External Learning Strategies and Technological Search Output: Spinout Strategy and Corporate Invention Quality

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Published in Organization Science: https://doi.org/10.1287/orsc.2018.1233

Abstract

The strategic management of knowledge spillovers to employee ventures may provide firms with knowledge spill-ins, or the potential to learn from the ventures they have spun out. However, the mechanisms underlying knowledge spill-ins and their importance for external learning in uncertain technology environments have not been examined in detail. This article compares corporate venturing (CV) spinouts that are supported by parent firms with independent, employee spinouts, as well as with other strategies for external learning, such as investments and alliances. An analysis of the patenting activities of leading corporations operating in the information and communication technology industry reveals that, *ceteris paribus*, when firms recombine unfamiliar knowledge components developed by their CV spinouts, their inventions are associated with higher quality than comparable firms' inventions that recombine knowledge from the firm's corporate venture capital portfolio ventures, allies, or employee spinouts. This effect is especially pronounced when CV spinout inventors hold parent-specific technological expertise. The results are robust across several econometric specifications that account for selection and intrinsic differences in external learning strategies. Furthermore, the results indicate that CV spinouts benefit their parent firms by reducing uncertainty, relative to other strategic formats for external learning in unfamiliar technological areas. The detailed theoretical and practical implications derived from this research reflect perspectives on technology strategy and corporate renewal.

Keywords: External learning; Uncertainty; Spinouts; Knowledge spill-ins; Corporate venturing; Patent quality index

Acknowledgements
I am gratefully indebted to Stefano Brusoni and Giovanni Valentini for their help and encouragement through the review process. I thank the senior editor, Rajshree Agarwal, and two anonymous reviewers for their contribution to the development of this article. I thank Francesco Castellaneta, Raffaele Conti, Francesco Di Lorenzo, Ludovic Dibiaggio, Gianluigi Giustiziero, Tomi Laamanen and Lionel Nesta, as well as seminar participants at Catolica Lisbon, EPFL and SKEMA Business School, for useful comments and suggestions. A previous version of this article received the Best Dissertation Award in Technology and Innovation Management at the 2013 Academy of Management annual meeting. Arusyak Zakaryan and Pegah Sajadi helped collect supplemental data. All remaining errors are mine.

Introduction

In high-tech industries, spinouts (defined as entrepreneurial ventures created by ex-employees) increasingly provide strategic mechanisms for incumbents' growth (Agarwal et al. 2007). Spinouts emerge endogenously from incumbents' initial investments in knowledge. Firms often create far more knowledge assets than they are in a position to exploit (Moore and Davis 2004). Employees may perceive abundant value-appropriating opportunities and decide to venture out with firm's knowledge (Klepper and Sleeper 2005). Implicit in this view is the idea that spinouts are critical conduits for the spillover of knowledge that otherwise might have remained undervalued and unused (Agarwal et al. 2004). Although spinouts are often costly in terms of market share and human capital (Moore and Davis 2004), they may also benefit their parents by developing complementary positions in the value chain to better exploit unused technologies (Agarwal et al. 2007). As one exemplary account details,

> "at Fairchild, we began to encourage and support [spinouts] that could provide us with necessary components to our research and manufacturing processes. Later, Intel adopted an outright technology policy that we would use none of our own equipment. We knew we couldn't keep up with too many technologies, or dedicate the resources to be at the leading edge in all areas simultaneously" (Moore and Davis 2004: 11; see also Agarwal et al. 2007).

In contrast with such anecdotal evidence, prior literature suggests that spinouts often emerge from a lack of knowledge complementarity (Cassiman and Ueda 2006) or formal support from parents (Klepper 2007), in which cases parents do not take a voluntary role (see Klepper 2015). Yet there is an intriguing possibility that firms' strategic management of spillovers through corporate venturing (CV) could result in knowledge spill-ins, or capability enhancement effects, that provide parent firms with the potential to learn from the ventures they have spawned (Agarwal et al. 2007). Prior research documents knowledge transfers from incumbents to corporate-backed ventures (e.g., Chesbrough 2003), as well as interorganizational knowledge flows due to employee mobility (e.g., Corredoira and Rosenkopf 2010, Kim and Steensma 2017). Yet we still know little about the mechanisms underlying knowledge spill-ins or learning from spinouts. Are spinouts better conduits of knowledge spill-ins than alternative strategies for external learning? Do spill-ins differ when the spinouts are supported by parent firms or not?

