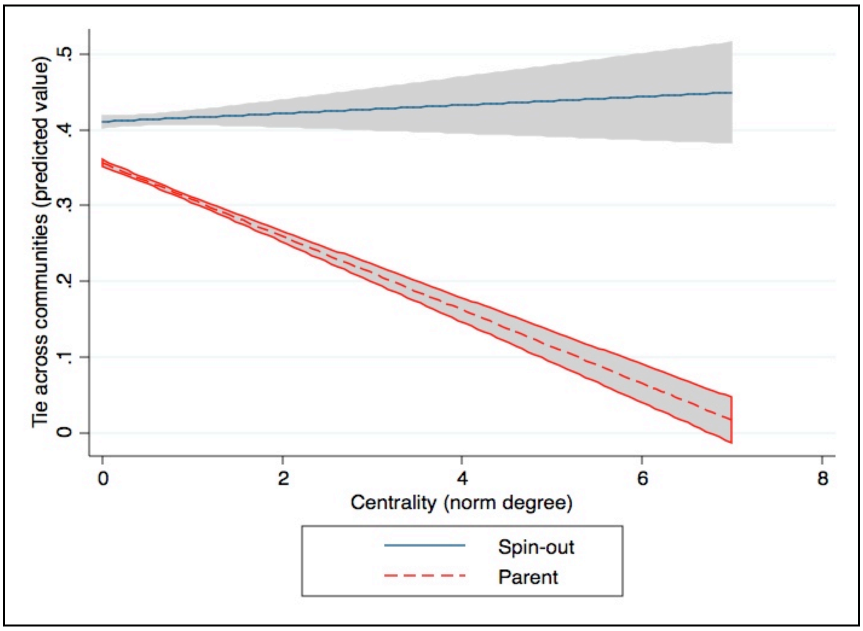


FIGURE 7. Effect of Centrality on the predicted value of New Community conditional on Spin-out



4. DO CORPORATE SPIN-OUTS BENEFIT THE PARENT ORGANIZATION?

4.1 Introduction

The generation of corporate spin-outs may be beneficial to the parent innovation performance. This notion builds on the organizational learning literature assumptions that the level of knowledge developed by units or subunits in a system may influence the returns to investing in learning for the system as a whole (e.g., March, 1991; Levinthal and March, 1993). In line with it, this chapter aims at advancing the idea that knowledge developed by spin-outs may enrich the pool of knowledge into which the parent organization searches and, hence, contribute to the subsequent parent innovation performance.

The literature on innovation has emphasized the role of corporate spin-outs in capturing value from promising ideas that do not fit with the parent core businesses. Hence, spin-outs have been mostly presented as strategies for capitalizing on corporate untapped technology (Chesbrough 2002a).

Substantial evidence exists that spin-outs eventually pursue new scientific and technological developments, which can benefit the parent corporation. Examples are corporate spin-outs generated by several large corporations such as Xerox, Lucent Technologies, Thermo Electron, Unilever, Philips Electronics (e.g., Allen 1998, Chesbrough 2002a, Chesbrough and Garman 2009). Notwithstanding these important insights, little research has focused on the role of spin-outs for parent's innovation performance. To what extent does knowledge produced by corporate spin-outs come to the advantage of the originating firms?

The literature on innovation has highlighted the role of external knowledge in helping incumbents move away from local search, and reposition themselves technologically (e.g., Stuart and Podolny 1996, Nagarajan and Mitchell 1998, Rosenkopf and Nerkar 2001). Likewise, the best strategy to avoid myopia in learning is often to focus attention on successful exploration carried out by other firms

(Levinthal and March 2003). Exploration beyond the firm boundaries and/or technological expertise domains significantly improves the extent to which a firm knowledge is incorporated in future technological developments by other firms (Rosenkopf and Nerkar 2001). The literature also shows that relying on strategic mechanisms, such as technological acquisitions (e.g., Ahuja and Katila 2001) and alliances (e.g., Stuard and Podolny 1996, Valentini 2011), provides significant improvements in the firm innovation performance.

In this work, I challenge the traditional view on spin-outs as technological exits (e.g., Chesbrough 2002b) and I address the idea that spin-outs may provide technological opportunities for the parent organization. As regard, I consider a spin-out as high-tech if it has owned intellectual property rights in the time window of this study (i.e., if it has either applied or traded patents). I develop a set of hypotheses on the effects of *(i)* high-tech vs low-tech spin-out events and of *(ii)* the parent use of spin-out knowledge on the parent firm subsequent innovation performance. I measure performance by means of innovation impact, i.e., a citation weighted patent count.

I test hypotheses using panel data on the patenting activities of a sample of 50 leading corporations in global chemicals, pharmaceuticals, electronics, semiconductors, computers, and telecommunications. First, I distinguish spin-outs in high-tech and low-tech according on whether they deal with patents or not, and I show that important differences exist in their impact on parent innovation performance. Second, I show that parent use of spin-out knowledge significantly improve its innovation performance, and it does so to a higher extent than the use of other firms knowledge.

Building on organizational learning (e.g., March 1991, Levinthal and March 1993) and the 'absorptive capacity' argument (e.g., Cohen and Levinthal 1989), I interpret my results as evidence that exploration carried out by technological spin-outs may increase returns to learning in the parent corporation, and that learning from spin-outs may be more effective than learning from other firms.

Eventually, my results contribute to literature understanding of corporate spin-outs as strategic mechanisms for providing technological opportunities to parent organizations.

4.2 Corporate Spin-outs

Extant literature refers to ‘spin-off’ and ‘spin-out’ mostly as synonyms. For example, Agarwal et al. (2004) define spin-outs as new ventures founded by a former employee that enters the same industry and competes with the parent organization, which has no equity on it. The same definition is used in other papers (e.g., Klepper and Thompson 2007, McKendrick et al. 2009) that, on the contrary, use the term spin-off. Other studies (e.g., Chesbrough 2002a, 2003) refer to technology spin-offs as modes of technology entry in industries or technologies new for the parent organization.

Literature does not make a clear stand on the differences between corporate spin-outs and spin-offs. I refer to corporate spin-outs as new ventures composed by former employees, a unit or a division of the parent organization that (i) are voluntarily created by the parent organization (e.g., Chesbrough 2003), (ii) which invests an equity, transfer assets, and/or stipulates exclusive agreements with the spin-out (e.g., technology licensing) (iii) with the purpose to explore a market or a technology that is far from the parent organization core business (i.e., the spin-out does not directly compete with the parent organization - Chesbrough 2003). The spin-out is part of the parent corporate organization (i.e., either a subsidiary or a participated organization), which may eventually decide to either reintegrate it back or sell it out[8].

Remarkably, despite the increasing interest on spin-out and spin-offs, only a few studies have touch upon the effects of spin-outs on the parent innovation performance. On the one hand, extant literature provides a comprehensive enquiry on the emergence process and performance of spin-outs/spin-offs firms. A first

[8] To this end, I do not refer to spin-offs, i.e., start-ups initiated by former employees with either no agreements or strategic disagreement with the parent firm (e.g., Klepper and Thompson 2007)

research stream enquires why and how spin-outs/spin-offs spawn from parent corporations (e.g., Chesbrough 2002a, Agarwal et al. 2004, Klepper and Sleeper 2005). Other studies look at antecedents of spin-outs/spin-offs performance in several high tech industries, such as medical devices (e.g., Chatterji 2009), disk drive industry (e.g., Christensen 1993, Agarwal et al. 2004, Franco and Filson 2004), semiconductors (e.g., Braun and Macdonald 1982), lasers (e.g., Klepper and Sleeper 2005).

On the other hand, only a few studies enquire parents post spin-out innovation performance. A stream of studies on corporate finance suggests that spin-offs (by means of divestitures) may improve parent financial performance (i.e., equity value) because of reduced diversification and increased efficiency of internal governance and control (e.g., Desai and Jain 1999, Chemmanur and Yan 2004, Moschieri and Mair 2008).

Important insights on spin-out effects on parent innovation performance can be found in the "Open Innovation" paradigm. Chesbrough (2003, 2006) refers to "technological spin-offs" as an approach for taking internal knowledge out to the external market through corporate venturing. Accordingly, spin-outs are identified as a strategy for capturing value from corporate untapped innovation that does not fit with the corporate dominant business model (e.g., Chesbrough 2003). In line with it, other studies suggest that spin-outs help parents refocusing on core businesses and realigning with the changing environment (e.g., McKendrick et al. 2009). As regard, literature has focused primarily on the short term disrupting effects of spin-outs/spin-offs, and it fails acknowledging that the ongoing relationships between parents and spin-outs may affect parent innovation performance[9].

