Organization Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

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Organization Science
Vol. 25, No. 6, November–December 2014, pp. 1764–1784
ISSN 1047-7039 (print) | ISSN 1526-5455 (online)
http://dx.doi.org/10.1287/orsc.2013.0868

The Rejuvenation of Inventors Through Corporate Spinouts

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This article focuses on corporate spinouts as a strategy that can rejuvenate the inventive efforts of inventors with a long tenure in the same company. We rely on an unbalanced panel of 5,604 inventor-year observations to study a matched sample of 431 inventors employed by the Xerox Corporation and find evidence in support of three predictions. First, inventors who join a spinout increase the extent of exploration in their inventive activities. Second, they decrease the extent to which they rely on the parent organization's knowledge. Third, because long-tenured employees, through socialization, tend to progressively adopt more exploitative behavior than short-tenured members, they benefit relatively more from the spinout experience. These results are robust to several econometric specifications that try to account for the endogeneity of the inventors' decision to join the spinout, for the fact that spinouts' inventive activity may be intrinsically different from that of the parent company, and for the possible presence of novel external stimuli for those who join spinouts. The data provide large-sample evidence consistent with the idea that socialization reduces opportunities for organizational learning; we discuss the implications for theory and practice.

Keywords: exploration; exploitation; socialization; corporate entrepreneurship; spinouts
History: Published online in *Articles in Advance* November 8, 2013.

Introduction

Spinouts, or new ventures founded by employees with the support of an originating organization, have become an increasingly common strategic choice for established companies. Programs to sustain spinouts launched by leading organizations include Philips Electronics' new business initiative, Siemens's Technology Accelerator, and Shell's GameChanger program. Most extant literature analyzes these spinouts as mechanisms for dealing with inventions that do not fit the parent organization's core strategy (e.g., Chesbrough 2002, 2003); the parent organization actively invests in and transfers assets to a new, independent organization to exploit market opportunities derived from technologies outside its core focus (Chesbrough 2003, Franco and Filson 2006). Spinouts also allow parent organizations to focus on their core businesses by redirecting strategic resources toward established innovation processes in traditional businesses (McKendrick et al. 2009). Thus we have learned much about spinouts' decisions, antecedents, and consequences from the point of view of the parent company (Campbell et al. 2012); we know little about the effects on the core actors of this process, though, on those who leave the parent organization to set up the spinout.

In this study, we propose that spinout experiences provide new life to explorative efforts undertaken by inventors, building on March's (1991) original idea of socialization as a driving force of exploitation and, ultimately, inertia. Socialization is the process by which members of an organization grow more alike and align with the prevailing organizational code, which hinders their learning. As socialization unfolds, new members accept the organizational codes and beliefs, thus learning slows down (March 1991). This process is a fundamental concern for established organizations that hope to remain innovative and creative.

We tackle this issue in the context of corporate spinout policies by theorizing that joining a spinout provides inventors with opportunities to detach from old organizational codes (i.e., desocialization). These organizational members then unlearn the roles and expectations for "appropriate" behavior ingrained in the parent organization's code, which grants them the chance to explore new ideas. In particular, with a sample of inventors employed by the Xerox Corporation and its spinouts during 1975–2008, we show that those who joined a spinout demonstrated greater exploration in their inventive activity; i.e., they increased their propensity to develop patents of higher technological distance from prior art and in technological domains that are new for the inventor. What makes this finding interesting is that the rational for setting up spinouts is not to explore new technological fields but rather to exploit commercially technologies already developed in the parent organization. We also show that inventors who join a spinout reduced the extent to which they relied on Xerox's organizational knowledge, in contrast with comparable inventors who remained with the parent organization.

Furthermore, the effect of spinouts appears stronger for inventors who experienced greater socialization in the originating organization. Following prior literature (Chao et al. 1994, March 1991), we measure the extent to which inventors were subject to socialization with two complementary proxies. First, we operationalize it according to organizational tenure. Socialization increases with time spent in the organization, as employees learn how the organization works, what is expected from them, and what kinds of support they can expect to receive (Chao et al. 1994, Taormina 1997). In a corporate research and development (R&D) setting, longer tenure tends to reduce the likelihood that inventors contribute to progress in technological fields other than the organization's main fields of expertise; over time, inventors become more exploitative. Second, we operationalize it using an observable outcome—namely, inventors' propensity to patent in the parent company's core technology sectors. We anticipate that a more socialized inventor will tend to develop inventions that fit the firm's central technological interests.

To support our theoretical claims empirically, we consider several alternative mechanisms that may explain greater exploration in spinout organizations. Our results remain robust to several econometric specifications that we use to account for the endogeneity of inventors' decisions to join the spinout, as well as for the intrinsic differences that might mark spinouts' strategies, compared with those of the parent company. If the effects were consequences of strategy (e.g., corporate mandates), we should find no variance across employees with different levels of socialization in the parent organization. We also account for the presence of novel external stimuli that accompany mobility. Compared with the influences of internal mobility (e.g., job change) and external mobility (e.g., moves to other firms), the spinout effect is stronger. Our results therefore are consistent with the idea that spinouts enable detachment from the old organizational code, which helps revamp individual-level innovativeness.

Our study, in turn, extends understanding of how established corporations can reawaken explorative activity among their inventors. We offer detailed theoretical and practical implications from the perspectives of corporate entrepreneurship, technology strategy, and organizational learning.

Background

As they grow, organizations tend to become inert and prefer to exploit old certainties rather than exploring new possibilities. Sorensen and Stuart (2000) show that a larger organization 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. Ahuja and Lampert (2001) also 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.

This process appears driven by mutual positive feedback between experience and competence (Cohen and Levinthal 1990, Levinthal and March 1993). Experience with a given technology leads to greater competence with it. Greater competence with a technology, in turn, fosters increased use, which then again increases experience with the technology. Also, Nystrom and Starbuck (1984) describe how organizational learning leads to inertia, as a result of the process of socialization and the promotion of conformity with prescribed roles. However, the relationship between experience and learning is a nuanced one. For example, Dokko et al. (2009, p. 52) find evidence that "the effects of prior related experience on task-relevant knowledge and skill in the current firm diminish the longer a person is employed at the current firm."

March (1991) proposes a model to formalize these intuitions, in which firms consist of an "organizational code" that represents their beliefs about reality. Individual members modify their own beliefs through their socialization by adapting to this code. The organizational code also could adapt to the beliefs of members that offer a better representation of reality. In this learning process, individual beliefs affect other members not directly but rather through their influence on the organizational code. Improved knowledge results when the code mimics the beliefs of individuals and then other individuals mimic the code. This process implies that, over time, individual members become more homogeneous in their knowledge, and eventually, equilibrium occurs such that all members and the code reflect the same (though not necessarily accurate) beliefs about reality. The resulting stable interactions allow colleagues to converge in their understanding and experiences (March 1991), but they also increase groupthink and reduce openness to external ideas (Katz and Allen 1982).

According to March (1991), socialization is the process by which people learn from the organizational code. It reduces diversity in individual beliefs and thereby decreases the efficiency of organizational learning (Fang et al. 2010), because members come to rely on stable, repetitive, socially accepted routines (Nelson and Winter 1982). Highly socialized members, in particular, are likely to build new knowledge only within the organization's existing fields of expertise. This process is not without benefits. The organization gains cohesion, and members may benefit from socialization; applied psychology research (Feldman 1981, Louis 1980, Schein 1968) indicates a positive link between socialization and individual career progress, job satisfaction, and salary levels (Ashforth et al. 2007, Feldman 1989). Despite these short-term benefits of socialization, only organizations that balance exploration with exploitation will succeed in the long run (Benner and Tushman 2003, He and Wong 2004). Accordingly, socialization-induced inertia becomes a problem to overcome.

March (1991) notes the potential utility of maintaining some variety in the organization, perhaps through personnel turnover. Turnover introduces less socialized people into the firm, increases exploration, and improves aggregate knowledge. The resultant gains come from diversity, not necessarily superior capabilities. Rosenkopf and Almeida (2003) also show that mobility is associated with interfirm knowledge flows, which might support the exploration of technologically distant knowledge (Song et al. 2003). Another source for diverse inputs is open innovation (Chesbrough 2003, 2006), which helps established organizations maintain and enhance their connections to external environments, obtain different knowledge, and use it to generate new ideas. The idea that such external knowledge helps firms avoid inertial forces is well established. Stuart and Podolny (1996) trace the technological trajectory of the 10 largest Japanese semiconductor producers between 1982 and 1992 and show that only Matsushita was able to reposition itself technologically; by moving away from local searches and engaging in extensive alliances with other firms, Matsushita then had access to different technologies. Rosenkopf and Nerkar (2001) also find that inventive efforts that do not span organizational boundaries exert lower effects on subsequent technological evolutions.

Previous literature thus generally has suggested that access to new external stimuli offers the primary solution to excessive socialization, because it can modify and update organizational codes. As Levinthal and March (1993) note, though, such access is only one solution. We focus on another tool available to established organizations. With spinouts, organizational members gain a new context in which they can contribute to the definition of a new organizational code. This process of unlearning the old code and defining a new one is prominent when workers change employers (Ashforth et al. 2007), because a novel environment motivates people to learn new things and embrace change (Lewin 1951). Combining research in organizational learning and applied psychology, we argue that spinouts generate such desocialization, which enables inventors to revamp their explorative activities.

From the Spinout Decision to Exploration

Previous literature uses "spin-off" and "spinout" mostly as synonyms. For example, Agarwal et al. (2004) define spinouts 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 (Klepper and Thompson 2007, McKendrick et al. 2009). Still other research (Chesbrough 2002, 2003) refers to either spinouts or technology spin-offs as modes of entry into product markets that are new to the parent organization. For the purposes of this study, and following Chesbrough (2003), we define corporate *spinouts* 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 spinouts from spin-offs. First, the parent organization voluntarily creates corporate spinouts. Second, it invests equity in, stipulates exclusive agreements with, and transfers assets to this spinout company for the purpose of exploiting untapped technology into new product markets. The spinout is thus part of the parent organization—whether a subsidiary or a partner that employs the parent's employees—that the parent eventually may decide to reintegrate or sell.

If they join the spinout, employees change their formal affiliation (Hoisl 2007), though they do not necessarily engage in *geographic* mobility. However, spinouts generally are associated with some mobility event, which can have varying effects on active agents. In studies of interfirm mobility (Groysberg et al. 2008, Huckman and Pisano 2006), knowledge workers appear to experience performance decrements after moving to new organizations because they cannot transfer their human capital easily across firms. Groysberg et al. (2008) argue that high-performing employees rely on intangible, firm-specific, critical knowledge, which comes from the "collective mind" of shared objectives, mutual accountability, and group norms among teams of colleagues (Weick and Roberts 1993). Mobility events are disruptive transitions that challenge people to adjust to unfamiliar organizational settings (Louis 1980). Therefore, the difficulties of transferring human capital through mobility events may account for the variability in individual performance.