To shed light on these questions, the current study considers spinout strategies in the context of firms' external learning in uncertain technological areas. In particular, it compares *corporate venturing (CV) spinouts* (i.e., employee ventures that benefit from the support of the parent firm) with *employee spinouts* (i.e., employee ventures that are independent of and have no formal agreement with their parent firm), as well as with other strategies for external learning, such as *corporate venture capital (CVC) investments* (i.e., corporate backing of ventures that did not originate with corporate research) and *alliances*. Acknowledging the contextual differences associated with each strategy, I posit that CV spinouts offer parent firms less uncertain external learning than CVC investments, alliances, or employee spinouts, for two reasons. First, due to CV spinouts incubation period, parents gain social capital and low information asymmetry with CV spinouts, as opposed to having adverse selection problems with CVC investments and alliances (Almeida et al. 2002) or experiencing disruptions in their social capital with employee spinouts (Phillips 2002). Second, due to parent–CV spinout organizational imprinting, parents are more effective in transferring their preferred routines and procedures to their CV spinouts, as opposed to encountering barriers with CVC investments and alliances (Almeida et al. 2003, Mawdsley and Somaya 2016) or having no managerial control over transfers to employee spinouts. Parents thus should enjoy a greater probability of selecting and integrating impactful CV spinouts' knowledge, while also limiting the failures associated with uncertainty in external learning (Fleming 2001, Rosenkopf and Nerkar 2001).

To test these arguments, I examine the patenting activities and external learning strategies of a sample of U.S. firms operating in the information and communication technology (ICT) industry between 2000 and 2009. To better understand the phenomena of interest, I conducted exploratory interviews with research scientists and R&D managers at three leading corporations in this industry. With regression analyses and a quasi-experimental research design, I show that a firm's patents that cite the firm's CV spinouts' patents (treated units) are associated with higher patent quality (Lanjouw and Schankerman

2004) than the firm's comparable patents that build on comparable knowledge sources (control units), such as CVC ventures, allies, or employee spinouts, when those patents cite previously unused, unfamiliar knowledge components. Furthermore, this effect appears stronger when the inventors in CV spinouts also are experts with regard to the parent's knowledge, routines and procedures, as measured by the match between their technological expertise and the parent's area of technological expertise (Song et al. 2003). Workers with parent-specific expertise can negotiate better initial technological endowments and spin out with complementary assets (Campbell et al. 2012). They also have a better understanding of the firm's organizational practices and idiosyncratic needs (Cohen and Levinthal 1990), leaving them more effective in carrying key routines that help their parent select and integrate their spinout's unfamiliar components.

The results are robust across several econometric specifications that account for intrinsic differences in external learning strategies, such as geographical, industrial, and technological proximities to external knowledge sources. With these insights, this study robustly affirms Agarwal et al.'s (2007) intuition that firms can strategically manage knowledge spill-ins from new entrants they have spun out, offering large-sample evidence of the mechanisms underlying this phenomenon. By focusing on invention quality, this study also sheds light on the economic importance of knowledge spill-ins. I offer detailed theoretical and practical implications, from the perspectives of technology strategy and corporate renewal.