I focus on a specific dimension of parent innovation performance, i.e., *Innovation Impact.* It is a citation weighted patent count, which is commonly used in the innovation literature as a proxy for the influence of a firm innovation on the path of

[9] A notable exception is the work by McKendrick et al. (2009), which suggest that spin-off effects last for several years after the spin-off event. Though, they do not argument on post spin-out relations.

subsequent technological developments undertaken by other firms[10]. I aim to shed a light on two important contingencies that are critical for understanding the effect of spin-outs. First, it is important to acknowledge that not all spin-outs are alike, and their initial effects likely vary according to spin-out innovation related characteristics. Second, not only do spin-outs take corporate knowledge out to external markets, so also do they pursue new scientific and technological developments, new original patterns, and bring about exploration in novel technological fields that may eventually turn to the advantage of the parent corporation.

4.3 Theory and Hypotheses

4.3.1 High-tech and low-tech corporate spin-outs

The spin-out of inventors, units, or divisions can influence the parent firm innovation impact by different means. Spin-outs may cause a disruption in parent innovation processes and harm its innovation capacity. In a study on spin-offs in the hard disk drive industry, McKendrick et al. (2009) suggest that spin-off events are detrimental to parent innovation capacity because the departure of key personnel may disrupt existing routines in the parent innovation processes. First, personnel leaving to found a new firm will likely bring resources and routines from the parent firm (Phillips 2002). Because routines are socially constructed (e.g., Nelson and Winter 1982, Kogut and Zander 1992) the integrity of existing routines may be hurt in cases of collective departures from an organization. Following this logic, Wezel et al. (2006) suggests that routine dissolution is higher in cases where mobility involves groups of individuals. Routine disruption increases parent firm failure rate in the short term (Amburgey et al. 1993, Wezel et al. 2006).

Second, Phillips (2002) also suggests that the departure of high-ranking employees may cause uncertainty and disruption in the social organization of the parent. By leaving the parent organization individuals bring critical resources such as social capital, and it causes a loss of expertise in the parent firm that is difficult to

[10] For a comprehensive description of innovation impact see Rosenkopf and Nerkar (2001).

replace (Phillips 2002).

Spin-outs with a strong technological success hurt the parent firm by depriving critical expertise and social capital. Spin-outs may take away internal technological assets (e.g., Chesbrough 2006), hence reducing the parent knowledge base and weakening its ability to absorb and utilize external knowledge (Cohen and Levinthal 1989).

Notwithstanding this logic, it is not clear whether the departure of employees, of resources, or the disruption of routines may hurt the innovation performance of the parent firm. On the contrary, spin-offs may actually benefit parent innovation by introducing turnover (e.g. March, 1991) and helping the organization realign with its environment (McKendrick et al., 2009). However, McKendrick et al. (2009) show that the disruptive effect of spin-offs on the innovation rate of the parent organization varies according to the average technology of the spin-off. Spin-offs that achieve low-tech innovation output will actually benefit the parent innovation performance in the short run (McKendrick et al., 2009). In line with it, it is possible that the effect on parent innovation varies according to the spin-out involvement with technological assets. Accordingly, I distinguish spin-outs in high-tech and low-tech according on whether they either deal with patents[11] or not, and I hypothesize that:

Hypothesis 1.a. High-tech spin-outs will negatively affect the parent innovation impact.

Hypothesis 1.b. Low-tech spin-outs will positively affect the parent firm innovation impact.

4.3.2 Parent exploration of spin-outs technological knowledge

As I defined above, an important characteristic that defines corporate spin-outs is the existence of an ongoing relationship with the parent organization[12]. Substantial

[11] In particular, I define high-tech spinouts as those who engage in either patenting or trading of patents.

[12] In the sample of spin-outs I use for this study, parents usually hold an equity in their spin-outs for several years until spin-outs are sold out to the market (exit), reintegrated back (acquisition), or they fail.

evidence suggests that spin-outs may pursue new scientific and technological knowledge, new original patterns, exploration in novel technological fields that may even go beyond the ideas, projects, exploration of product/market combinations that made them spun out the parent organization. Knowledge produced by corporate spin-outs may turn to the advantage of the entire corporation. An important example is Xerox Corporation, which has given birth to more than 30 corporate spin-outs in the last 30 years (e.g., Chesbrough 2002a, 2003, 2006). Chesbrough (2003) reports that the spin-out formation process was also intended to create new growth opportunities for the parent to move beyond its current businesses. In another work, the author introduces the case of 3Com, a firm spun out from Xerox in 1979[13], and he notes (Chesbrough 2002a):

> 'Many of the early companies were created when Xerox felt it had little to gain from further investigation in a particular area. This strategy was first illustrated by 3Com, which was formed when Xerox decided to exploit a component technology, Ethernet, by spinning it out of the company.' . . . 'While this feature proved to be quite valuable for computers later on, it offered real and immediate benefits to copiers as well. It enabled Xerox to offer a variety of equipment configurations in its copiers and printers with a single wiring harness. Xerox first included this capability in its Xerox 1075 copier in 1982' . . . 'This configuration flexibility provided a valuable savings to Xerox.' (Chesbrough 2002a: 812)

Lucent Technologies is another striking example. Chesbrough (2002b) notes that:

> . . . 'Three of the more than 30 technology spin-offs [i.e., corporate spin-outs] created so far by the New Venture Group[14] have been reacquired by Lucent. Ultimately, those technologies were deemed strategically valuable to the company, either because the market had changed or because the technology

[13] 3Com spun out Xerox in 1979 with no parent equity but a license agreement on four Xerox patents on the Ethernet technology. As a spin-out, it was eventually disposed by Xerox in 1984 (Chesbrough 2006).
[14] New Venture Group is a Lucent company created in 1997 to commercialize technologies that did not fit with Lucent core businesses (Chesbrough 2006).

> had progressed further than had been expected. One of such spin-off is Lucent Digital Video, which created analog-to-digital converters to move on analog networks. After the New Ventures Group spun out this business, Lucent began winning new business by selling its own equipment in combination with the new company's products. It soon began clear that digital technology would unlock significant growth for Lucent' . . . (Chesbrough 2002b: 8)

If spin-out events may reduce the parent innovation impact because of a reduction in parent knowledge base, subsequent exploration carried out by spin-outs may turn to the advantage of the parent corporation. As the case of Lucent makes clear, technological spin-outs may provide new knowledge combination opportunities for the entire corporation. Klepper and Sleeper (2005) provide an interesting insight on this argument by arguing on the social (system-level) consequences of spin-offs. The authors suggest that spin-off fosters overcoming of inertia (which generally affects parent innovation processes) and it spurs innovation in unpredictable and diverse ways. As in the case of 3Com, Xerox spin-outs came into being because of the parent indecision about carrying on pioneering technologies. After spinning out the parent organization, Xerox units explored new knowledge that eventually provided Xerox with new product configuration opportunities (e.g., Chesbrough 2006).

Organizational learning literature (e.g., Levinthal and March 1981, March 1991) frames this problem by means of the established organizations challenges in balancing refinement of existing knowledge (i.e., exploitation) and invention of new one (i.e., exploration). Exploration of new alternatives reduces the speed of improvements in existing skills and procedures (March 1991, Levitt and March 1988) and this causes experimentation with pioneering technologies to be less attractive than exploitation in the domain of core businesses. In evolutionary theory (e.g., Nelson and Winter 1982, Hannan and Freeman 1987) the same problem is framed by means of balancing variation and selection of knowledge. Not only is effective selection essential for survival, so also is the generation of alternatives (i.e., variation) that provides a relative advantage in relatively unstable environments (e.g., Cohen 1986, March 1991). Hence, spin-outs may offer a solution to parent organizations, allowing them to refocus on exploitation and selection, while pursuing exploration in decentralized organizational structures (e.g., Siggelkow and Levinthal 2003). Klepper and Sleeper (2005) recognize that, in the context of high-tech industries, spin-offs are important actors driving the industry's rate of technological change through diversity in the nature of innovations they produce. Levinthal and March (1993) provide a similar idea by arguing that returns to investing in learning depend on the level of knowledge developed by others actors or units in a system. Accordingly, if spin-outs produce unpredictable and diverse knowledge outcomes, because of their connections with the parent organization, the entire corporation may benefit of self-reinforcing learning that will eventually lead to organizational renewal and growth (Levinthal and March 1993).

In high-tech industries, the systematic use of other firms' knowledge is a key for overcoming inertia in innovation processes (e.g., Rosenkopf and Nerkar 2001). For example, firms rely on mergers, acquisitions, and strategic alliances to tap for external knowledge, improve innovation performance (e.g., Ahuja and Katila 2001, Valentini 2011) and change technological trajectory (e.g., Stuart and Podolny 1996, Nagarajan and Mitchell 1998). In a study on optical disk industry, Rosenkopf and Nerkar (2001) show that using other firms' knowledge is more efficient on the firm innovation impact than using internal (firm proprietary) knowledge. Likewise, innovation carried out by technological spin-outs will increase the elements of external knowledge available for the parent firm.

Accordingly, I hypothesize that:

Hypothesis 2. The use of spin-out knowledge will have a positive effect on the innovation impact of the parent firm.