Such studies tend to focus on work environments in which efficiency and efficacy are of paramount importance, rather than creativity (e.g., cardiac surgery in Huckman and Pisano 2006). Research into inventors' mobility depicts a different picture. Turnover and mobility often introduce variety into organizations (Almeida and Kogut 1999, Miller et al. 2006, Rosenkopf and Almeida 2003); Trajtenberg (2005) shows that, on average, mobile inventors are more likely to produce highly cited inventions and patents with greater economic value. 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, possibly because of the contacts they gain with different sources of knowledge.

For this study, our key claim is that spinouts enhance explorative behaviors—i.e., the extent to which inventions are of higher technological distance from prior art in technological domains that are new for the inventor—through an additional, compelling mechanism. Not only do they allow inventors to connect with different information, but, consistent with March's (1991) original argument, they also desocialize organizational members from an environment that provides few nonredundant stimuli.

Consistent with extant research in social psychology and social learning theory (e.g., Ashforth et al. 2007), we theorize that spinouts detach inventors from an old organizational code and allow for the construction of a new one. Anecdotal evidence supports the idea that corporate spinouts offer a new, unique socialization environment in which no stable rules have emerged yet, so people participate actively to build new organizational codes. Noting the organizational differences between the Xerox Corporation and one of its spinouts, Inxight, Chesbrough (1998a, p. 3) states that

> One of the biggest surprises is how different the cultures within the spinouts are from the typical Xerox culture. In the Xerox culture, managers invest significant time "managing up"—so that senior managers may spend a day or two every week in Stamford, making sure they get "face time," so that top management knows what they are doing. In these [spinouts], the culture is to set up the charter and ground rules, and then avoid the internal hierarchy as much as possible.

The spinout thus can prompt organizational members to unlearn roles and expectations of appropriate behavior (Chao et al. 1994, Starr and Fondas 1992), which grants them the opportunity to experiment with new knowledge. Tsang and Zahra (2008) also suggest that episodic organizational change triggers unlearning of prior norms and restructuring of established routines, and more generally, social learning theory (Bandura 1977) provides strong foundations for our main argument.

March's (1991) model suggests that people's level of experimentation with new knowledge decreases with their socialization in organizations, consistent with vast research in organization behavior and applied psychology (Taormina 1997). As employees adjust to their roles, they increase their psychological commitment to established routines, standards, norms, attitudes, and values (Pfeffer 1983). Batel and Jackson (1989) show that this commitment reduces the innovativeness of tenured workers, because over time they adapt to the organizational code, and their contributions to knowledge-generating activities decline. The theory underlying this argument is not knowledge obsolescence; organizations may refresh their knowledge, perhaps through new hires. But the contributions these new hires make to the code becomes marginal, because they are subject to socialization tactics designed to help them integrate into the organization (Jokisaari and Nurmi 2009). Once organizational members' beliefs come to align with organizational beliefs, as embodied in the code, there is no endogenous mechanism for learning, nor are there any deviant behaviors from which tenured members might learn (Markova and Folger 2012).

Job mobility instead helps employees break from socialization with the organizational code by requiring them to give up familiar and stable work patterns in favor of new ones (Katz 1981). As Schein (1968, p. 4, reported in Ashforth et al. 2007, p. 2) notes, interorganizational mobility can generate upending experiences, those "deliberately planned or accidently created circumstances which dramatically and unequivocally upset or disconfirm some of the major assumptions which the new man holds about himself, his company, or his job." When joining a spinout, the extreme experience can provide a challenging new context that is specifically useful to incumbents who are forced to challenge their assumptions and learn (and define) new ways of working and collaborating. On this basis, we offer the following hypothesis.

Hypothesis 1 (H1). *A spinout increases the extent of exploration by inventors who join it.*

Spinouts exert effects on not only the output of the inventive process but also the knowledge-generating process, as manifested in employees' knowledge searching behavior. With our interest in understanding the innovative outcomes of spinout decisions, we need to specify the sources of knowledge that inventors use to develop their ideas. The invention process is cumulative, such that inventors build on prior knowledge to develop new forms, as is often conceptualized as recombinant searches (Basalla 1988, Fleming 2001). This conceptualization has profound roots in prior literature and R&D practice (Fleming and Sorenson 2004, Nelson and Winter 1982). Inventors recombine pieces of knowledge from different sources. According to March's (1991) theory, the more a member is socialized, the more he or she relies on knowledge located in the immediate surroundings. Sorensen and Stuart (2000) also show that as firms grow old and establish long-standing routines, they become gradually insulated from external technological developments and are more likely to exploit established innovative domains within existing technological areas, rather than refining their areas of innovation. Applied psychology and organizational behavior literature also notes the functions of role models, such as providing inputs, suggestions, and limits on the activities of more junior organizational members (Louis 1980). When joining a brand new organization, members lack role models to imitate, so they expand their searches for ideas and advice. Starr and Fondas (1992, p. 71) also posit that in this context, entrepreneurs "must respond and adapt to not one, but several incumbents representing multiple organizational contexts." Thus, if joining a spinout helps inventors break their attachment to the old organizational code and its social and professional relations, those inventors should rely less on the former parent organization's knowledge. Thus we offer the following hypothesis.

Hypothesis 2 (H2). *A spinout decreases the extent to which inventors who join it rely on the parent company's knowledge in their inventive activities.*

We have suggested that the effect of spinouts on the content of innovation (H1) and search behavior (H2) occurs because members unlearn the parent's organizational code (desocialization). Joining a spinout also may rejuvenate inventors through different mechanisms, such as those associated with the mobility event (e.g., incentives, corporate mandates). These other potential causes should affect all inventors that join the spinout equally. In contrast, if the socialization mechanism that we propose is more influential, we should observe variance across inventors. We predict that as inventors become more socialized, they progressively adopt more exploitative behavior and rely on established organizational knowledge and norms, whereas spinouts reset the code. Therefore, our argument implies that the upending experience of joining a spinout will be particularly rewarding for inventors who are socialized into the organization and thus somewhat constrained by the code, whereas those with only low socialization have less to gain from desocialization in terms of explorative behavior. This prediction is consistent with March's (1991) discussion of the differential performance of slow and fast learners: the former contribute more to the code, but the latter benefit from it. Similarly, applied psychology and organizational behavior research argues that veterans are harder to resocialize and need extreme shocks to change their established ways of doing things (Feldman 1989). For employees who work in rapidly changing, creative environments, these effects may be particularly dysfunctional (Katz 1981). If desocialization explains heightened exploration by inventors, spinouts should be particularly effective for highly socialized inventors, for whom the effects of unlearning the prior organizational code will be strongest. We therefore argue the following hypotheses.

Hypothesis 3A (H3A). *The positive effect of spinouts on inventors' extent of exploration is stronger for highly socialized than for less socialized inventors.*

Hypothesis 3B (H3B). *The negative effect of spinouts on the extent to which inventors rely on the parent company's knowledge is stronger for highly socialized than for less socialized inventors.*

Methods

Data

We seek to establish the effect of spinouts on inventors' behavior. In particular, we contend that participating in spinouts increases inventors' extent of exploration (H1) and decreases the extent to which inventors build on the parent firm's knowledge (H2), and that these effects are stronger for highly socialized inventors (H3). To test these hypotheses, we use data pertaining to the patenting activities of a sample of inventors employed by the Xerox Corporation and its spinouts over the period from 1975 to 2008. Xerox is a highly innovative company that provides researchers with an enormously fertile study environment (Gompers et al. 2005). It is also an important example of an organization associated with a closed innovation mind-set, including an inwardly focused approach to organizing R&D and knowledge production activities (Chesbrough 2006), that has had trouble responding to radical changes that might cannibalize established organizational processes (Gompers et al. 2005). Moreover, Xerox is well known for having generated many spinouts in the past 35 years. Although Xerox has been widely discussed (e.g., Chesbrough 2002, 2003), most prior studies consider either the constraints on the company's efforts to commercialize new technologies or the financial performance of its spinouts. It represents an ideal empirical setting for testing our theoretical questions. Focusing on Xerox facilitates the collection of reliable data about its spinouts, but by focusing on one firm, we can automatically control for unobserved confounding factors at the parent level. This choice is also coherent with our theoretical framing: we are interested in understanding the extent to which desocialization from 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 that we attempt to substantiate relates to the extent of socialization and ensuing lack of diversity (March 1991). We do not test for the outcomes of different organizational codes (i.e., more innovative versus more conservative), so it is meaningful to compare a sample of spunout inventors with a sample of inventors who stayed with the original company.

To determine the effect of desocialization, we need to consider spinout events as distinct from spin-off events. In the latter case, members might never have fit with the code of the parent company. A spin-off could represent an event in which an unsocialized inventor abandons the parent to explore areas of his or her own interest. In contrast, spinouts are generated through discussions with the parent organization and powerfully signal the inventor's integration into the organizational code.

To determine unique spinout effects, we rely on patent statistics. Empirically speaking, in computer and office equipment industries, 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). Thus, they provide a valid indicator of technological performance. As we explain subsequently, our measures of the extent of inventors' exploration and the extent to which inventors build on the parent firm's originating knowledge are based on similar patent statistics.

We gathered information about spinouts (e.g., founding event, declared strategy, governance) from several sources, including academic papers (Chesbrough 2003, Chesbrough and Rosenbloom 2002), teaching case studies (Chesbrough 1998a, b), and news releases (e.g., Xerox press releases, spinout press releases, news from Factiva). We identify corporate spinouts according to four complementary criteria (Chesbrough 2002): (1) a Xerox employee, unit, or division departs the parent organization with Xerox's permission to launch a new incorporated organization; (2) the organization is voluntarily released by Xerox to exploit Xerox's proprietary, untapped technology by entering a new product market with it; (3) the spunout firm employs former Xerox inventors; and (4) Xerox's ownership of the new independent firm varies from 0% (no equity) to 100% (wholly owned) of the spinout's initial capital. In cases of no equity, we looked for agreements about the use of Xerox's proprietary knowledge by spinouts. Twenty-five companies fit these four selection criteria and have received patents[1] from the U.S. Patent and Trademark Office (USPTO).

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 spinout by searching the patent assignees (Almeida and Kogut 1999, Hoisl 2007), then identified those who had patented with Xerox prior to the spinout initiation date. Of the 25 spunout companies, only 8 earned patents that were applied for by former Xerox inventors. Of these companies, five had been successfully disposed by Xerox through initial public offerings or acquisitions after a few years, two had been shut down, and one remained under Xerox's control at the time of this study (PARC). Although our results might not generalize to all of Xerox's spinouts, Chesbrough (2003) reports similar performance and survival rates for Xerox's population of spinouts. The final sample includes 149 inventors who generated or joined a spinout and displayed patenting activities both before and after this spinout event. We refer to this sample as the *treated* group.