Background and Hypotheses

In high-tech industries, firms' survival depends on their ability to recombine existing with new knowledge (Basalla 1988, Kogut and Zander 1992). Firms often face impediments to internal knowledge developments and thus adopt strategies to access and absorb new knowledge from external sources (Cohen and Levinthal 1990, Rosenkopf and Nerkar 2001). For example, Stuart and Podolny (1996) show that extensive engagement in alliances helps semiconductor firms access other incumbents' knowledge and reconfigure their own knowledge bases. Similarly, Schildt et al. (2005) and Wadhwa and Kotha (2006) argue that CVC investments grant firms access to new ventures' knowledge and help improve their ability to learn from external sources. However, the resultant search often is limited to familiar technological areas (Ahuja and Katila 2001, Stuart and Podolny 1996).

This argument applies the assumption of bounded rationality to knowledge search (Nelson and Winter 1982). The set of external knowledge components available to a firm is nearly infinite, yet firms hold limited information about which components and combinations are important and useful (Fleming 2001). Research in organizational learning suggests that firms rely on their past search experience, as encoded in organizational routines and procedures, to drive the search for new knowledge (March 1991, Levitt and March 1993). Routines adapt to experiences, incrementally and in response to feedback about new search outcomes (Levitt and March 1993). Firms thus tend to recombine locally, with previously used, familiar sets of knowledge components (Cohen and Levinthal 1990), which are associated with more certain recombination outputs (Fleming 2001). In contrast, recombinations from previously unused, unfamiliar sets of knowledge components are less desirable, because they involve substantial outcome and procedural uncertainty. Firms and their members lack information about the performance of unfamiliar components (Fleming 2001), and their established search routines are not efficient for recognizing or interpreting new, relevant information, even if it is available (Cohen and Levinthal 1990). Despite the benefits of proximate search, recombining only from familiar sets of knowledge components reduces the potential for impactful innovations (Ahuja and Katila 2001, Fleming 2001, Rosenkopf and Nerkar 2001). Therefore, uncertainty in external learning strategies constitutes a problem to overcome.

External Learning Strategies and Uncertainty

Uncertainty in external learning strategies has been investigated from different perspectives. One research stream notes the relation-specific information asymmetry that arises in external searches (Larsson et al. 1998). Because knowledge is key for developing competitive advantages, the circulation of information often is critical in interorganizational relationships, including CVC investments and alliances, in which partners tend to limit their disclosures to protect their core technology and assets. Dushnitsky and Shaver (2009) present the case of Advanced Micro Devices and the corporate-backed venture Sainfun to show that CVC-backed ventures exhibit caution when disclosing information to investors, which tend to have strong capabilities and inclinations to copy the venture's invention and expropriate its value. Similarly, partners in alliances may experience learning inefficiencies, because the risk of uncontrolled information disclosure of core competencies to partners disrupts the flow of information (Hamel 1991, Larsson et al. 1998). Therefore, information about the value of external knowledge often is costly to obtain or unavailable (Osborn and Hagedoom 1997, Folta 1998), and firms face adverse selection problems that might postpone or deter their decision to recombine internal with external knowledge.

In addition, uncertainty typically arises due to dissimilarities between firms' learning environments. Cohen and Levinthal (1990) argue that external learning tends to be less than optimal when firms search broadly for new knowledge, because the small technological overlap that exists between these firms and the external sources reduces their ability to recognize and recombine external knowledge. For example, Dushnitsky and Lenox (2005) show that firms reduce their learning from CVC investments if they lack expertise related to the CVC portfolio ventures' knowledge. Similarly, Vasudeva and Anand (2011) find that a lack of shared experiences between allied partners increases the effort required to exploit new knowledge from the firm's alliance portfolio. Beyond knowledge differences, alliance partners encounter operational differences, in their routines and procedures, which limit their interactions and knowledge exchanges (Lavie et al. 2012).

Prior research thus highlights the comparative disadvantages of CVC investments and alliances for pursuing external learning in conditions of technological uncertainty. Recent theoretical insights offer a possible solution though, with the compelling idea that a firm's strategic management of knowledge spillovers to employee ventures may provide it with increased potential to learn from ventures it spawns (Agarwal et al. 2007). Building on this insight, I argue that CV spinouts may offer parents less outcome and procedural uncertainty in external learning in unfamiliar, uncertain technological areas.