The advantage of using external knowledge is that firms may select well-regarded, superior technology (Rosenkopf and Nerkar 2001). Literature on 'absorptive capacity' (e.g., Cohen and Levinthal, 1989; Cohen and Levinthal, 1990) posits that a firm needs prior related knowledge to recognize value in new external information, integrate and utilize it. Prior firm knowledge includes individual skills, shared languages, and cognitive structures that define a firm's ability to exploit external knowledge (Cohen and Levinthal, 1990). To develop 'absorptive capacity', it is not sufficient to expose individuals to relevant knowledge. On the contrary, it is important that learning is built up over practice and effective communication (Cohen and Levinthal, 1990). On the one hand, similar elements in the knowledge bases of who transfers and who acquires knowledge, shared knowledge and common expertise may ease communication and learning of technical knowledge (e.g., Cohen and Levinthal 1989, Kogut and Zander 1992, Grant 1996). On the other hand, an active network of close external relationships is essential to hold information on where critical knowledge resides and who can exploit it (e.g., Von Hippel 1988, Cohen and Levinthal 1990).

Direct or indirect contact with knowledgeable individuals outside the organization is one way through which R&D units can stay informed about technological and scientific developments outside the organization (Lee and Allen 1982). Accordingly, another important argument that might explain the role of spin-out knowledge on parent firm innovation impact builds on the particular relationship that exists between the parent corporation and its technological spin-outs. First, corporate spin-outs and parents may hold similar knowledge backgrounds, which may enhance parent capacity of absorbing spin-out knowledge. In diversified firms, because of impediments to the search and transfer of knowledge researchers may be more willing to search for knowledge inside the organization boundaries (e.g., in other divisions) instead of looking for external knowledge (Miller et al. 2007). Prior literature on spin-outs/spin-offs (e.g., Agarwal et al. 2004, Klepper and Sleeper 2005, Chatterji 2009) suggests that spin-outs inherit technical knowledge from their parents. By sharing common past experience and knowledge, individuals who move to spin-out organizations master similar skills and technical knowledge of their former colleagues in parents. It enhances effective communication (e.g., Cohen and Levinthal 1989).

A second related argument relates to similarity in spin-out and parent routines. Klepper and Sleeper (2005) posit that in several high-tech industries, such as software, biotech, and semiconductors, spin-offs likely engage in replication of parent routines. Likewise, Wezel et al. (2006) propose that in cases of voluntary out-mobility events (the case of corporate spin-outs is an important example) parent firms may deliberately transfer their routines to the new organizations. According to Cohen and Levinthal (1990), having internal technologies, and hiring scientists who are familiar with organizational procedures, routines and external relationships is essential for the integration of complex and sophisticated knowledge. Therefore, the existence of common routines between spin-outs and parents may ease transfer of complex technical knowledge.

Third, as part of the corporation, spin-outs may establish rich communication channels with their parents. Studying out-mobility in the semiconductor industry, Corredoira and Rosenkopf (2010) identify two important mechanisms that generate knowledge flows between firms hiring inventors and the old firms. First, interpersonal relationships between former colleagues endure over time and they are an important interpersonal communication channel for the disclosure of technical information (Fleming et al. 2004, Corredoira and Rosenkopf 2010). Second, out-mobility events shift firms' attention to monitoring knowledge produced by the hiring organizations (Corredoira and Rosenkopf 2010). This may be particularly true in cases of voluntary out-mobility, and an increased monitoring in spin-out innovation outputs may provide parents with critical information on where superior knowledge resides and who can exploit it (e.g., Cohen and Levinthal 1990).

Following this logic, parent organizations may hold more effective communication channels with their spin-outs than with any other firm. It follows that technological spin-outs may be of strategic importance for parent firms in accessing external complex knowledge. Indeed, the high effectiveness of communication channels may result in a more effective use of spin-outs knowledge than other firm's knowledge.

Accordingly, I hypothesize that:

Hypothesis 3.The use of spin-out knowledge will have a higher effect than the use of other firms' knowledge on the innovation impact of the parent firm.

4.4 Method

4.4.1 Selection of Parent firms and Spin-outs

I test hypotheses on a multi-industry longitudinal data set comprising the patenting activities of a sample of 50 large corporations. These firms have been identified among leading firms that are active in generating corporate spin-outs in global chemicals, pharmaceuticals, electronics, semiconductors, computers, software, telecommunications and petroleum industry. Focusing on large corporations is essential for obtaining reliable data on corporate spin-outs. I selected these companies from the annuals of the Fortune Global 500 rankings by identifying corporations who engaged in the generation of corporate spin-outs from 1975 to 2008. For each corporation in the rankings I searched on the Factiva database for news releases about the firm generation of spin-outs. I identify corporate spin-outs according to three criteria:

1) An employee, unit, or division departs from the parent organization to establish a new firm.
2) The spin-out is sponsored by the parent in order to either product-market technologies originally incubated within the parent organization or explore/develop new technologies.
3) The parent owns from 0% (no equity) to 100% (wholly owned) of the spin-out's initial capital. In case of no equity, I distinguished spin-outs from divestitures by searching for agreements between spin-outs and parent for the future licensing or transferring to the parent of technologies eventually developed by spin-outs in the future.

Conditional on these criteria, I further cross-checked parent and spin-out web sites in search for congruent information on the origins and aims of the new firm as sponsored by the parent organization. I was able to identify 230 corporate spin-out events from 23 American, 20 European, and 7 Japanese parent firms. In the time window of this study, these spin-outs have belonged to their parent corporations for a mean of 5.96 years (4.00 years variance) until they have been disposed, reintegrated back, or they failed.

4.4.2 Data

Consistent with other research on firm's R&D and innovation impact (e.g., Rosenkopf and Nerkar 2001) I use data on patent applications granted at the United States Patent and Trademark Office (USPTO). The primary source for my data is the patent data set developed by Lai and colleagues (2009). It includes data on all applications of patents granted from 1975 to 2008. In the time window 1975-2008 I identified 287,085 utility patents filed and granted to the 50 parent firms[15], and 8,577 to spin-out firms.

Each patent reports a list of citations made by the focal patent to prior patents. I used this information to (i) tabulate a list of all patent cited by each parent firm and match it with patents granted to their spin-out organizations, and to (ii) count all citation that parent patents received by subsequent patents.

This study uses an unbalanced panel dataset with unit of analysis in the parent firm-year. The dataset includes longitudinal data for a mean of 24.3 years per parent firm between 1975 and 2008. The range of observations varies from a minimum of 8 years to a maximum of 34 years per firm and shows no missing values within each parent observation window. The final panel includes a total of 1,217 firm-year observations.

In addition to patent data, I used *Compustat* (*North America* and *Global*), to collect financial data (e.g., R&D expenditure), *Amadeus* and *Zephyr* databases to collect other information on ownership in spin-outs, and firms' characteristics. Unfortunately these databases report several missing values. Because of missing data in *Compustat Global*, I was not able to collect financial data for several European and Japanese firms prior 1986, which reduces the panel to 1,083 observations. For this reason I include controls for R&D expenditure in a separate model.

Descriptive statistics for data are shown in Table 15.

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[15] I identify patents assigned to the parent firm only, not to its subsidiaries. Since some corporations assign their patents to their subsidiaries (rather than their headquarter) it may result in an underestimation of innovation efforts.

Table 15 about here

4.4.2 Measures

Dependent Variable

This study uses patent data to estimate the effects of spin-out events and use of spin-out knowledge on one dimension of parent firm innovation performance, i.e., *Innovation Impact*. One of the main limitations in using patents as a measure of output is that, on the one hand, not all inventions are patentable and, on the other hand, not all industries rely on patents to protect from imitation and appropriate value in inventions (e.g., Trajtenberg 1990). However, firms in the sample operate in industries where patents can be considered effective in protecting product and process innovations (e.g., Levin et al 1987).

Innovation Impact. The dependent variable refers to the impact of firm *i*'s patents by means of forward citations they received by subsequent patents. The number of forward citations a patent receives is one dimension of patent quality (e.g., Trajtenberg 1990, Hall et al. 2001), it is an indication for the invention usefulness and importance for other firms and inventors (e.g., Albert et al 1991), it is a proxy for the overall monetary value of a patent (e.g., Gambardella et al. 2008). In year *t*, I measure impact as the total number of citations firm *i* receives to its patents applied in year *t*. It is important to note that this measure refers to forward citations received by other patents granted after the parent focal patents applied in year *t.* In this count I exclude self citations made by a firm to its prior patents.

Independent Variables

Except for citation measures, for all independent variables and controls I used the lagged version (1 year) of the variables shown below.