Focusing on a sample of inventors employed in corporate spinouts may expose our study to two potential sources of bias. On the one hand, spinouts may be created with a mandate to explore new technological fields. However, evidence from academic (Chesbrough 2002) and popular (Factiva) sources suggests that the spinouts in our sample were mainly created to exploit or commercialize technology that existed and already had been patented by Xerox. In other words, further exploration in new technological domains was not explicitly included as a core objective for these spinouts. For example, Xerox PARC was spun out in 2002, a period of financial crisis for Xerox. In the process, Xerox set its Innovation Group to screen internal, untapped research and technologies to find a quick way to market (Ramgopal and Mathew 2006). Similar tactics applied to the other spinouts (Chesbrough 1998a, b).

Next, we cannot assume random assignments of inventors to spinouts. We cope with the endogeneity in the spinout decision by building an untreated sample of Xerox inventors who did *not* move to a spinout and stayed with the Xerox Corporation for the entire time period of this study. This sample consisted of 282 inventors who (1) copatented with the inventors who moved to a spinout, (2) displayed similar pre-spinout outputs (matched on a set of relevant pretreatment variables), and (3) continued patenting with the parent organization after spinout events. The inventors in this control group patented with inventors in the treated group, prior to the spinout, on 17.36% of the total patents. All inventors in both groups were observed every year, from their first year in Xerox to either their last observed year in a spinout (treated) or their last observed year in Xerox (control). By merging the treated and control groups, we obtained an unbalanced panel data set with 5,604 inventor-year observations.

Measures and Statistical Approach

Dependent Variables. Our first dependent variable is the *extent of exploration* by inventor i in year t, measured as the number of claims contained in patents applied for by inventor i in year t that belong to a new patent class (i.e., in which the inventor has never patented before). If there are multiple classes, following Benner and Waldfogel (2008), we refer to the first class listed in the patent document.[2] 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 his or her personal prior experience, as well as to the external world. The patent classes established by the USPTO identify the technological areas to which the knowledge encompassed in the patent belongs. Patenting in a new class is a common measure of exploration (e.g., Banerjee and Campbell 2009, Fleming 2002). However, patent claims seek to differentiate the invention from prior art in the same technological field. The number of claims thus defines the 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).

Our second dependent variable, *share of citations to Xerox*, relates to the extent to which inventors rely on parent organization knowledge for their inventive activities. We measure it as the proportion of citations to prior patents assigned to Xerox contained in the patents each inventor applies for in any given year. Citations represent instances of the use of the cited firm's knowledge (Correidoira and Rosenkopf 2009), so we used the proportion of the focal inventor's citations to Xerox's patents divided by the total number of backward citations as a proxy for the extent to which he or she builds on the originating parent's organizational knowledge.

Independent Variables. Our main independent variable, *spinout*, captures inventors' affiliation at any moment in time. Specifically, it takes a value of 1 if the patents awarded to inventor i at time t are assigned to a spinout and 0 otherwise. In our sample, 3,015 patents were awarded to Xerox inventors who moved to a spinout, and 802 of them relate to the period in which inventors were affiliated with a spinout.

To test our theory, we also needed to measure the extent to which individuals were subject to socialization in the Xerox Corporation. Socialization is a complex construct with different content areas (Chao et al. 1994, Taormina 1997). Literature has mostly operationalized it using two proxies. First, the extent to which an inventor is socialized relates to his or her tenure in the parent organization. We measured inventor's *tenure* (*in Xerox*) with a "tenure clock" that captures the amount of time, in years, elapsed since the first patent he or she applied for with the parent organization. This clock stops with mobility events and reports a maximum value thereafter. Second, because socialization involves learning a particular content area (Chao et al. 1994) or an organization's core knowledge domain (March 1991), we included a proxy, *experience in Xerox's core technologies*, that captures the extent to which inventors' prior innovations fit with Xerox's core areas. To assess this measure, we followed Song et al. (2003) and Palomeras and Melero (2010) and identified Xerox's core technologies for each year in our panel. A patent falls into its core if the U.S. Patent Classification (USPC) class in which it is granted coincides with some of the most frequent USPCs in Xerox's patent portfolio. Xerox patents are highly dispersed across technological classes, so we adopted an approach similar to the one Palomeras and Melero (2010) recommend and identified core classes as those with a frequency greater than 3% in a five-year moving window (i.e., from $t-5$ to $t-1$). In so doing, we found 12 time-variant core USPC classes per year. Next, for all inventor-year observations, we coded *experience in Xerox's core technologies* as the proportion of patents applied for by inventor i in Xerox's core classes from his or her first year in Xerox up to year $t-1$. Finally, because we use this measure to proxy for the extent of inventor socialization in Xerox, for all inventor-year observations after spinout events, we report the proportion of patents observed in the inventor's last year with Xerox.

Statistical Approach and Control Variables. To test our hypotheses about inventor i's extent of exploration at time t (H1 and H3A), our basic specification estimates the following model:

$$\begin{aligned} &\mathit{Extent\_of\_exploration}_{it} \\ &\quad = f(\mathit{Spinout}_{it}, \mathit{Tenure}_{it}, \mathit{Experience}_{it}, \mathit{Spinout} \\ &\qquad \times \mathit{Tenure}_{it}, \mathit{Spinout} \times \mathit{Experience}_{it}, X_{it}; \beta), \end{aligned} \tag{1}$$

where X is a vector of control variables, and β is a vector of parameters to be estimated. The dependent variable, *extent of exploration*, is a count variable that takes only nonnegative 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.

To test our hypotheses about inventors' proportion of backward citations to the parent company's patents (H2 and H3B), our basic specification estimates the following model:

$$\begin{aligned} &\mathit{Share\_of\_citations\_to\_Xerox}_{it} \\ &\quad = f(\mathit{Spinout}_{it}, \mathit{Tenure}_{it}, \mathit{Experience}_{it}, \mathit{Spinout} \\ &\qquad \times \mathit{Tenure}_{it},\ \mathit{Spinout} \times \mathit{Experience}_{it}, X_{it}; \gamma), \end{aligned} \tag{2}$$

where X is a vector of control variables, and γ is a vector of parameters to be estimated. The dependent variable, *share of citations to Xerox*, is a fractional response variable by construction that takes values between 0 and 1. Accordingly, we use a fractional probit model (Papke and Wooldridge 2008).

In these analyses, we control for several variables that might influence inventors' patenting behavior. Previous literature (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 backgrounds. We therefore include several covariates suggested by prior research: *knowledge generality* (dispersion of an inventor's prior patenting activity across different technological fields), *no patents* (count of consecutive, unproductive years by inventor), *patents per year* (number of patents applied every year), *total patents* (total number of patents applied prior to year t), *backward citations* (number of citations to prior patents), *solo patents* (proportion of patents for which inventor i is the sole inventor in year t), and *team size* (mean number of inventors listed on patents awarded to inventor i at year t).

A potential mechanism explaining our results is the inventor's experience in dealing with risky technologies. Accordingly, we control for technological risk associated with inventor's prior patenting experience. We proceeded as follows. First, for each year and USPC class we observe in our data, we computed the variance of forward citations received by all USPTO patents applied for in the given class and year. This captures the extent to which the economic value of patents in the class varies in a given year (e.g., Gambardella et al. 2008). Next, for each patent in our sample, we reported the variance associated with its USPC/year. Finally, for each inventor-year observation in our panel, we coded *experience with risky technologies* as the sum of the variances thereby reported in all inventor's patents applied prior to year t. High values of this variable indicate that the inventor had previously patented in technological classes associated with uncertain economic returns.

Another potential mechanism involves the mere effects of job mobility on an inventor's patenting behavior. Inventors' desocialization from the parent's organizational code might result from hiring outsiders and allocating new staff to spinout organizations. Accordingly, to isolate the spinout effect, we include two controls in the inventors' collaboration environment (Almeida and Kogut 1999, Song et al. 2003): (1) *newcomers* (the proportion of inventors new to inventor i's organization within a time window of two years) and (2) *new coinventors* (extent to which inventor i copatents in year t with someone with whom he or she has never copatented before). Because knowledge exploration activities in spinouts also may relate to individual incentives, we included *inventor's ownership* (percentage of employee's initial ownership in the spinout) and *spinout CEO* (dummy for whether inventor i is a founder or chief executive officer (CEO) of the spinout).

Then, because not all spinouts are the same, we included additional controls. First, *spinout program* reports whether the inventor had ever been exposed to Xerox's incubation program, designed to establish the feasibility of a product market strategy (Chesbrough 2002, 2003). Second, the *Xerox ownership* levels in the spinouts may relate to its control and emphasis on transferring knowledge. Third, integrating Chesbrough's (2003) typology, we included a set of governance-type dummy variables to account for different management approaches to spinouts: (1) laissez-faire (i.e., indicating Xerox's inexperience in creating spinouts), (2) ad hoc (i.e., spinouts as diversification initiatives), (3) Xerox Technology Ventures (i.e., reorganizations to capitalize on Xerox's promising technologies), or (4) Xerox New Enterprises (i.e., no Xerox commitment to subsequent technology development). To these categories we added two typologies for spinouts released as either (5) joint ventures or (6) prior divisions. To control for spinouts' ability to revise the organizational code, we also accounted for their *geographical distance* (miles) from the parent unit's headquarters.

Finally, we included inventor fixed effects and firm and year dummies. Table 1 contains a description of all the variables. In Table 2, we provide the summary

Table 1 Description of Main Variables

Variable	Measure
Extent of exploration	$\sum$ (no. of claims in patent k | patent k is assigned to an USPC class new to inventor i's prior records) for all patents k applied for in year t
Share of citations to Xerox	Percentage of backward citations made by inventor i in year t to prior Xerox's patents
Spinout	Dummy for inventor i's affiliation with a spinout in year t
Experience in Xerox's core technologies	(*share of* all patents k applied by inventor i prior to year t in Xerox's core USPC classes | spinout = 0); (*share of* all patents k applied in Xerox's core USPC classes before mobility to spinout | spinout = 1)
Tenure	(Tenure clock in Xerox at year t | spinout = 0); (max prior tenure clock in Xerox | spinout = 1)
Knowledge generality	Complement to 1 of Herfindahl index of distribution of inventor i's prior patents across USPCs
Experience with risky technologies	For all patents k applied by inventor i prior to year t, $\sum_t \sum_{kj}$ [var(forward citations received by all USPTO patents $\in$ USPC j by year) | patent k obtained by inventor i at time $t \in$ USPC j)
No patents	No. of consecutive years (including year t) with no patents applied by inventor i
Patents per year	$\sum$ all patents k applied by inventor i in year t
Total patents	$\sum$ all patents k applied by inventor i prior year t
Backward citations	$\sum$ all citations made by inventor i in year t to prior USPTO patents
Solo patents	Percentage of patents awarded to inventor i in year t and for which inventor i is the sole inventor
Team size	*Mean* (no. of inventors in patents k by inventor i at year t)
Newcomers (two years)	Percentage of new inventors observed in ($t-1$, t) in inventor i's focal firm (either Xerox or a spinout)
New coinventors	Dummy for inventor i copatenting in year t with at least one inventor new to i's prior record
Inventor's ownership	(Percentage of of spinout j shares owned by employees | spinout = 1); (0 | spinout = 0)
Spinout CEO	Dummy for inventor i as founder or CEO of a spinout
Spinout program	Dummy for spinout j by inventor i incubated by Xerox in the pre-spinout period
Xerox ownership	(Percentage of of shares in spinout j owned by Xerox | spinout = 1); (0 | spinout = 0)
Governance-type dummies	Fixed effects on Xerox's governance type of spinout j: (1) laissez-faire, (2) ad hoc, (3) Xerox Technology Ventures, (4) Xerox New Enterprises, (5) spinout is a joint venture, (6) spinout is a Xerox division
Geographical distance	(Distance in miles between spinout headquarters and its parent unit | spinout = 1); (Distance in miles between inventor i's unit and Xerox's headquarters | spinout = 0)