Spinout Strategy and External Learning

Prior studies address various types of employee ventures, such as those that the originating organization helps enter a new industry or market, as exemplified by the many employee ventures spun out of the Xerox Corporation. Chesbrough (1998, 2003) identifies both *technology spinouts* and *technology spin-*

offs as strategies for creating real options in new product markets. Cirillo et al. (2014) note Xerox's *corporate spinouts*—broadly defined as incorporations of new, independent organizations that are either entrepreneurial ventures or former units of the parent organization—as a form of strategy that helps foster explorative outcomes for corporate inventors. Gompers et al. (2005) use the example of Xerox too, to define *entrepreneurial spawns* as corporate-backed ventures that are born to commercialize disruptive innovations. However, another stream of research identifies employee ventures that begin without the support of their prior employer, as an antecedent of unintentional knowledge flows from a firm to the industry. Agarwal et al. (2004) define *employee spinouts* as new ventures founded by former employees that enter the same industry as the parent firm; other studies refer to this same scenario as a *spin-off* (Klepper 2007, McKendrick et al. 2009) or *spawn* (Chatterji 2009).

This study seeks to distinguish clearly between employee ventures that are formally supported by their parents and those that are not. For clarity, and following Chesbrough (2003), I define *CV spinouts* as employee ventures that benefit from the support of the originating organization. Following Agarwal et al. (2004), I refer to *employee spinouts* as employee ventures that originated independently, such that they receive no formal support from their parent. These two definitions exclude spinouts or spinoffs as divestitures—that is, the cases in which a business unit or division is purposefully sold or spun off by a corporation (e.g., Semadeni and Cannella 2011).

For this study, the key claim is that CV spinouts offer parent organizations less uncertain external learning than CVC investments and alliances, or employee spinouts for two reasons: CV spinout incubation in the parent and parent–CV spinout organizational imprinting. When a venture originates within the corporation, the level of information asymmetry between the corporation and the venture tends to be low (Dushnitsky and Shaver 2009). The CV spinouts exist mainly to capture value from unused corporate inventions (Chesbrough 2002; Christensen 1997). Projects developed by these ventures may relate to, or even be a continuation of, work carried out by the inventors while they were still employed by the parent (Cirillo et al. 2014). The decision to spin out projects thus should depend on available opportunities to develop complementary resources for the parent firm's own R&D and manufacturing activities (Moore and Davis 2004, Cassiman and Ueda 2006). In this sense, unlike other firms, CV spinouts benefit from an incubation period, which likely features discussions between inventors and top managers about the feasibility of the product market strategy (Chesbrough 2002, 2003). Parent firms thus gain social capital, such as formal and informal relations, which persist after spinout events and facilitate access to information about new knowledge. For example, a founder of a CV spinout described his collaboration with corporate former colleagues to me this way:

> "There was an ongoing interaction with our former colleagues…. It was more like just remaining friends, because most of the things that we had in [CV spinout name] were pretty well worked out by the time we spun out, and they were onto the next research and so the collaboration … there was, you know, just the kind of stuff that happens in natural collaborations, you are just having lunch together and you say stuff, and that inspires them to work on this or that."

Another interviewee, a research scientist in a large electronics company, confirmed the importance of informal relations with his former spun-out colleagues as a channel to convey information about the spinout's new technological achievements:

> "I was certainly aware of what [CV spinout name] was doing with the [technology], and I was certainly collaborating with them on expanding their capabilities. That came out in some patents that we co-signed. To that extent, I was pushed to think about some more applied work to do.… [The CV spinout] was originally located in the nearby building, so I'd just go there and talk to them. This was in [parent]'s interest and there was no explicit financial incentive for me to do it. But it was also clear that it would be looked well on by [the parent] if I did this."