Number of high-tech spin-outs. After identifying the year of incorporation of each corporate spin-out through the above mentioned criteria, I consider a spin-out as high-tech if it has at least owned intellectual property rights. I used patent data to code a spin-out as high-tech if *(i)* it has applied patents at USPTO[16] or *(ii)* it has traded (i.e., acquired ownership) patents granted at the USPTO. I include the latter in order to partially correct for a possible bias in underestimating high-tech spin-outs where patent application data is not available. To this aim, I collected data on patent assignments at USPTO. The transfer of a patent ownership has to be filed at USPTO in order to be legally binding (Serrano 2010). Patent assignments acknowledge the rationale of the transfer, the names of the buyers and sellers, patent numbers, and the date when the parties signed the private agreement. I used the USPTO Patent Assignment Database to extract all patent assignments where *(a)* spin-outs could be identified as either buyer or seller of a patent, and *(b)* the rationale of the assignment acknowledges the outright sale of patents (i.e., *assignor of interest*)[17].

In the sample of 230 corporate spin-outs, 120 spin-outs have been granted at least one patent at USPTO. Of the remaining corporate spin-outs, 44 have bought at least one US patent from either its parent firm or other firms in the time window of this study. I coded these 164 spin-outs as *high-tech*. Using this information I built the independent variable (*High-Tech Spin-outs*) as a count of high-tech spin-outs that have been released by firm *i* in year *t-1.* Of the 50 parents in my sample, 44 have generated at least one high-tech spin-out in the time window of this study.

Number of low-tech spin-outs. Finally, the remaining 66 corporate spin-outs that do not show patents either assigned or traded at USPTO were coded as *low-tech.* The variable (*Low-tech Spin-outs*) is a count of low-tech spin-outs released by firm *i* in year *t-1*.

Use of spin-out knowledge. Following Corredoira and Rosenkopf (2010), I consider citations of a parent firm to its spin-outs patents as an instance of the parent firm's using of spin-out knowledge. The variable (*Citations to Spin-outs*) is a count of all citations firm *i* has made in year *t* to prior patents granted to its corporate spin-

[16] The sample of 230 spin-outs comprehends several firms that are based in non-US countries (in particular 76 in Europe, 26 in Japan). Since using USPTO data might bias the categorization of high-tech vs low-tech firms, I have also controlled for spin-out patenting activities at European Patent Office (EPO), World Intellectual Property Organization (WIPO) and Japan Patent Office (JPO). I can show that the distribution of spin-outs in high-tech vs low-tech does not change significantly.
[17] I excluded cases in which patent ownership is transferred because of M&As.

outs. It is important to note that this backward citations are to spin-out patents granted earlier than the focal parent patent. applied in year *t*. Here, the absence of a lag structure in necessary in order to capture the effect on my dependent variable.[18] The count does not include repeated citations to the same patents, which are counted once. In other words, for every spin-out patent I count only the very first time it is cited by the parent.

Controls

In order to control for alternative mechanisms that might explain variance in innovation output and impact, I include the following controls in regressions.

Spin-out knowledge. As I claim, not all spin-outs have an impact on parent firms' subsequent impact, and the extent of which knowledge transfers from corporate spin-out to parent firms may depend on the size of the spin-out knowledge. I refer to Ahuja and Katila (2001) and I use two different measures to account for the spin-out knowledge. First, I computed *spin-out absolute knowledge*. For each corporate spin-out I prepared a list of all patents successfully applied and all patents cited by corporate spin-outs in a 5 year-window prior year *t-1*. Then I summed all patents in the list and I aggregated data for all corporate spin-outs owned by firm *i* at year *t-1*.[19]

Finally, I computed a measure of *knowledge relatedness*. The measure is computed as the number of patents that are listed both in *spin-out absolute knowledge* and patent firm absolute knowledge (which is computed following the same procedure as above). It accounts for the extent to which spin-out and parent firm build on a common knowledge base. The measure is aggregated for all spin-outs owned by firm *i* at year *t-1*.

Patent assignments. I included controls on the trading of patents between parent organizations and corporate spin-outs, such as the total number of patents transferred from *technological spin-outs* to parent firm *i* in year *t-1* (*AssignmentsIn*),

[18] The same consideration holds for other citation measures I use in this study (i.e., *Self Cites* and *Other Cites*).
[19] I found no significant differences in using a control on the number of patents granted to spin-outs in year *t-1*.

and the total number of patents transferred from parent firm *i* to its *technological spin-outs* in year *t-1* (*AssignmentsOut*).

Other controls. Other control variables include the total number of citations made by firm *i* at year *t* to other firm's patents (*Other Cites*), the total number of self citations made by firm *i* at year *t* (*Self Cites*)[20], the number of spin-outs acquired back by parent firm *i* in year *t-1* (*Spin-out Reintegration*), the sum of all equities in spin-out organizations by parent firm *i* in year *t-1* (*Spin-out Equity*), a control on firm diversification (*Diversification*) based on a measure of entropy (Palepu 1985) built on patent SIC of use from Silverman concordance (1996), and the natural logarithm of R&D expenditure of firm *i* at year *t-1* (*Ln(R&D expenditure)*). I also included dummies for American, European, and Japanese parent firms, and a measure for national differences between spin-outs and parent firms (*Foreign Spin-out*). The latter is a count of spin-outs owned by firm *i* in year *t-1* that are based in a different country than the parent corporate headquarters[21].

In Column (6) I also include the firm heterogeneity control *Presample*. For all year observations in the panel, the variable is coded as the sum of all forward citations firm *i* received to parents it applied in the 3 years before this study panel observations.

Finally, I include dummies for firm primary SIC codes, and application year dummies.

4.4.3 Analysis

The dependent variable is a nonnegative count variable that is skewed and over-dispersed around the mean. Following previous research on innovation I use a negative binomial estimation as main model. The Hausman specification test reports non-systematic differences between conditional fixed effects and random effects estimations. Except for Column 3 and 4 (where I include random effects) I include

[20] As for *Citations to Spin-outs*, I counted just once each patent cited by the firm.
[21] 107 of the 230 spin-outs have been established in a different country (or state for US) than parent headquarters.

firm fixed-effects to account for time-invariant unobserved heterogeneity across firms that might influence innovation impact.

As a second model I present a quasi-maximum likelihood (QML) estimation based on a conditional fixed effect Poisson model (Hausman, Hall and Griliches 1984) with robust standard errors clustered at the firm level. Since the Poisson model is a generalized linear model, it allows for a more fine-grained interpretation of estimates across different models (Singh and Agrawal 2011) and QML standard errors are robust to arbitrary patterns of serial correlation (Wooldridge 1999). I implement this estimation using the *xtpqml* Stata procedure, which corrects standard errors for overdispersion in the fixed effects conditional Poisson model (Rysman and Simcoe 2008). Finally, I also use a presample GEE poisson estimation as further robustness check.

Table 16 about here

4.4.4 Results

Table 16 presents models for estimating the effect of spin-outs on *Innovation Impact*. In hypotheses 1 I predicted that spin-out events would cause different effects on the parent firm innovation impact depending on the extent to which the spin-out involves a technological component. The significant negative coefficient of *High-tech Spin-outs* ($p < .05$) is confirmed in all regression models, which suggests that the spin-out of individuals, units, or divisions who engage in innovation that involves property rights has disruptive effects on the parent firm ability to create value through innovation. This result supports hypothesis 1a.

Overall, the coefficient for *Low-tech Spin-outs* is non significant. It turns to be positive and significant in the random effect negative binomial estimation (Column 3) and in the Poisson QML estimation (Column 5). It may be evidence that when the spin-out involves low-tech component (i.e., neither patenting or trading of patents) it may help the parent firm improve its innovation impact. A plausible explanation for this result may be that the departure of low technological units allows parents to refocus resources on technology intensive innovation processes. Overall, results provide little support to hypothesis 1b that low-tech spin-outs have positive disruptive effects on parent innovation performance.[22]

In hypothesis 2, I predicted that the use of knowledge developed in spin-outs would improve the impact of the patent firm innovation efforts. The coefficient of *Citations to Spin-outs* is positive and significant ($p < .05$) in all regression models. Thus, results support hypothesis 3.

Beyond its significance, this result bears important implications when compared to spin-out related control variables and other citations controls. First, neither *Knowledge Relatedness* nor *Spin-out Absolute Knowledge* are significant. On the one hand, *Knowledge Relatedness* shows a positive significant sign only when controlling for R&D expenditure, which may support the absorptive capability argument. Prior literature on acquisitions (e.g., Ahuja and Katila 2001, Zollo and Singh 2004) suggests that relatedness may imply an higher ability of transferring and absorbing knowledge (e.g., Cohen and Levinthal 1990) and thus a positive impact on innovation. However, when two knowledge recipients are too similar there is a little gain from transferring knowledge (e.g., Ahuja and Katila 2001). It may explain the inconsistent results on *Knowledge Relatedness.* On the other hand, the insignificant positive coefficient for *Absolute Knowledge* may indicate that knowledge produced by spin-outs does not provide any effect on the parent firm innovation impact per se. It is in line with my argument that spin-out knowledge may provide an impact only when it is coped with parent exploitative selection of such knowledge.