Table 2 Correlation Matrix and Descriptive Statistics

Variable	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1 *Extent of exploration*	8.500	18.840	0	263																			
2 *Share of citations to Xerox*	0.170	0.250	0	1	0.08																		
3 *Spinout*	0.060	0.230	0	1	0.21	−0.13																	
4 *Experience in Xerox's core technologies*	0.230	0.290	0	1	−0.08	0.14	−0.10																
5 *Tenure*	8.380	6.720	0	31	−0.01	0.17	0.00	0.15															
6 *No patents*	0.720	0.770	0	2	−0.26	−0.44	−0.13	0.08	0.01														
7 *Patents per year*	1.820	2.490	0	21	0.47	0.35	0.13	−0.05	0.09	−0.52													
8 *Total patents*	14.30	19.50	0	157	0.11	0.28	0.16	−0.03	0.53	−0.34	0.46												
9 *Knowledge generality*	0.650	0.360	0	1	0.23	0.09	0.13	−0.07	0.33	−0.13	0.17	0.21											
10 *Experience with risky technologies*	1.030	2.650	0	43.17	−0.03	−0.09	−0.04	0.03	0.01	0.12	−0.08	−0.09	−0.02										
11 *Backward citations*	30.100	83.50	0	1,738	0.29	0.14	0.19	−0.05	0.07	−0.27	0.61	0.29	0.10	−0.04									
12 *Solo patents*	0.300	0.860	0	12	0.16	0.09	−0.02	−0.08	0.07	−0.24	0.37	0.20	0.11	−0.02	0.18								
13 *Team size*	2.410	2.630	0	21	0.30	0.43	0.14	0.00	0.04	−0.55	0.43	0.22	0.13	−0.09	0.32	−0.09							
14 *Newcomers* (two years)	0.170	0.070	0	1	−0.11	−0.17	−0.10	0.00	−0.32	0.16	−0.18	−0.33	−0.22	0.14	−0.17	−0.04	−0.19						
15 *New coinventors*	0.420	0.494	0	1	0.37	0.45	0.11	0.05	0.03	−0.53	0.54	0.21	0.13	−0.07	0.26	−0.01	0.65	−0.13					
16 *Inventor's ownership*	0.007	0.076	0	1	−0.01	−0.04	0.05	−0.04	0.01	−0.00	−0.00	0.03	0.02	−0.01	−0.01	−0.02	−0.02	0.06	0.00				
17 *Spinout CEO*	0.010	0.090	0	1	−0.00	−0.02	0.10	−0.03	−0.02	−0.03	0.05	0.12	0.01	0.05	−0.00	−0.01	−0.00	0.02	0.00	0.07			
18 *Spinout program*	0.030	0.190	0	1	0.01	−0.07	0.12	−0.08	−0.05	−0.01	0.04	0.08	0.01	0.15	−0.02	−0.02	−0.03	0.02	−0.00	0.09	0.22		
19 *Xerox ownership*	0.040	0.180	0	1	0.19	−0.14	0.91	−0.09	0.01	−0.12	0.09	0.13	0.13	−0.04	0.11	−0.03	0.13	−0.06	0.10	0.01	0.03	0.05	
20 *Geographical distance*	604	1,194	0	2,978	0.14	−0.11	0.36	−0.18	−0.12	−0.05	0.03	−0.04	0.09	0.00	0.02	−0.00	0.03	−0.06	0.06	−0.04	−0.05	−0.02	0.38

Notes. $N = 5{,}604$. All correlations above $|0.03|$ are significant at $p < 0.01$.

statistics of the main variables, as well as the pairwise correlations for observations related to both the treated and control groups.

Additional Econometric Analyses. Estimating the effect of spinouts on inventors' extent of exploration and backward citations may be challenging because of the potential endogeneity of the decision to found or join a spinout. This decision is not the outcome of a random assignment process. Spinouts might be generated by the most explorative inventors in the parent organization, and their observed impact may relate to work actually carried out by the inventor when he or she was still employed by the parent. A greater extent of exploration and a lower self-citation rate associated with spinouts might reflect a trend already in place or common unobserved factors, which could lead to biased empirical results. We seek to minimize these potential issues in several ways.

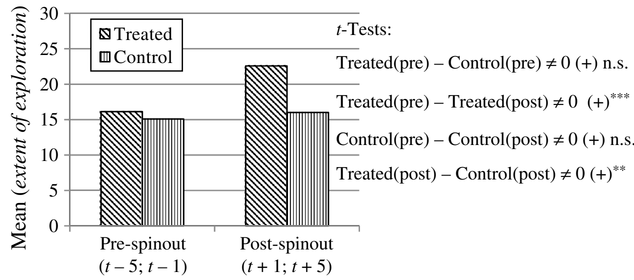
First, because the spinout could be motivated by explorative research carried out in the parent organization prior to the spinout, in some model specifications, we exclude all patents applied for in the first year of the spinout's incorporation. Of the 5,604 total inventor-year observations, 149 relate to inventors' first years in spinouts. By excluding them, we reduced the size of our panel for these models to 5,455. Second, we estimated additional models based on matching estimators (e.g., Imbens 2004) to assess the effect of the spinout event on inventors' extent of exploration (H1) and the proportion of citations to Xerox (H2). Third, we also address potential endogeneity related to H1 and H2 by estimating two-step Heckman (1979) models and weighting sample observations for their propensity score (Hirano et al. 2003).

Results

We have argued that spinouts increase the extent of exploration of inventors who join them (H1) and diminish the extent to which inventors rely on a parent company's knowledge in their inventive activities (H2). Figures 1 and 2 report the average values of the extent of exploration and backward citations for treated and control groups before and after the spinout event; the evidence clearly is consistent with our hypotheses. We therefore discuss the results of additional, more sophisticated empirical analyses that confirm this initial finding.

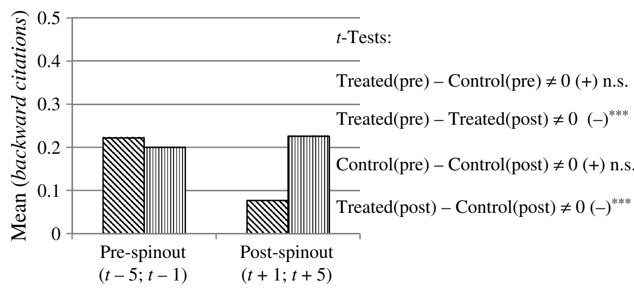
Table 3 contains the models estimating Equation (1), with inventors' extent of exploration as the dependent variable (H1 and H3A). We begin with the baseline model with control variables, then add *spinout*, *tenure*, and *experience in Xerox's core technologies*. The positive and significant parameter estimates for the spinout variable ($p < 0.05$) indicate that spinouts enhance individual efforts in technologies that are new with respect to the individual experience, as well as with respect to the state of the art in that specific technological field. The parameter estimates of spinout are consistently

Figure 1 Difference-in-Differences Between Matched Inventors in Treated and Control Groups: Extent of Exploration



$^{**}p < 0.01$; $^{***}p < 0.001$.

Figure 2 Difference-in-Differences Between Matched Inventors in Treated and Control Groups: Backward Citations



$^{**}p < 0.01$; $^{***}p < 0.001$.

positive and highly significant across different specifications in support of H1.

Columns C–F in Table 3 report the results of the test for the moderating effect of our two proxies for socialization—*tenure* and *experience in Xerox's core*—on the inventor's *extent of exploration* (H3A). We computed the interactions between spinout and the moderating variables by centering the latter on their means; these interaction terms are positive and statistically significant. However, we do not obtain robust results for the interaction between spinout and tenure (column E). Perhaps our measure of organizational tenure, based on patent data, is not precise enough. To ensure the robustness of the H1 and H3A results, column F contains the results when we applied the same model but dropped observations for the first year after a spinout, to exclude the potential effect of projects incubated in Xerox and patented in the very first year of the spinout.

Noting the nonlinearity of our estimation model (1), we follow Cameron and Trivedi (1998) and Hilbe (2011) and interpret the interactions as multiplicative effects or risk ratios. Specifically, we categorized our predictors into quartiles and computed the incidence rate ratios (IRRs) of the interaction of *tenure* with *spinout* with the following formula (Hilbe 2011), using estimates from Table 3, column F:

$$\mathrm{IRR}_{\mathrm{spinout}\times\mathrm{tenure}} = \exp[\beta_{\mathrm{spinout}} + \beta_{\mathrm{spinout}\times\mathrm{tenure}} \cdot (\mathit{Tenure} - \mathrm{Mean}(\mathit{Tenure}))]. \quad (3)$$

Table 3 Negative Binomial Regressions of Spinout on the Extent of Exploration

	Estimation method: Inventor fixed effects negative binomial					
Variable	A[a]	B[a]	C[a]	D[a]	E[a]	F[b]
Independent						
Spinout		1.902*	1.752*	1.737*	1.703*	0.983**
		(0.763)	(0.765)	(0.750)	(0.769)	(0.321)
Experience in Xerox's core technologies		−0.608***	−0.666***		−0.603***	−0.573***
		(0.143)	(0.142)		(0.143)	(0.114)
Tenure		−0.014*		−0.021**	−0.017*	−0.014**
		(0.006)		(0.006)	(0.007)	(0.005)
Spinout × *Experience in Xerox's core technologies*[c]			1.347**		1.270*	1.184*
			(0.481)		(0.497)	(0.477)
Spinout × *Tenure*[c]				0.029*	0.022	0.025†
				(0.014)	(0.014)	(0.014)
Control						
No patents	−0.455***	−0.430***	−0.437***	−0.441***	−0.426***	−0.443***
	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)	(0.055)
Patents per year	0.182***	0.177***	0.181***	0.176***	0.176***	0.179***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)
Total patents	−0.018***	−0.016***	−0.018***	−0.015***	−0.015***	−0.021***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Knowledge generality	2.990***	3.003***	2.975***	3.047***	3.030***	2.566***
	(0.140)	(0.139)	(0.139)	(0.140)	(0.140)	(0.121)
Experience with risky technologies	0.004	0.008	0.004	0.010	0.008	0.015
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.012)
Backward citations	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Solo patents	0.165***	0.162***	0.161***	0.165***	0.162***	0.139***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.018)
Team size	0.098***	0.098***	0.099***	0.098***	0.099***	0.096***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.010)
Newcomers (two years)	−0.783	−0.695	−1.051	−0.931	−1.106	1.233
	(0.845)	(0.845)	(0.846)	(0.852)	(0.849)	(1.179)
New coinventors	1.118***	1.159***	1.155***	1.129***	1.162***	1.103***
	(0.076)	(0.077)	(0.077)	(0.076)	(0.077)	(0.074)
Inventor's ownership	−1.263**	−1.331**	−1.335**	−1.294**	−1.338**	−1.079**
	(0.457)	(0.459)	(0.462)	(0.456)	(0.459)	(0.400)
Spinout CEO	0.007	−0.022	−0.015	−0.014	−0.022	0.310
	(0.386)	(0.385)	(0.384)	(0.386)	(0.384)	(0.276)
Spinout program	0.034	0.025	0.023	0.019	0.012	0.238
	(0.350)	(0.352)	(0.351)	(0.351)	(0.352)	(0.223)
Xerox ownership	0.339	0.190	0.467	0.349	0.472	−0.491
	(0.292)	(0.296)	(0.301)	(0.294)	(0.300)	(0.386)
ln(*Geographical distance*)	−0.091	−0.088	−0.086	−0.095	−0.085	−0.027
	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.028)
Governance-type dummies	Included	Included	Included	Included	Included	Included
Firm dummies	Included	Included	Included	Included	Included	Included
Application year dummies	Included	Included	Included	Included	Included	Included
Constant	−3.851***	−3.950***	−3.918***	−3.964***	−3.999***	−3.976***
	(0.475)	(0.479)	(0.477)	(0.477)	(0.480)	(0.451)
No. of observations	5,604	5,604	5,604	5,604	5,604	5,455[b]
Log likelihood	−7,596	−7,581	−7,580	−7,588	−7,576	−9,281

[a]Standard errors (in parentheses) estimated from the observed information matrix. Inventor fixed effects included.
[b]First year in spinout dropped for 149 treated inventors. Standard errors (in parentheses) estimated from the observed information matrix. Inventor random effects included.
[c]Mean-centered.
†$p < 0.1$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Table 4 Interpretation of Interactions: Risk Ratios for Hypothesis 3A

Spinout × *Tenure*						*Spinout* × *Experience in Xerox's core technologies*					
Tenure	Quartile (%)	IRR	S.E.	95% CI		Experience	Quartile (%)	IRR	S.E.	95% CI	
12	75	2,925	0,161	2,626	4,955	0, 4	75	3,177	0,187	2,972	6,195
7	50	2,581	0,155	2,347	4,316	0, 13	50	2,374	0,164	2,258	4,302
3	25	2,336	0,154	2,128	3,898	0	25	2,035	0,156	1,967	3,629

We adopted the same formula for the interaction between *experience in Xerox's core technologies* and *spinout*. Table 4 reports the ratios, their corrected standard errors, and the confidence intervals (95%) for the quartile values of *tenure* and *experience in Xerox's core technologies*.

The lower bound of all ratios is significantly higher than 1 ($p < 0.05$), so these results confirm the smaller estimates for low levels of tenure and experience in Xerox's core. After joining a spinout, the extent of exploration increases by 2.33 times for inventors with 3 years of tenure in Xerox and by 2.92 times for those with 12 years of tenure. Moreover, the extent of exploration increases by 2.03 times for inventors with no prior patent applied in Xerox's core technologies and by 3.18 times for those who applied at least the 40% of their prior patents in Xerox's core technologies.

In Table 5, we present the results of the Equation (2) model estimation, with the *share of citations to Xerox* as the dependent variable (H2 and H3B). All specifications support a negative and significant effect ($p < 0.001$) of spinout on citations to Xerox; mobility in a spinout context reduces the extent to which inventors build on the parent organization's originating knowledge. Columns C–F in Table 5 provide the results of the test for the moderating effects, which are consistently positive and significant. The nonsignificant direct effect of *tenure* on the *share of citations to Xerox* suggests that our two proxies capture different mechanisms of the socialization construct. In particular, people may socialize at different times or rates, which would produce inconclusive results about the effect of tenure on our process dimension of exploration.

To further test H3A and H3B, we referred to Venkatraman (1989), who posits that subgroup analysis is appropriate for obtaining a better estimation of the different effects of certain strategies across different contexts. Accordingly, we split the samples of treated and control inventors into two sets of subsamples. To define the groups, we considered cutoff values equal to the median values of our two proxies for socialization. That is, we defined long (short)-tenured inventors as those who had been with Xerox for more (less) than seven years. Then, we defined expert (inexpert) inventors as those for whom more (less) than 13% of their prior patents applied to Xerox's core technological classes. For each group, we generated a spinout variable that we used as a regressor in the estimations of models (1) and (2) to replace our spinout and the moderating variables. The results in Table 6 consistently show that the effects of spinout for highly socialized persons (long-tenured or expert) are higher in magnitude than those of less socialized individuals (short-tenured or inexpert). The differences in group coefficients are always statistically significant, in support of H3A and H3B.

Robustness Checks

Endogeneity

To control for the endogeneity of the decision to join the spinout, we used matching estimators to calculate the average effect of joining a spinout on inventors' productivity.[3] Different matching estimators exist; we adopt the one proposed by Abadie et al. (2004). This estimation requires two key decisions: how many comparison units to consider and whether to match with replacement (i.e., are the same control units 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. For this study, we chose to estimate two models with replacement and three comparison units. The results of the estimation, presented in Table 7, support H1 and H2 and are robust to the use of two or four units of comparison.

The composition of our sample makes it difficult to generalize the effect of spinouts (e.g., PARC dominates our sample), so to probe the generalizability of our results, we also include matching estimators for two sets of subsamples in Table 7. First, we distinguish PARC (inventors and controls) from all other spinouts (inventors and controls). Second, we distinguish small and large spinouts, according to the median size in our sample (i.e., 200 employees). The results support the generalization of our claims to a broad range of spinouts; they do not depend on spinout size.

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. Therefore, we computed several additional estimations to test H1 and H2.

Table 5 Fractional Response Regressions of Spinout on Share of Citations to Xerox

	Estimation method: Fractional probit					
Variable	A[a]	B[a]	C[a]	D[a]	E[a]	F[a,b]
Independent						
Spinout		−3.565*** (0.215)	−3.487*** (0.217)	−3.343*** (0.215)	−3.319*** (0.215)	−2.238*** (0.239)
Experience in Xerox's core technologies		0.060*** (0.008)	0.012* (0.005)		0.020** (0.007)	0.035** (0.012)
Tenure		0.014 (0.018)		0.018 (0.016)	0.020 (0.016)	0.024* (0.011)
Spinout × *Experience in Xerox's core technologies*[c]			−0.882*** (0.107)		−0.773*** (0.137)	−0.497** (0.193)
Spinout × *Tenure*[c]				−0.024*** (0.005)	−0.019*** (0.005)	−0.010** (0.004)
Control						
No patents	−0.554*** (0.002)	−0.557*** (0.002)	−0.559*** (0.002)	−0.555*** (0.002)	−0.559*** (0.002)	−0.559*** (0.002)
Patents per year	0.001 (0.001)	0.000 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.000 (0.001)
Total patents	0.001 (0.000)	0.001 (0.000)	0.001 (0.000)	0.001 (0.000)	0.001* (0.000)	0.000* (0.000)
Knowledge generality	0.277*** (0.013)	0.275*** (0.012)	0.274*** (0.014)	0.272*** (0.006)	0.270*** (0.009)	0.270*** (0.007)
Experience with risky technologies	0.000 (0.002)	−0.001 (0.001)	−0.001 (0.001)	−0.000 (0.002)	−0.001 (0.002)	−0.001 (0.001)
Solo patents	0.090*** (0.003)	0.091*** (0.003)	0.091*** (0.003)	0.091*** (0.003)	0.091*** (0.003)	0.090*** (0.002)
Team size	0.074*** (0.002)	0.074*** (0.002)	0.074*** (0.002)	0.074*** (0.002)	0.074*** (0.002)	0.074*** (0.002)
Newcomers (two years)	−0.429 (0.264)	−0.383* (0.164)	−0.070 (0.315)	−0.196 (0.127)	0.084 (0.192)	0.296 (0.476)
New coinventors	0.351*** (0.004)	0.350*** (0.005)	0.350*** (0.004)	0.350*** (0.005)	0.349*** (0.005)	0.352*** (0.005)
Inventor's ownership	−0.421*** (0.006)	−0.427*** (0.007)	−0.422*** (0.006)	−0.425*** (0.008)	−0.426*** (0.008)	−0.430*** (0.007)
Spinout CEO	−0.446*** (0.010)	−0.456*** (0.025)	−0.445*** (0.009)	−0.464*** (0.025)	−0.464*** (0.023)	−0.473*** (0.016)
Spinout program	−0.758*** (0.149)	−0.917** (0.348)	−0.773*** (0.139)	−0.952** (0.343)	−0.985** (0.322)	−1.100*** (0.145)
Xerox ownership	−1.614*** (0.043)	−1.584*** (0.061)	−1.747*** (0.060)	−1.619*** (0.059)	−1.725*** (0.076)	−1.937*** (0.088)
ln(*Geographical distance*)	0.238*** (0.003)	0.274*** (0.049)	0.237*** (0.004)	0.285*** (0.047)	0.289*** (0.046)	0.428*** (0.044)
Governance-type dummies	Included	Included	Included	Included	Included	Included
Firm dummies	Included	Included	Included	Included	Included	Included
Inventor fixed effects	Included	Included	Included	Included	Included	Included
Application year dummies	Included	Included	Included	Included	Included	Included
Constant	−1.707*** (0.002)	−1.505*** (0.237)	−1.673*** (0.002)	−1.443*** (0.215)	−1.393*** (0.203)	−1.358*** (0.140)
No. of observations	5,604	5,604	5,604	5,604	5,604	5,455[b]
Log likelihood	−1,507	−1,506	−1,506	−1,506	−1,506	−1,488

[a]Robust standard errors (in parentheses) are clustered by firm.
[b]First year in spinout dropped for 149 treated inventors.
[c]Mean-centered.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table 6 Subgroup Analysis

	Estimation method			
	Fixed effects negative binomial		Fractional probit	
Independent variable	A	B	C	D
Spinout by long tenured[a]	1.898** (0.742)		−3.532*** (0.215)	
Spinout by short tenured[a]	1.462† (0.767)		−3.103*** (0.216)	
Spinout by expert in Xerox's core technologies[b]		2.119** (0.766)		−3.543*** (0.216)
Spinout by inexpert in Xerox's core technologies[b]		1.205 (0.781)		−3.251*** (0.227)
All other control variables	Included	Included	Included	Included
No. of observations	5,604	5,604	5,604	5,604
Log likelihood	−7,584.31	−7,556.77	−1,505.24	−1,506.28
Null hypotheses:	Signs and significance of coefficient differences:			
β(*Spinout by long tenured*) − β(*Spinout by short tenured*) = 0	(+)$p < 0.01$		(−)$p < 0.001$	
β(*Spinout by expert*) − β(*Spinout by inexpert*) = 0		(+)$p < 0.001$		(−)$p < 0.001$

Note. The dependent variable in columns A and B is *extent of exploration*; in columns C and D, *share of citations to Xerox*. Group dummies (included as controls) are time-variant within clusters (i.e., inventors).