Second, interesting differences exist in the relative importance of citations to spin-out patents as compared to citations to other patents. In hypothesis 3, I suggest that the effect of exploring knowledge developed in spin-outs will be higher than exploring other firms knowledge. To start with, the coefficient for *Self Cites* is negative and

[22] Results for hypotheses 1a and 1b are robust when using alternative specifications for the high-tech and low-tech independent variables, i.e., *(i)* the number of high-tech and low-tech spin-outs owned by firm *i* at year *t-1* and *(ii)* the firm experience with high-tech and low-tech spin-out events (i.e., the number of spin-out events till year *t-1*).

significant (p <.001), with an exception for Column (2) and (3). Then, the coefficient for *Other Cites* is positive and significant (p < .001), with an exception for Column (5). This result is in line with previous literature on knowledge diffusion and exploration in high-tech industries (e.g., Rosenkopf and Nerkar 2001, Miller et al. 2007) which provides evidence on (i) the negative effects of local (path dependent) exploration (i.e., self citations) on impact and on (ii) the importance of boundary spanning exploration (i.e., citations to other firms and other technological domains) for the firm impact on subsequent technological evolution. The low magnitude of both effects is reasonable considering that this is a mean effect estimated in a multi-industry context and that the impact of boundary spanning may vary across industries at different levels of knowledge intensity. Although the ratios of regression coefficients for *Citations to Spin-outs*, *Self Cites*, and *Other Cites* explain a little portion of variance in *Innovation Impact*, Wald tests on differences in the coefficients demonstrate that citations to spin-out patents persistently provide a significant higher effect on Innovation Impact than all other cites[23]. Accordingly, although citations to spin-outs are relatively few with respect to all other citations made by each firm every year, they consistently provide a higher positive and significant effect on firm innovation impact. Thus, results support hypothesis 3.

Among other controls in Columns (1) - (6) in table 16, *Diversification* is positive and significant. Prior studies show diverging results on the impact of diversification on innovation (e.g., Cohen and Levin 1989, Ahuja and Katila 2001). According to Ahuja and Katila (2001), diversification provides a loss of focus in specific technological areas and it is negatively related to patenting frequency. However, the authors recognize that diversification may also enhance innovation by leading to cross fertilization of ideas (Ahuja and Katila 2001). As regard, my result may suggests that this latter instance should be observed in quality dimensions (rather than quantity) of innovation performance.

[23] Wald tests (not reported here) show that the effect of *Citations to Spin-outs* on *Innovation Impact* is significantly (and consistently) different (p < .01) than other citation variables in all Columns (1) - (6). For this analysis I used nonlinear hypothesis testing (command *testnl* in Stata 11).

Foreign Spin-outs is positive and significant in Columns (0) to (3), suggesting that spinning out R&D units in distant geographical contexts provide a significant effect on increasing innovation impact. This result is in line with literature on geography (e.g., Almeida and Kogut 1997) and suggests that spin-outs may also enable parents overcome embeddedness in their own geographical contexts.

Coefficients for primary SIC dummies are significant for computers, softwares, and petroleum industry. Finally, except for 1977-1981 and 1999-2002, all coefficients for year dummies (not reported in table) are significant. Overall, they are positive in the period 1982-1998, and negative in the period 2002-2007.

A further evidence of the importance of looking forward spin-out events can be also interpreted by viewing the distribution of *Citations to Spin-outs* per year. Figure 8 displays the number of *Citations to spin-outs* by the number of years from spin-out events. Citations are distributed around a mean of 8.15 years after spin-out events, with a variance of 6.09 years.

Figure 8 about here

Likewise, figure 9 shows the distribution of *Citations to spin-outs* by the number of years from spin-out (cited) patent application year. In this case, citations are distributed around a mean of 4.00 years after spin-out patent application, with a variance of 3.27 years.

Figure 9 about here

Clearly, parents use knowledge developed by spin-outs several years after spin-out events. If we also recall that parents own spin-outs around a mean of 5.96 years (with a variance of 4.00 years), it means that most citations refer to innovation patented when spin-outs were still part of their corporations (i.e., before disposition events).

Finally, it is important to note that of the 50 parent firms in the sample, only 22 have cited at least one patent granted to their spin-outs in the time window of this study. This evidence may suggest that, although 44 parents (out of 50) have generated at least one high-tech spin-out, firms may adopt heterogeneous approaches to spin-outs. There are different interpretations of why parents may be not willing to cite spin-outs. First, it may be that parents conceive their spin-outs exclusively as 'graceful exits' (e.g., Chesbrough 2002a) and pay no attention to their further technological developments. Second, parents may recognize no strategic value in spin-out knowledge. Third, parents may adopt a centralized approach to intellectual property right ownership and get all spin-out patents assigned to the headquarter[24]. With reference to this issue, in order to partially account for possible unobserved heterogeneity I run another conditional fixed-effects negative binomial estimation controlling for parents that have never cited their high-tech spin-outs. Results (not reported here for conciseness) do not report any significant difference with the main estimation model I use for this study.

4.5 Discussion and Conclusion

Extant literature has emphasized corporate spin-outs as strategies for taking internal knowledge out to the market (e.g., Chesbrough 2006). Unlike previous studies, this work sheds a light on another compelling facet: spin-outs can be strategies for bringing external knowledge into parent organizations.

My results show that it is important to distinguish spin-outs on the basis of their involvement with technology. First, I show that high-tech and low-tech spin-out events imply opposing short-term effects on parent innovation performance. When they involve low technological component, spin-outs may be beneficial for the short-term parent innovation impact, which may be the result of the redirecting of internal resources into more sophisticated technological projects. On the contrary, when they involve patents, spin-outs may be detrimental for parent innovation impact by dispossessing the parent of important technological assets and thus hurting its innovation capacity. Second, I also show that spin-outs may prove to be beneficial if

[24] In this case, there may be an underestimation of spin-out knowledge and, as a consequence, of a spin-out effect.

the parent firm integrates spin-outs technological developments into its innovation processes. I have also shown that the effect of this reverse knowledge transfer is higher than the use of external knowledge from other firms, which I explain as the result of a higher absorptive capacity toward spin-out knowledge.

Though this results should be carefully interpreted, I argue that this may be evidence of an important characteristic of spin-outs that has been overlooked by literature. Spin-outs act as strategic mechanisms for providing long-term technological opportunities for the parent organization. My argument builds on evolutionary theory prescription on the need of balancing exploitative selection with exploratory variation for survival in rapidly changing environments (e.g., Nelson and Winter 1982, Hannan and Freeman 1987). In the strive for survival, firms persistently cope with a well-known problem, i.e., they have higher incentives to emphasize the exploitation of similar knowledge residing within the firm instead of the exploration of knowledge into new domains (e.g., March 1991, Levinthal and March 1993, Rosenkopf and Nerkar 2001). The problem, and a feasible solution, is well described by Levinthal and March (1993), who note:

> 'The fruits of successful exploration, whether new technologies, product ideas, or modes of management, tend to diffuse over populations of organizations. They are public goods. In contrast, the risks and costs of exploration are private goods; they tend to be borne by organizations carrying out such initiatives. The result is that the best strategy for any individual organization is often to emphasize the exploitation of successful explorations of others.' (Levinthal and March 1993: 103-104)

In line with this perspective, I argue that spin-outs may help the parent firm manage the trade-off between exploration and exploitation. Christensen (1997) argues that the best way to address a rapid and effective response to a changing competitive environment is the creation of independent businesses to explore new business initiatives. The spin-out of explorative units may be a way of improving learning activities in the entire corporation. Following spin-out events parents may indulge in exploitation (e.g., Chesbrough 2002a, 2006). At the same time spin-outs may bear the costs and risks of exploration initiatives. Eventually, exploration carried out by spin-outs may increase returns to invest in learning for other units in the corporation (e.g., Levinthal and March 1993). In other words, spin-outs may become beneficial in the long run, when their persistence exploration is paired with the parent exploitation of such knowledge. As Levinthal and March (1993) argue, this setting provides *'self-reinforcing spirals of knowledge-generating activity leading to high levels of organizational renewal and growth'* **(**Levinthal and March 1993: 104).

I acknowledge that several limitations of this study may limit the generalizability of my results. In particular, by using patent data this study can only explore performance of inventions that can be successfully patented. Firms in my sample operate in high-tech industries where patents are widely considered a good indicator of innovation output and value. Though, innovation does not necessarily results in patents. Accordingly, this study can only capture the effect from the use of knowledge developed in high-tech spin-outs. Further examination on other dimensions of spin-out knowledge outputs should be undertaken to further support this study results.

Though this caveats, this study contributes to the literature by several means. First, it adds important considerations to the existing literature on corporate spin-outs. Unlike previous studies, it shows that it is important to (i) discern the effects according to the technological characteristics of spin-out firms, and to (ii) recognize that the ongoing relationship with the parent organization brings about important implications for parent innovation performance. As regard, it provides evidence that spin-outs provide options on new technological developments, which may be also incremental to established businesses.