[a]Long (short)-tenured threshold set on the median value of *tenure* (i.e., seven years' tenure).

[b]Expert (inexpert) threshold set on the median value of *experience in Xerox's core technologies* (i.e., 13% of patents in Xerox's core technologies).

†$p < 0.1$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

We started by using two-step Heckman (1979) models. Specifically, we first used a set of instruments in a probit estimation and predicted the likelihood of engaging in a spinout for each inventor-year. Then we used these predictions to create the inverse Mills ratio, which we included as a regressor in our main estimation models to obtain unbiased parameter estimates (Hamilton and Nickerson 2003).

To build our instruments, we considered that founding or joining a spinout may be a risky career choice; as one researcher who left Xerox to become CEO of LiveWorks, one of Xerox's spinouts, noted, "Researchers … were concerned about lifestyle issues, worried, for instance that a spinout couldn't possibly maintain the [parent unit's] work environment … [researchers'] lifestyles would change fairly dramatically" (Chesbrough 1998b, p. 9). We generated two proxies for risk neutrality in the face of such a career change: the number of prior residence changes the inventor had undertaken and the intensity of venture capital (VC) investments in

Table 7 Matching Estimation of Spinout on the Extent of Exploration (Panel A) and Citations to Xerox (Panel B)

Independent variable: *Spinout*	All spinouts	Only PARC	Except PARC	Small[d] spinouts	Large[d] spinouts
Panel A: Dependent variable = Average *extent of exploration* in (t_1, t_5)					
Coefficent[a]	9.173***	8.550***	5.243*	9.298†	9.843***
S.E.[b]	(1.219)	(1.384)	(2.082)	(4.778)	(1.271)
Total no. of matched inventors (treated + control)[c]	431	339	333	309	411
Max no. of matches for each treated individual	3	3	3	3	3
Panel B: Dependent variable = Average *share of citations to Xerox* in (t_1, t_5)					
Coeffient[a]	−0.109***	−0.136***	−0.144***	−0.191***	−0.109***
S.E.[b]	(0.016)	(0.019)	(0.026)	(0.053)	(0.017)
Total no. of matched inventors (treated + control)[c]	431	339	333	309	411
Max no. of matches for each treated individual	3	3	3	3	3

[a]Estimation of sample average treatment effect.

[b]Robust heteroskedasticity-consistent standard errors estimated using three matches across observations of the same treatment level.

[c]Matching variables: Mean *experience in Xerox's core technologies* (t_0), *tenure* (t_0), *years elapsed from first patent* (t_0), *backward citations* (t_{-5}, t_0), *knowledge generality* (t_{-5}, t_0), *solo patents* (t_{-5}, t_0), *patents per year* (t_{-5}, t_0), *total patents* (t_0). *team size* (t_{-5}, t_0), *newcomers* (t_{-5}, t_0), and *new coinventors* (t_{-5}, t_0). Weighting matrix: inverse variance.

[d]Threshold for spinout size is greater than 200 employees. Accordingly, in our sample, four spinouts are coded as small and four as large.

†$p < 0.1$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

the inventor's city (we obtained these latter data from VentureXpert). We then predicted, for each inventor-year observation, the probabilities of joining a spinout using a probit regression on spinout, as we show in column A of Table 8. We then used the results of the probit estimation to construct the inverse Mills ratio and included it as a regressor in our main models (see Table 8, columns C and E). In addition, as Hirano et al. (2003) show that weighting observations for the propensity score (i.e., probability of being subject to treatment) to create some balance between the treated and control units results in a semiparametric efficiency bound, we also used the predicted probabilities from model A to weight each inventor-year observation in columns B and D.[4] All the results we obtain continue to support H1–H3.

Mobility and a New Environment

We argued that inventors who join a spinout increase their explorative activities because of their desocialization from the old organizational code, but they also might do so simply because mobility provides new, diverse inputs and stimuli that our controls did not

Table 8 Robustness Checks: First Stage, Weighted Observations, and Inverse Mills Ratio

	Estimation method				
	Probit (First stage)	FE negative binomial (Second stage)		Fractional probit (Second stage)	
Independent variable	A[a]	B[b]	C	D[b]	E
Spinout		1.826*** (0.482)	1.705* (0.771)	−3.943*** (0.192)	−3.345*** (0.217)
Experience in Xerox's core technologies		−0.567*** (0.096)	−0.608*** (0.144)	0.030** (0.009)	0.020** (0.007)
Tenure		−0.015** (0.005)	−0.017** (0.007)	0.026† (0.014)	0.020 (0.016)
Spinout × *Experience in Xerox's core technologies*[c]		1.287*** (0.358)	1.278* (0.497)	−1.057*** (0.128)	−0.773*** (0.137)
Spinout × *Tenure*[c]		0.011 (0.011)	0.022 (0.014)	−0.015*** (0.004)	−0.019*** (0.005)
Inverse Mills ratio			−0.032 (0.068)		0.162† (0.095)
All other control variables		Included	Included	Included	Included
Constant		−4.038*** (0.472)	−3.952*** (0.489)	−1.418*** (0.185)	−2.153*** (0.651)
Instrument 1 (No. of VC investments in inventor's city)	0.097*** (0.024)				
Instrument 2 (No. of inventor's prior residence changes)	0.161** (0.061)				
No patents	−0.046 (0.139)				
Patents per year	−0.031 (0.031)				
Total patents	−0.005 (0.003)				
Knowledge generality	0.344 (0.253)				
Experience with risky technologies	0.024 (0.043)				
Solo patents	−0.119 (0.083)				
Team size	−0.051 (0.034)				
No. of observations	3,269[a]	5,604	5,604	5,604	5,604
Log likelihood	−270.5	−16,749	−7,576	−7,748	−1,506

Note. The dependent variable in column A is *spinout*; in columns B and C, extent of exploration; and in columns D and E, *share of citations to Xerox*.
[a]Inventor-year observations censored at spinout events.
[b]Observations weighted on (1 − *predicted probability of spinout*) computed from the first stage.
[c]Mean-centered.
†$p < 0.1$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

identify (i.e., unobservable variables linked with mobility). We therefore estimated a model to compare inventors who joined a spinout with not only inventors who remained in the parent organization but also inventors who moved internally within Xerox but to a different geographic location and inventors who moved to other established firms. Thus, we first built a group of 147 inventors who changed their work location within Xerox. To detect inventor *internal mobility*, we used patent data that indicated geographical locations (Lai et al. 2009) and identified any changes in the zip codes listed in each inventor's patent record.[5] Next, we selected a group of 65 Xerox inventors who moved to 58 other established organizations during our study period. With this *external mobility* group, we can test whether the spinout effect that we observed in the treated group was simply due to interorganizational mobility.

The results in Table 9, related to these various kinds of mobility, confirm the positive effect of spinouts. Internal mobility does not seem to have any specific effect: even though inventors likely encounter new stimuli, the organizational code remains the same, so their inventive activities tend to follow established routines and patterns. External mobility exerts some effect in the expected direction, in particular, on citations to Xerox, but economically, this effect is clearly less significant than that of spinouts. As literature on inventor mobility (e.g., Singh and Agrawal 2011, Song et al. 2003) suggests, established firms may hire inventors specifically to exploit their experience with certain knowledge, so mobility to other firms may be associated with a higher rate of citations to Xerox if an external firm has sought to exploit Xerox's inventions. Furthermore, socialization literature (Allen 2006, Jokisaari and Nurmi 2009, Louis 1980) suggests that as workers move to other established firms, they get rapidly exposed to socialization strategies, which may prevent them from exploring new solutions, free from the constraints of any established organizational code.

Finally, we checked for specific contingencies that may explain an inventor's ability to alter the organizational code, such as experience with risky (different) technologies, new stimuli, and geography.[6] The results (not reported here for conciseness) again support our hypotheses.

Discussion and Conclusion

This study suggests that spinouts revamp the explorative behavior of inventors: compared with a control group of similar others, inventors who join spinouts produce inventions that are of higher technological distance from prior art in technological domains that are new for the inventor. In doing so, spunout inventors rely significantly less on the parent company's knowledge. Moreover, our findings indicate that these effects are stronger for inventors with higher socialization in the originating organization. We have argued that this evidence is consistent with March's (1991) intuition about the impact of

Table 9 Estimation of Spinout, External Mobility, and Internal Mobility

	Estimation method			
	Fixed effects negative binomial	Fixed effects Poisson QML	Pooled fractional probit	GEE
Independent variable	A[a]	B[b]	C[c]	D[c]
Spinout	2.649***	1.954***	−3.975***	−1.523***
	(0.712)	(0.299)	(0.192)	(0.274)
External mobility	0.124	0.420*	−0.751***	−0.292***
	(0.677)	(0.189)	(0.019)	(0.065)
Internal mobility	0.102	0.259	0.080***	0.133*
	(0.104)	(0.158)	(0.003)	(0.058)
Controls	Included	Included	Included	Included
No. of observations[d]	8,514	8,514	8,514	8,514
Wald χ^2				56.21***
Log likelihood	−10,709	−51,972	−2,346	
Null hypotheses:	Signs and significance of coefficient differences:			
$\beta(\textit{Spinout}) - \beta(\textit{External Mobility}) = 0$	$(+)p < 0.01$	$(+)p < 0.001$	$(-)p < 0.001$	$(-)p < 0.001$
$\beta(\textit{Spinout}) - \beta(\textit{Internal Mobility}) = 0$	$(+)p < 0.001$	$(+)p < 0.001$	$(-)p < 0.001$	$(-)p < 0.001$

Notes. The dependent variable in column A is *extent of exploration*; in columns C and D, *share of citations to Xerox*. GEE, generalized estimating equations; QML, quasi-maximum likelihood.
[a]Inventor fixed effects. Standard errors are estimated from the observed information matrix.
[b]Inventor fixed effects. Robust standard errors are shown.
[c]Robust standard errors are clustered by firm.
[d]Total of 596 inventors in treated, control, external mobility, and internal mobility groups.
$^{\dagger}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

socialization rates on learning: spinouts could act as desocialization mechanisms that allow inventors to diverge from past behavior, heuristics, and established routines.

That the effect of spinouts is stronger for inventors with a high organizational tenure, though consistent with our predictions, may seem counterintuitive because people with longer tenure seemingly should be less explorative and intrinsically less prone or able to change. Yet this conventional wisdom actually sparks considerable debate in organizational behavior literature. Beyer and Hannah (2002), in studying the consequences of mobility events in the semiconductor industry, find that interviewed engineers with more prior experience in a prior content domain adjusted more rapidly to a new context. This effect related to their prior work experience with a richer repertoire of possible solutions to the problems posed by adapting to new organizational contexts. Brett (1984) also argues that people with more work experience have richer schemata, which enable them to make sense of new organizational contexts. These proposals are consistent with the idea of March et al. (2000) that when organizations release restrictions, employees with more knowledge of the prior rules—that is, those highly socialized to the code—take quicker action to revise those rules than do people with less rich knowledge. These results align with the evidence we offer in support of H3A and H3B.

Our results provide significant implications for extant literature on corporate entrepreneurship, innovation, and organizational learning. Whereas prior literature (Chesbrough 2002, 2003) has analyzed spinouts mainly as organizational choices driven by *previous* explorative efforts, whose results could not be exploited by the parent organization, we show that spinouts can reinvigorate explorative behavior. Thus they may result from the desire to exploit untapped knowledge in new product markets but also prompt exploration in novel technological fields. In suggesting that the desocialization of inventors who previously belonged to the parent organization can explain this result, we contribute to corporate entrepreneurship literature and offer spinouts as another tool that organizations can use to foster their members' search and exploration.

Our findings also speak to extensive literature on organizational ambidexterity (e.g., Benner and Tushman 2003, O'Reilly and Tushman 2004), disruptive innovation (Christensen 1997), and the "skunk works model" of innovation (e.g., Fosfuri and Rønde 2009), which suggest that novel technologies should be developed and engineered in structurally independent units, only loosely coupled with an existing management hierarchy. Our results are consistent with this intuition, and we add robustness by offering the first large-sample analysis of the phenomenon. We explore the ex post effects of this organizational choice on inventors' innovativeness, adding a new angle to the discussion about structural ambidexterity. An important extension of this study would be to analyze the extent to which parent organizations might appropriate the benefits of inventors' renewed innovativeness.

The relationship between spinouts and inventive activity is also relevant for research into the organizational determinants of technological performance. Although extant literature has analyzed the determinants of patenting quantity, we still know little about the determinants of the quality and value of inventions (Fleming 2002). Exploring drivers of invention quality is important, because producing new ideas and knowledge is a necessary but insufficient condition to sustain superior performance. Not all inventions are equally useful and valuable (Gambardella et al. 2008). We provide evidence that spinouts are associated with greater exploration, especially in the claims of patents produced by inventors who move to a new organization. By focusing on patent claims, we also shed light on a dimension of patents' underlying, unobserved quality, which Lanjouw and Schankerman (2004) identify as a determinant of research productivity and firms' market value. 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 offer good indicators of inventions' economic value—in particular, in microelectronics (Lanjouw and Schankerman 2004).

To explain the effects of spinouts, we considered desocialization (March 1991) a compelling mechanism. Providing an empirical test of one of March's key arguments, we contribute to organizational learning literature. Furthermore, our work relates to a stream within this literature that focuses on organizational unlearning. Nystrom and Starbuck (1984) observe that though learning is key to organizational functioning and growth, organizations also must unlearn to survive. Before organizations can embrace new ideas, they must unlearn old ones, which is not easy. Tsang and Zahra (2008) associate unlearning with a type of organizational change; consistent with Weick and Quinn (1999), they suggest that unlearning might come from both continuous and episodic changes. Our study provides an instance of episodic change that may allow people to unlearn prior norms and explore new patterns. Our comparison between spinout and external mobility also shows that important differences may exist according to the context in which (re)socialization happens. With spinouts, organizational members would gain a new context in which they can contribute to the definition of a new organizational code. In an established organization instead, mobile inventors are socialized (possibly very quickly) into a preexisting organizational code. The effects on explorative behavior appear quite different. An interesting extension of this line of reasoning would detail the relationship between unlearning (of the old organizational code) and learning (of the new organizational code that the inventor contributes to develop or adopt in his or her new environment). We do not mean to imply that routines are inherently conducive to inertia; rather, excessive socialization in established routines generates myopic learning (Levinthal and March 1993). Routines are necessary for effective organizational life (Feldman 2000, Nelson and Winter 1982), so the question is how spunout inventors design and institutionalize new routines in their new organizations to define a new organizational code. More specifically, this line of reasoning resonates with recent calls to integrate studies of mobility with the analysis of the specific microlevel cognitive and psychological processes that underpin the ability of individuals to leverage, or not, their skills in new environments. The work by Dokko et al. (2009), for example, provides evidence that is complementary to our own. They discuss what factors affect the ability of people to benefit from their prior knowledge if transferred to a different work environment. More generally, work in sociology on the relationship between embeddedness and social capital on the one side and individual-level productivity on the other (e.g., Castilla 2005) also stresses the importance of looking at how social relations affect the ability of individuals of benefiting from their work environment.

By attempting to support our theoretical claims empirically, we also considered alternative mechanisms that may explain the spinout effect. An increase in the extent of exploration might be driven endogenously by the spinout decision, because spinouts by definition are devoted to entering new product markets. In this respect, though, we observe that spinouts do not necessarily lead to a change in the innovation strategy. For example, Xerox PARC offers a clear example of an R&D unit that did not change its strategic orientation. The strategic aim of Xerox PARC, formerly one of the few Xerox's R&D labs, has always been to explore and develop novel ideas. Even if spinouts were endogenously intended to be explorative, a simple mandate to investigate new technological areas or the allowance of greater freedom does not necessarily work. Augsdorfer (2005) analyzes so-called bootlegging innovative activities—R&D activities that ignore management directives and include covert action, in which inventors decide how to invest company resources and pursue autonomous innovation ideas. Bootlegging induces an incremental, continuous, trial-and-error learning process in R&D, and its uncertainty is not different from that of "normal" corporate R&D. Finally, our comparison of highly and less socialized inventors shows that the former exhibit a stronger effect. If the effect we observe were a pure endogenous consequence, it should not be any stronger for highly socialized inventors. This result, along with our attempts to account for alternative mechanisms, is consistent with the argument that desocialization contributes to the spinout effect. Notwithstanding these observations, we realize that in our nonexperimental context, we cannot indisputably prove causality.

In addition to theory and strategy research, our results contribute to managerial practice. Rapid technological change and short product life cycles have made continuous innovation critical to sustainable competitive advantages. From the perspective of a practicing manager, a mechanism that can help overcome inertia and increase employees' propensity to explore new technological paths is of great importance, especially considering the associated economic stakes.

Finally, this study offers further avenues for research. We focused on two proxies for the process of socialization; additional research could refine the content and dimensions of organizational socialization, explore the constructs of desocialization and resocialization into organizational codes (and how they differ between spinouts and established firms), and derive better empirical measures. Furthermore, to provide a more complete picture of the economic outcomes of spinouts and compare them with alternative strategies for achieving exploration, researchers should investigate the extent to which a parent organization can capture the value potential created through exploration by spinout firms, as well as the factors that influence this process. Our results offer a first step in validating a key theoretical proposition by Levinthal and March (1993): the returns of local exploitation investments depend on system-level investments in explorative activities. Spinout decisions expand explorative activities at the system level, which might benefit the parent organization by indirectly increasing variety in its external environment. Yet we still know very little about how such benefits can be appropriated.

Thus, much work remains to be done to explain one of the most fundamental issues of strategy research—the drivers of organizational and individual change. With this study, we hope to have contributed to the development of a stronger, more explicit link between empirical research on mobility and theoretical research on organizational learning and innovation.

Acknowledgments

This paper is based on chapter 1 of B. Cirillo's doctoral dissertation; the other authors are listed in alphabetical order. The authors thank Brian Boyd, Gianluca Carnabuci, Raffaele Conti, Nicole Rosenkranz, and Richard Priem, as well as seminar participants at the Católica Lisbon School of Business and Economics, EPFL, Katholieke Universiteit Leuven, SKEMA Business School, Tilburg University, and Università della Svizzera Italiana in Lugano for useful comments on previous versions of this paper. The authors are also grateful to the senior editor, Lori Rosenkopf, and the reviewers for their help in improving the manuscript through a most constructive review process.

Endnotes

[1]Selecting spinouts according to patenting activities may expose our study to survival bias. However, patenting does not necessarily explain spinout success rate. Many of Xerox's

spinouts offered software as their dominant products (see Chesbrough 2003).

[2]We refer to USPC classes, as reported in the data set of Lai et al. (2009). Overall, the patents in our final data set were distributed across 372 primary classes.

[3]Matching estimators provide a possible solution to the fundamental problem of causal inference that arises when estimating a causal effect from nonexperimental data. In essence, we lack counterfactual evidence of what would have happened to inventor i if he or she had not moved, provided this inventor actually moved. If treated and control inventors systematically differ, then the average outcome value of nonmoving inventors is a biased estimate of our counterfactual outcome (Heckman and Navarro-Lozano 2004). Matching estimators impute the missing outcomes of treated individuals in the control condition using the outcomes for individuals with similar values on the relevant pretreatment variables but that were not exposed to treatment. A variable is relevant to the extent that it affects the probability of being subject to treatment.

[4]We obtain robust results with both importance and sampling weights. The Stata command xtnbreg supports only the importance weights option, and it requires constant weights within clusters. We weighted the observations by $[1 - \text{mean}(p)]$.

[5]To obtain a reliable measure of geographical mobility, we only referred to the first digit of the zip code.

[6]We estimated models (1) and (2) by also including interactions between our *spinout* variable and *experience with risky technologies, new coinventors*, and *geographical distance*.

References

Abadie A, Imbens G (2002) Simple and bias-corrected matching estimators for average treatment effects. NBER Technical Working Paper 283, Cambridge, MA.

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

Agarwal R, Echambadi R, Franco AM, Sakar MB (2004) Knowledge transfer through inheritance: Spinout generation, development and survival. *Acad. Management J.* 47(4):501–522.

Ahuja G, Lampert CM (2001) Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. *Strategic Management J.* 22(6–7):521–543.

Allen DG (2006) Do organizational socialization tactics influence newcomer embeddedness and turnover? *J. Management* 32(2):237–256.

Almeida P, Kogut B (1999) Localization of knowledge and the mobility of engineers in regional networks. *Management Sci.* 45(7):905–917.

Arora A, Ceccagnoli M, Cohen W (2008) R&D and the patent premium. *Internat. J. Indust. Organ.* 26(5):1153–1179.

Ashforth BE, Sluss DM, Harrison SH (2007) Socialization in organizational contexts. Hodgkinson GP, Ford JK, eds. *International Review of Industrial and Organizational Psychology*, Vol. 22 (John Wiley & Sons, Chichester, UK), 1–70.

Augsdorfer P (2005) Bootlegging and path dependency. *Res. Policy* 34(1):1–11.