Second, by also using citation data of a multi-industry context this study contributes to a better understanding of the role of boundary spanning exploration for a firm innovation impact on subsequent technological developments (e.g., Rosenkopf and Nerkar 2001). In line with the absorptive capacity argument (e.g., Cohen and Levinthal 1989) my results suggest that the effectiveness in the acquisition of external knowledge may be enhanced when a firm integrates its absorptive capacity with the spin-out of firm specific innovation assets. As regard, an important question that is still open relates to what extent spin-outs may be a valid alternative to internal direct investments in innovation, and whether they increase or reduce a firm absorptive capacity. By the same token, future research should further investigate whether generating technological spin-outs allow parent firms to build capabilities for the exploration of external knowledge, a priori.

Third, this study makes a clear contribution to managerial practice. It shows that corporate spin-outs may provide parents with new technological opportunities in high-tech industries. However, I also show that, relatively to other sources of knowledge, parents rarely use technological developments developed by their spin-outs. As regard, this study aimed at challenging the traditional view of spin-outs as 'graceful exits' (e.g., Chesbrough 2002b) by showing that, if properly managed, spin-outs may provide parents with valuable exploration for innovation performance. Accordingly, future research should shed a light on why the use of spin-out knowledge by parents is so rare.

References

Agarwal, R., Echambadi, R., Franco, A.M., M.B. Sarkar. 2004. Knowledge Transfer Through Inheritance: Spin-Out Generation, Development And Survival. *Academy of Management Journal* **47** 501-522.

Ahuja G., R. Katila. 2001. Technological Acquisitions And The Innovation Performance Of Acquiring Firms: A Longitudinal Study. *Strategic Management Journal* **22** 197-220.

Albert, M.B., Avery D., Narin F., P. Mcallister. 1991. Direct Validation Of Citation Counts As Indicators Of Industrially Important Patents. *Research Policy* **20**(3) 251-260.

Allen, J. 1998. Capital markets and corporate structure: The Equity Carve-outs of Thermo Electron. *Journal Of Financial Economics* **48** 99-124.

Amburgey, T.L., Kelly, D., W.P. Barnett. 1993. Resetting the clock: The dynamics of organizational change and failure. *Administrative Science Quarterly* **38**(1) 51–73.

Braun, E., S. Macdonald. 1982. Revolution In Miniature: The History And Impact Of Semiconductor Electronics, Cambridge University Press, Cambridge.

Chesbrough, H.W. 2002a. Grateful Exits and Missed Opportunities: Xerox's Management of its Technology Spin-off Organizations. *The Business History Review* 76 803-837.

Chesbrough, H.W. 2002b. Making sense of corporate venture capital. *Harvard Business Review* **80**(3) 90-99.

Chesbrough, H.W. 2003. The governance and performance of Xerox's technology spin-off companies. *Research Policy* **32**(3) 403-421.

Chesbrough, H.W. 2006. *Open innovation: researching a new paradigm*. Oxford University Press, USA.

Chesbrough, H.W., A.R. Garman. 2009. How Open Innovation Can Help You Cope in Lean Times. *Harvard Business Review,* December.

Christensen, C.M. 1993. The Rigid Disk Drive Industry: A History Of Commercial And Technological Turbulence. *The Business History Review* **67** 531-588.

Christensen, C.M. 1997. The Innovator's Dilemma. Harvard Business School Press, Boston, MA.

Cohen, M.D. 1986. Artificial Intelligence And The Dynamic Performance Of Organizational Designs, in *Ambiguity and Command: Organizational perspectives On Military decision Making,* March, J.G., R. Weissinger-Baylon (Eds.), 53-71. Boston, MA: Ballinger.

Cohen, W.M., D.A. Levinthal. 1989. Innovation and Learning: The Two Faces Of R&D. *Economic Journal* **99** 569-590.

Cohen, W.M., D.A. Levinthal. 1990. Absorptive Capacity: A New Perspective On Learning and Innovation. *Administrative Science Quarterly* **35** 128-152.

Desai, H., P.C. Jain. 1999. Firm Performance and Focus: Long-run Stock Market Performance Following Spin-offs. *Journal of Economics* **54** 75-101.

Fleming, L., Colfer, L., Marin, A., J. McPhie. 2004. Why the valley went first: agglomeration and emergence in regional inventor networks. Paper presented at the 2004 Academy of Management Conference, New Orleans, LA.

Franco, A.M., D. Filson. 2006. Spin-outs: knowledge diffusion through employee mobility. *RAND Journal of Economics* **37**(4) 841-860.

Grant, R.M. 1996. Toward A Knowledge-Base Theory Of The Firm. *Strategic Management Journal* **17** 109-122.

Hall, B.H., Jaffe, A.B., M. Trajtenberg. 2001. The NBER patent citation data file: lessons, insights and methodological tools. NBER working paper no. 8498.

Hannan, M.T., J. Freeman. 1987. The Ecology Of Organizational Foundings: American Labor Unions, 1836-1985. *American Journal Of Sociology* **92** 910-943.

Hausman J., Hall B., Z. Griliches. 1984. Econometric Models For Count Data With An Application To The Patents–R&D Relationship. *Econometrica* **52** 909-938.

Klepper, S., P. Thompson. 2007. Spin-offs in high-tech industries: motives and consequences. F. Malerba, S. Brusoni, eds. *Perspectives on Innovation*. Cambridge University Press, Cambridge.

Klepper, S., S. Sleeper. 2005. Entry by spinoffs. *Management Science* **51**(8) 1291-1306.

Kogut B., U. Zander. 1992. Knowledge Of The Firm, Combinative Capabilities, And The Replication Of Technology. *Organization Science* **3**(3) 383–397.

Lai, R., D'Amour, A., L. Fleming. 2009. The careers and co-authorship networks of U.S. patent-holders, since 1975. http://hdl.handle.net/1902.1/12367 UNF:5:daJuoNgCZlcYY8RqU+/j2Q== Harvard Business School, Harvard Institute for Quantitative Social Science [Distributor] V3 [Version].

Levin, R.C., Klevorick, A.K., Nelson, R.R., Winter, S.G., Gilbert, R., Z. Griliches. 1987. Appropriating The Returns From Industrial Research And Development: Comments And Discussion. *Brookings Papers On Economic Activity* **3** 783-831.

Levinthal, D.A., J.G. March. 1993. The Myopia of Learning. *Strategic Management Journal* **14** 95-112.

Levitt, B., J.G. March. 1988. Organizational Learning. *Annual Review Of Sociology* **14** 319-340.

March, J.G. 1991. Exploration And Exploitation In Organizational Learning. *Organization Science* **2** 71-87.

McKendrick, D.G., Wade, J.B., J. Jaffe. 2009. A good riddance? Spin-offs and the technological performance of parent firms. *Organization Science* **20**(6) 979-992.

Miller, D.J., Fern, M.J., L.B. Cardinal. 2007. The Use of Knowledge for Technological Innovation within Diversified Firms. *Academy of Management Journal* **50**(2) 308-326.

Moschieri C., J. Mair. 2008. Research on corporate divestitures: A synthesis. *Journal of Management and Organization* **14**(4) 399–422.

Nagarajan A., W. Mitchell. 1998. Evolutionary Diffusion: Internal And External Methods Used To Acquire Encompassing, Complementary, And Incremental Technological Changes In The Lithotripsy Industry. *Strategic Management Journal* **19**(11) 1063–1077.

Nelson, R.R., R.G. Winter. 1982. *An Evolutionary Theory of Economic Change.* Harvard University Press, Cambridge, MA.

Palepu, K. 1985. Diversification Strategy, Profit Performance And The Entropy Measure. *Strategic Management Journal* **6**(3) 239-255.

Phillips, D. 2002. A Genealogical Approach To Organizational Life Chances: The Parent-Progeny Transfer Among Silicon Valley Law Firms, 1946–1996. *Administrative Science Quarterly* **47** 474-506.

Rosenkopf, L., A. Nerkar. 2001. Beyond Local Search: Boundary-Spanning, Exploration, And Impact In The Optical Disc Industry. *Strategic Management Journal* **22**(4) 287-306.

Rosenkopf, L., G. Padula. 2008. Investigating the microstructure of network evolution: Alliance formation in the mobile communications industry. *Organization Science* **19**(5) 669-687.

Rosenkopf, L., P. Almeida. 2003. Overcoming local search through alliances and mobility. *Management Science* **49**(6) 751-766.

Rysman, M., T. Simcoe. 2008. Patents And The Performance Of Voluntary Standard-Setting Organizations. *Management Science* **54**(11) 1920-1934.

Silverman, B.S. (1996). Technological Assets And The Logic Of Corporate Diversification. Phd Dissertation, University Of California At Berkeley, Haas School Of Business.