Bandura A (1977) Self-efficacy: Toward a unifying theory of behavioral change. *Psych. Rev.* 84(2):191–215.

Banerjee PM, Campbell BA (2009) Inventor bricolage and firm technology research and development. *R&D Management* 39(5):473–487.

Basalla G (1988) *The Evolution of Technology* (Cambridge University Press, Cambridge, UK).

Batel KA, Jackson SE (1989) Top management and innovations in banking: Does the composition of the top team make the difference? *Strategic Management J.* 10(S1):107–124.

Benner M, Tushman MI (2003) Exploitation, exploration, and process management: The productivity dilemma revised. *Acad. Management Rev.* 28(2):238–256.

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

Beyer JM, Hannah DR (2002) Building on the past: Enacting established personal identities in a new work setting. *Organ. Sci.* 13(6):636–652.

Brett JM (1984) Job transitions and personal and role development. Rowlan K, ed. *Research in Personnel and Human Resources Management*, Vol. 2 (JAI Press, Greenwich, CT), 155–185.

Cameron C, Trivedi PK (1998) *Regression Analysis of Count Data* (Econometric Society Monograph 30) (Cambridge University Press, Cambridge, UK).

Campbell BA, Ganco M, Franco AM, Agarwal R (2012) Who leaves and why to worry? Employee mobility, entrepreneurship and effects on source firm performance. *Strategic Management J.* 33(1):65–87.

Castilla EJ (2005) Social networks and employee performance in a call center. *Amer. J. Sociol.* 110(5):1243–1283.

Chao GT, O'Leary-Kelly AM, Wolf S, Klein HJ, Gardner PD (1994) Organizational socialization: Its content and consequences. *J. Appl. Psych.* 79(5):730–743.

Chesbrough HW (1998a) *Inxight: Incubating a Xerox Technology Spinout* (Harvard Business School Press, Boston).

Chesbrough HW (1998b) *PlaceWare: Issues in Structuring a Xerox Technology Spinout* (Harvard Business School Press, Boston).

Chesbrough HW (2002) Making sense of corporate venture capital. *Harvard Bus. Rev.* 80(3):90–99.

Chesbrough HW (2003) The governance and performance of Xerox's technology spin-off companies. *Res. Policy* 32(3):403–421.

Chesbrough HW (2006) *Open Innovation: Researching a New Paradigm* (Oxford University Press, Oxford, UK).

Chesbrough H, Rosenbloom RS (2002) The role of the business model in capturing value from innovation: Evidence from Xerox Corporation's technology spin-off companies. *Indust. Corporate Change* 11(3):529–555.

Christensen CM (1997) *The Innovator's Dilemma: When New Technologies Cause Great Firms to Fail* (Harvard Business School Press, Boston).

Cohen WM, Levinthal D (1990) Absorptive capacity: A new perspective on learning and innovation. *Admin. Sci. Quart.* 35(1): 128–152.

Correidoira RA, Rosenkopf L (2009) Should the acquaintance be forgot? The reverse transfer of knowledge through mobility ties. *Strategic Management J.* 31(2):159–181.

Dehejia RH, Wahba S (2002) Propensity score-matching methods for nonexperimental causal studies. *Rev. Econom. Statist.* 84(1):151–161.

Dokko G, Wilk SL, Rothbard NP (2009) Unpacking prior experience: How career history affects job performance. *Organ. Sci.* 20(1):51–68.

Fang C, Lee J, Schilling MA (2010) Balancing exploration and exploitation through structural design: The isolation of subgroups and organizational learning. *Organ. Sci.* 21(3):625–642.

Feldman DC (1981) The multiple socialization of organization members. *Acad. Management Rev.* 6(2):309–318.

Feldman DC (1989) Socialization, resocialization, and training: Reframing the research agenda. I. L. Goldstein and Associates, ed. *Training and Development in Organizations* (Frontiers of Industrial and Organizational Psychology) (Jossey-Bass, San Francisco), 376–416.

Feldman MS (2000) Organizational routines as a source of continuous change. *Organ. Sci.* 11(6):611–629.

Fleming L (2001) Recombinant uncertainty in technological search. *Management Sci.* 47(1):117–132.

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

Fleming L, Sorenson O (2004) Science as a map in technological search. *Strategic Management J.* 25(8–9):909–928.

Fleming L, Mingo S, Chen D (2007) Collaborative brokerage, generative creativity, and creative success. *Admin. Sci. Quart.* 52(3):443–475.

Fosfuri A, Rønde T (2009) Leveraging resistance to change and the skunk works model of innovation. *J. Econom. Behav. Organ.* 72(1):274–289.

Franco AM, Filson D (2006) Spinouts: Knowledge diffusion through employee mobility. *RAND J. Econom.* 37(4):841–860.

Gambardella A, Harhoff D, Verspagen B (2008) The value of European patents. *Eur. Management Rev.* 5(2):69–84.

Gompers P, Lerner J, Scharfstein D (2005) Entrepreneurial spawning: Public corporations and the genesis of new ventures, 1986 to 1999. *J. Finance* 60(2):577–614.

Groysberg B, Lee L-E, Nanda A (2008) Can they take it with them? The portability of star knowledge workers' performance. *Management Sci.* 54(7):1213–1230.

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

Hamilton BH, Nickerson JA (2003) Correcting for endogeneity in strategic management research. *Strategic Organ.* 1(1):51–78.

He Z-L, Wong P-K (2004) Exploration vs. exploitation: An empirical test of the ambidexterity hypothesis. *Organ. Sci.* 15(4):481–494.

Heckman J (1979) Sample selection bias as a specification error. *Econometrica* 47(1):153–161.

Heckman J, Navarro-Lozano S (2004) Using matching, instrumental variables, and control functions to estimate economic choice models. *Rev. Econom. Statist.* 86(1):30–57.

Hilbe JM (2011) *Negative Binomial Regression* (Cambridge University Press, Cambridge, UK).

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

Hoisl K (2007) Tracing mobile inventors—The causality between inventor mobility and inventor productivity. *Res. Policy* 36(5):619–636.

Huckman RS, Pisano GP (2006) The firm specificity of individual performance: Evidence from cardiac surgery. *Management Sci.* 52(4):473–488.

Imbens G (2004) Nonparametric estimation of average treatment effects under exogeneity: A review. *Rev. Econom. Statist.* 86(1):4–29.

Jokisaari M, Nurmi JE (2009) Change in newcomers' supervisor support and socialization outcomes after organizational entry. *Acad. Management J.* 52(3):527–544.

Katz R (1981) *Career Issues in Human Resource Management* (Prentice-Hall, Englewood Cliffs, NJ).

Katz R, Allen TJ (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, Thompson P (2007) Spin-offs in high-tech industries: Motives and consequences. Malerba F, Brusoni S, eds. *Perspectives on Innovation* (Cambridge University Press, Cambridge, UK), 187–218.

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

Lanjouw JO, Schankerman M (2004) Patent quality and research productivity: Measuring innovation with multiple indicators. *Econom. J.* 114(495):441–465.

Levinthal AD, March JG (1993) The myopia of learning. *Strategic Management J.* 14(1):95–112.

Lewin K (1951) Cartwright D, ed. *Field Theory in Social Science: Selected Theoretical Papers* (Harper & Brothers, New York).

Louis MR (1980) Surprise and sense making: What newcomers experience in entering unfamiliar organizational settings. *Admin. Sci. Quart.* 25(2):226–251.

March J, Schulz M, Xueguang Z (2000) *The Dynamics of Rules: Change in Written Organizational Codes* (Stanford University Press, Palo Alto, CA).

March JG (1991) Exploration and exploitation in organizational learning. *Organ. Sci.* 2(1):71–87.

Markova G, Folger R (2012) Every cloud has a silver lining: Positive effects of deviant coworkers. *J. Soc. Psych.* 152(5):586–612.

McKendrick DG, Wade JB, Jaffe J (2009) A good riddance? Spin-offs and the technological performance of parent firms. *Organ. Sci.* 20(6):979–992.

Miller KD, Zhao M, Cantalone RJ (2006) Adding interpersonal learning and tacit knowledge to March's exploration-exploitation model. *Acad. Management J.* 49(4):709–722.

Nelson RR, Winter RG (1982) *An Evolutionary Theory of Economic Change* (Harvard University Press, Cambridge, MA).

Nystrom PC, Starbuck WH (1984) To avoid organizational crises, unlearn. *Organ. Dynam.* 12(4):53–65.

O'Reilly CA, Tushman ML (2004) The ambidextrous organization. *Harvard Bus. Rev.* 84(4):74–81.

Palomeras N, Melero E (2010) Markets for inventors: Learning-by-hiring as a driver of mobility. *Management Sci.* 56(5):881–895.

Papke LE, Wooldridge M (2008) Panel data methods for fractional response variables with an application to test pass rates. *J. Econom.* 145(1–2):121–133.

Pfeffer J (1983) Organizational demography. Cummings LL, Staw BM, eds. *Research in Organizational Behavior*, Vol. 5 (JAI Press, Greenwich, CT), 299–357.

Ramgopal P, Mathew M (2006) Xerox's Palo Alto Research Center: Getting inventions to the market. IBSCDC Case Study CCA0028, IBS Case Development Centre, Hyderabad, India.

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

Rosenkopf L, Nerkar A (2001) Beyond local search: Boundary-spanning, exploration, and impact in the optical disk industry. *Strategic Management J.* 22(4):287–306.

Schein EH (1968) Organizational socialization and the profession of management. *Indust. Management Rev.* 9:1–16.

Singh J, Agrawal AK (2011) Recruiting for ideas: How firms exploit the prior inventions of new hires. *Management Sci.* 57(1): 129–150.

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

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

Sorensen JB, Stuart TE (2000) Aging, obsolescence, and organizational innovation. *Admin. Sci. Quart.* 45(1):81–112.

Starr JA, Fondas N (1992) A model of entrepreneurial socialization and organization formation. *Entrepreneurship Theory Practice* 17(1):67–67.

Stuart TE, Podolny JM (1996) Local search and the evolution of technological capabilities. *Strategic Management J.* 17(S1):21–38.

Taormina RJ (1997) Organizational socialization—A multidomain continuous process. *Domains Organ. Socialization* 5(1):29–47.

Trajtenberg M (2005) Recombinant ideas: The mobility of inventors and the productivity in research. *Proc. 2005 CEPR Conf., Munich, Germany*.

Tsang EWK, Zahra SA (2008) Organizational unlearning. *Human Relations* 61(10):1435–1462.

Venkatraman N (1989) The concept of fit in strategy research: Toward verbal and statistical correspondence. *Acad. Management Rev.* 14(3):423–444.

Weick KE, Quinn RE (1999) Organizational change and development. *Annual Rev. Psych.* 50:361–386.

Weick KE, Roberts KH (1993) Collective mind in organizations: Heedful interrelating on flight deck. *Admin. Sci. Quart.* 38(3):357–381.

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