Singh, J., A. Agrawal. 2011. Recruiting for Ideas: How Firms Exploit the Prior Inventions of New Hires. *Management Science* **57**(1) 129-150.

Stuart, T.E., J.M. Podolny. 1996. Local Search And The Evolution Of Technological Capabilities. *Strategic Management Journal* **S17** 21-38.

Trajtenberg, M. 1990. *Economic Analysis Of Product Innovation: The Case Of CT Scanners*. Harvard University Press: Cambridge, MA.

Valentini, G. *Forthcoming*. Measuring the effect of M&A on patenting quantity and quality. *Strategic Management Journal*.

Von Hippel, E. 1998. Economics Of Product Development By Users: The Impact Of ‘Sticky’ Local Information. *Management Science* **44**(5) 629-644.

Wezel, F.C., Cattani, G., J.M. Pennings. 2006. Competitive Implications of Interfirm Mobility. *Organization Science* **17**(6) 691-709.

Wooldridge, J.M. 1999. Distribution-free estimation of some non-linear panel data models. *Journal of Econometrics* **90**(1) 77-97.

Zollo, M., H. Singh. 2004. Deliberate Learning in Corporate Acquisitions: Post-Acquisition Strategies and Integration Capability in U.S. Bank Mergers. *Strategic Management Journal* **25** 1233-1256.

TABLE 15. Descriptive statistics and correlations[a]

	Variable	Mean	SD	Min	Max	y	x1	x2	x3	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12	c13	c14
y	*Innovation Impact* $_{(t)}$	1480.22	2727.85	0	17,955																		
x1	*High-tech Spin-outs* $_{(t-1)}$	0.12	0.45	0	4	.05																	
x2	*Low-tech Spin-outs* $_{(t-1)}$	0.05	0.27	0	3	.12	.23																
x3	*Citations to Spin-outs* $_{(t)}$	0.36	2.04	0	31	.12	.13	.17															
c1	*Self Cites* $_{(t)}$	172.11	334.53	0	2,038	.47	.15	.18	.46														
c2	*Other Cites* $_{(t)}$	1291.54	2265.91	0	16,815	.60	.12	.15	.20	.83													
c3	*Spin-out Equity* $_{(t-1)}$	0.55	1.44	0	12.59	.05	.34	.41	.38	.25	.10												
c4	*Spin-out absolute knowledge* $_{(t-1)}$	236.26	1238.89	0	17,297	.01	.11	.11	.72	.44	.12	.37											
c5	*Knowledge relatedness* $_{(t-1)}$	0.12	1.34	0	33.4	.00	.06	.00	.12	.08	.09	.09	.01										
c6	*Spin-out reintegration* $_{(t-1)}$	0.01	0.28	0	8	.00	.02	.05	.13	.06	.01	.34	.11	.00									
c7	*Foreign Spin-outs* $_{(t-1)}$	0.51	1.52	0	12	.21	.36	.44	.44	.38	.24	.62	.40	.07	.11								
c8	*AssignmentsIn* $_{(t-1)}$	0.10	1.01	0	21	-.03	.00	.01	.11	.09	.04	.29	.14	.03	.32	.10							
c9	*AssignmentsOut* $_{(t-1)}$	2.55	33.87	0	859	-.01	.08	.00	.02	.04	.03	.03	.06	.02	.00	.03	.01						
c10	*Patents* $_{(t)}$	213.53	376.07	0	2,964	.68	.13	.14	.19	.78	.95	.11	.13	.09	.02	.24	.04	.03					
c11	*Firm diversification* $_{(t-1)}$	1.62	1.00	0	4.86	.23	.05	.03	.06	.31	.34	-.08	.03	.01	.00	.08	-.01	-.01	.31				
c12	*Ln(R&D expenditure)* $_{(t-1)}$ [b]	6.19	1.94	0.54	12.85	.32	.12	.08	.06	.33	.42	.12	.09	.07	.00	.12	.05	.07	.45	.12			
c13	*American parent firm*	0.66	0.47	0	1	.08	-.02	.00	.10	.11	.03	.03	.07	.02	.05	.18	.05	.03	.01	.14	-.24		
c14	*European parent firm*	0.33	0.47	0	1	-.17	.06	.03	-.09	-.18	-.18	-.07	-.07	.03	-.05	-.12	-.06	-.04	-.17	-.12	.13	-.57	
c15	*Japanese parent firm*	0.14	0.34	0	1	.35	.00	-.02	-.04	.19	.33	.08	-.02	.03	-.01	-.05	.05	.02	.42	.07	.38	-.30	-.29

[a] N = 1,217. All correlation above |.05| are significant at $p < .05$

[b] N = 1,083.

TABLE 16. Panel regressions on innovation impact (DV: Forward citations)[a]

Independent variables	*Neg. Bin. Fixed effects[b]*	*Neg. Bin. Fixed effects[b]*	*Neg. Bin. Fixed effects[b]*	*Neg. Bin. Random effects[c]*	*Poisson QML Fixed effects[d]*	*Poisson QML Fixed effects[d]*	*GEE Neg.Bin. Presample[e]*
	(0)	(1)	(2)	(3)	(4)	(5)	(6)
Spin-out events							
High-tech Spin-outs$_{(t-1)}$		-0.105*	-0.0982*	-0.0913*	-0.0732**	-0.0872**	-0.136*
		(.053)	(.038)	(.036)	(.027)	(.028)	(.061)
Low-tech Spin-outs$_{(t-1)}$		0.0591	0.129	0.140*	0.0339	0.0849*	-0.0943
		(.086)	(.069)	(.066)	(.033)	(.037)	(.112)
Use of spin-out knowledge							
Citations to Spin-outs$_{(t)}$		0.0322[+]	0.0332**	0.0329***	0.0300**	0.0230**	0.0475*
		(.016)	(.010)	(.010)	(.009)	(.007)	(.019)
Controls							
Self Cites$_{(t)}$	-0.0004**	-0.0004**	-0.0001	-0.0001	-0.0006*	-0.0004*	-0.0005*
	(.000)	(.000)	(0.000)	(.000)	(.000)	(.000)	(0.000)
Other Cites$_{(t)}$	0.0000*	0.0000*	0.0000**	0.0000**	0.0001	0.0000	0.0001**
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Spin-out Equity$_{(t-1)}$	-0.0867**	-0.0820**	-0.0358	-0.0342	0.0130	0.0387	0.0763*
	(.028)	(.029)	(.024)	(.023)	(.045)	(.039)	(.033)
Spin-out Absolute kn.$_{(t-1)}$	0.0000*	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Knowledge Relatedness$_{(t-1)}$	0.0152	0.017	0.0185	0.0185	0.0056	0.0119	0.0013
	(.012)	(.012)	(.010)	(.009)	(.007)	(.007)	(.018)
AssignmentsIn$_{(t-1)}$	0.0038	-0.0001	-0.0043	-0.0034	0.0279	0.0216	0.0325
	(.025)	(.026)	(.021)	(.020)	(.031)	(.019)	(.026)
AssignmentsOut$_{(t-1)}$	0.0007	0.0010	0.0004	0.0004	0.0017***	0.0018***	0.0011
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.001)
Firm Patents$_{(t)}$	0.0009***	0.0010***	0.0004***	0.0004***	0.0006	0.0006	0.0008**
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Firm Diversification$_{(t-1)}$	0.314***	0.318***	0.198***	0.209***	0.151**	0.0563	0.169***
	(.029)	(.029)	(.028)	(.027)	(.058)	(.048)	(.045)
N. of Spin-outs Reintegrated$_{(t-1)}$	0.199	0.175	0.103	0.0911	-0.0199	-0.0198	-0.0246
	(.106)	(.110)	(.102)	(.099)	(.059)	(.053)	(.092)
Foreign Spin-outs$_{(t-1)}$	0.0834***	0.0849***	0.0420*	0.0434*	0.0065	0.0045	-0.0311
	(.025)	(.026)	(.021)	(.020)	(.039)	(.028)	(.040)
Ln(R&D expenditure)$_{(t-1)}$			0.372***	0.385***		0.526***	0.481***
			(.031)	(.030)		(.082)	(.034)
Presample							0.0000*
							(.000)
American parent firm (23)	0.646***	0.659***	1.086***	1.006***	*(dropped)*	*(dropped)*	-0.0538
	(.170)	(.170)	(.200)	(.186)			(.226)
European parent firm (20)	-0.0797	-0.0761	-0.0726	-0.127	*(dropped)*	*(dropped)*	-0.448*
	(.165)	(.165)	(.187)	(.172)			(.224)
Japanese parent firm (7)	0.686**	0.697**	0.746**	0.728**	*(dropped)*	*(dropped)*	-0.468
	(.225)	(.224)	(.261)	(.243)			(.305)
Primary SIC (2 digits)	*(included)*	*(included)*	*(included)*	*(included)*	*(included)*	*(included)*	*(included)*
Year	*(included)*	*(included)*	*(included)*	*(included)*	*(included)*	*(included)*	*(included)*
Constant	0.118	0.176	-20.71	-25.50			-9.881***
	(.581)	(.584)	(441.7)	(3,327)			(2.985)
Observations	1,217	1,217	1,062	1,083	1,217	1,062	1,048
Number of parent firms	50	50	45	48	50	45	48
Wald chi2	1,837.9***	1,848.8***	2,607.2***	385,64***	607,49***	573,311***	4,274.9***
Degrees of freedom	59	62	62	39	47	47	49
Log Likelihood	- 6,958.91	- 6,954.91	- 6,099.43	- 6,586.37	- 160,191	-105,316.4	

*** p<0.001, ** p<0.01, * p<0.05

(cont'd table 16)
[a] Standard errors in parentheses.
[b] Conditional fixed effects negative binomial regression with standard errors estimated on the observed information matrix.
[c] Random effects negative binomial regression with standard errors estimated on the observed information matrix.
[d] Robust standard errors clustered at firm level.
[e] GEE population-averaged model with standard errors adjusted for clustering at firm level.

FIGURE 8. Distribution of *Citation to Spin-outs* by no. of years after Spin-outs

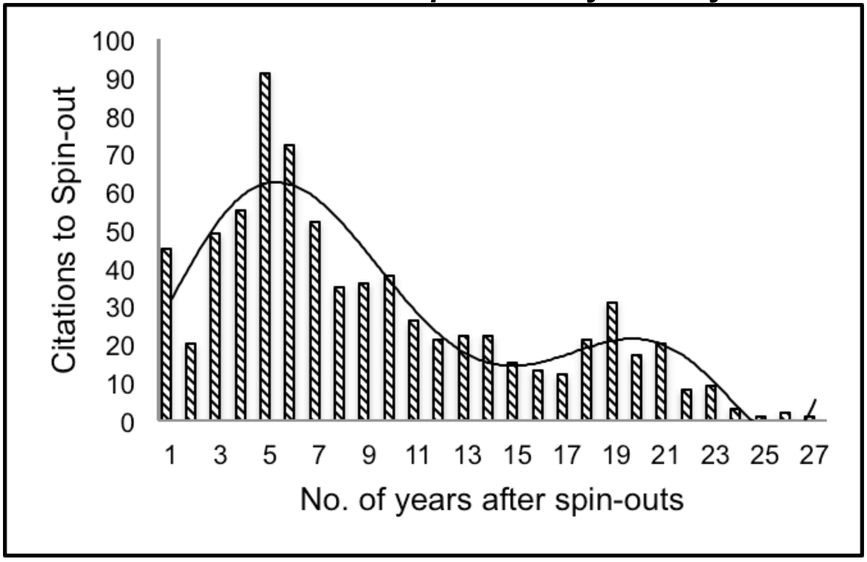
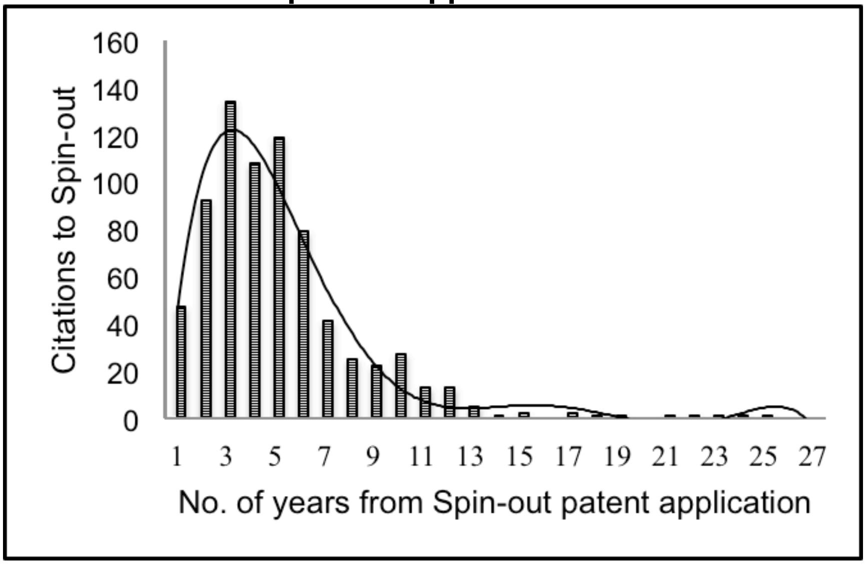


FIGURE 9. Distribution of *Citation to Spin-outs* by no. of years after Spin-outs patents application



5. CONCLUSION

'Rejuvenation, to be sustainable, requires change in structure, strategy, systems, technology and individual behaviour.' (Stopford and Baden-Fuller 1990: 399)

The aim of this dissertation was to show that corporate spin-outs might benefit parent innovation. It argued on an important flipside of corporate spin-outs: that spin-outs are corporate strategies that *(i)* can revitalize inventive behavior of oldtimers by overcoming inertia and producing diverse and unpredictable R&D outcomes, and that *(ii)* subsequent innovation efforts carried out by spin-outs provide technological opportunities to the originating organization.

To highlight these issues, this dissertation tried to address the following research questions: *(1) Do corporate spin-outs enable old-timers to develop explorative strategies? (2) Do corporate spin-outs loose inventor embeddedness in the collaboration network? (3) Do corporate spin-outs benefit the parent organization?*

The first question focused on the effects of inventor mobility to spin-out organizations on inventor behavior. To answer this question, I built on March's (1991) original idea of individual socialization with the organizational code as a driving force of exploitation and thus, ultimately, inertia. Building on the assumption that old-timers (i.e., inventors with a long tenure with the same company) are more socialized than newcomers, in chapter 2 I argued that spin-outs desocialize inventors from the constraints imposed by the organizational code, and that they rejuvenate old-timers explorative efforts.

The second research question shed a light on one of the possible mechanisms that may explain the spin-out effect on inventor behavior. In chapter 3, I built on notion of R&D departments of large corporations as sets of different knowledge communities and I argued that corporate spin-outs ease the generation of across-communities research collaborations and that they neutralize inventor embeddedness in the former collaboration network.

The third research question focused on the parent-level effects of spin-out events and use of spin-out knowledge on parent innovation performance. In chapter 4, I built on organizational learning (e.g., March 1991, Levinthal and March 1993) and the 'absorptive capacity' argument (e.g., Cohen and Levinthal 1989) and I provided evidence that exploration carried out by technological spin-outs may increase returns to learning in the parent corporation, and that learning from spin-outs may be more effective than learning from other firms.

My findings also related to traditional literature on architectural ambidexterity (e.g., Benner and Tushman 2003, O'Reilly and Tushman 2004), which suggests that the adoption of dual structures and strategies may simultaneously allow alignment and adaptability across the organization. By these insights, exploratory innovation should be developed and engineered in structurally independent units, only loosely coupled with the originating organization. Whereas exiting literature describes spin-outs as 'technological exits' (e.g., Chesbrough, 2002) that enable parent firms to align to their environments (e.g., McKendrick et al., 2009), this dissertation shed also a light on spin-outs as strategies that may enable parent adaptability to the future changing environment.

In conclusion, this dissertation enriched literature understanding of corporate spin-outs by making use of important concepts developed by studies on organizational learning. In organizational learning terms (e.g., Levinthal and March 1993), spin-outs provide corporations with the basis for overcoming inertia. By removing old-timers' constraints to high level exploratory innovation, by also enabling research communities to better interact to each other and engage in multi-domain R&D projects, technological spin-outs enrich the pool of knowledge into which the parent organization may search. Doing so, technological spin-outs may increase the parent returns in investing in knowledge related activities and significantly contribute to the rejuvenation of parent innovative efforts.

References

Benner, M., M.L. Tushman. 2003. Exploitation, exploration, and process management: the productivity dilemma revised. *Academy of Management Review* **28**(2) 238-256.

Chesbrough, H.W. 2002. Grateful Exits and Missed Opportunities: Xerox's Management of its Technology Spin-off Organizations. *The Business History Review* 76 803-837.

Cohen, W.M., D.A. Levinthal. 1989. Innovation and Learning: The Two Faces Of R&D. *Economic Journal* **99** 569-590.

Levinthal, D.A., J.G. March. 1993. The Myopia of Learning. *Strategic Management Journal* **14** 95-112.

March, J.G. 1991. Exploration And Exploitation In Organizational Learning. *Organization Science* **2** 71-87.

McKendrick, D.G., Wade, J.B., J. Jaffe. 2009. A good riddance? Spin-offs and the technological performance of parent firms. *Organization Science* **20**(6) 979-992.

O'Reilly, C., M.L. Tushman. 2004. The ambidextrous organization. *Harvard Business Review* **84**(4) 74-81.

Stopford, J.M., C. Baden-Fuller. 1990. Corporate Rejuvenation. *Journal of Management Studies* **27**(4) 399-415.