This argument also finds support in research on the relationship between workers' mobility and interorganizational learning. Employee outbound mobility increases the firm's awareness of the relevant knowledge being gathered by hiring firms (Corredoira and Rosenkopf 2010, Song et al. 2003). Corredoira and Rosenkopf (2010) note that outbound mobility shifts firms' cognitive attention; source firms monitor the knowledge produced by hiring firms, to determine how knowledge embedded in employees has moved, which leads to the development of new social ties. Mobility can also promote shared mental models between sourcing and receiving firms, which enhance new knowledge recognition, transformation, and application (Lane et al. 2006). Through these social ties, parents increase their awareness of the value of spinouts' projects, thus facilitating access to and the integration of valuable know-how from the CV spinout (Agarwal et al. 2007). Yet there also might be systemic differences between employee mobility to a CV spinout versus to established firms (Mawdsley and Somaya 2016), such as CVC ventures and allied partners. In the latter cases, mobility may be less effective in transferring social ties (Almeida et al. 2002).

Similarly, mobility to CV spinouts may be more effective in transferring routines and procedures available from the parent firm (Campbell et al. 2012, Mawdsley and Somaya 2016), because their basic foundation stems from the parental imprinting process (Stinchcombe 1965). That is, the initial resource conditions available to CV spinouts can be traced to the parent organization's resources, whether human, technological, or financial (Chesbrough 2003). When a firm's workers move to its CV spinout, they encounter an organizational environment that is free of well-established routines (Chesbrough 1998), so the parent can transmit its preferred routines and procedures to its CV spinouts. This foundation generates continuity in the knowledge-generating processes of parents and their spinouts (Ferriani et al. 2012), which likely share similar procedural environments. It also increases the parent's ability to select and learn its CV spinouts' knowledge (March 1991), more readily than it can other firms' knowledge. The same effect does not arise when exiting employees join preexisting CVC-backed firms or allied partners, where they encounter barriers to transferring routines and knowledge from the prior organization (Almeida et al. 2003, Mawdsley and Somaya 2016).

Due to the lower information asymmetry and more efficient transfers of routines and procedures, parent firms can better learn from their CV spinouts than they can from CVC ventures and alliances, especially when external learning is more uncertain. By expanding exploration activities at the corporate level, CV spinouts help enrich the recombinant opportunities of their parents, with new knowledge components. The parent firm's inventors can draw on the experiences of spun-out inventors: their social proximity should increase the likelihood of sharing information about the performance of unfamiliar components, and their procedural similarity should ease the recombination of such knowledge with the parent's existing knowledge. Because CV spinouts reduce the parent firm's uncertainty about using unfamiliar components, intragroup variance in the observed outcome should diminish as well (Fleming 2001). Recombining CV spinouts' unfamiliar components thus should be associated with inventions that perform better, as opposed to recombining CVC portfolio firms' or allied partners' knowledge, so parents also may be less likely to develop low quality or useless inventions. Formally,

HYPOTHESIS 1A (H1A). *When exploring unfamiliar components, firm patents that cite its own CV spinouts are of higher quality than its patents that cite CVC portfolio firms and allied partners.*

Although employee ventures likely confer an advantage on their parents, not all spinouts generate such opportunities to equal degrees. An implicit assumption in prior literature is that most employee ventures emerge with no formal support and are costly for their parents in terms of market share and human capital (Moore and Davis 2004, Klepper 2007). As Gordon Moore has stated,

> "noting that Silicon Valley has been a positive place for new firm formation, many observers make the mistake of understanding [spinouts] and spillouts only from the perspective of the new venture, and not recognizing an essential element of conflict in these firm formations.… Most established firms, Intel and other Silicon Valley firms included, would squelch most [spinouts] if they could" (Moore and Davis 2004, p.34).

The lack of formal support from parents may generate fewer opportunities for knowledge spill-ins. First, tensions likely arise in the social ties between employee spinouts and their parents, which increase information asymmetry. Studying law firms, Phillips (2002) finds that employee spinouts generate disruptions in the parent's social capital. Moreover, employee spinouts often leverage knowledge originally generated within the parent firm to enter related markets, such that they mostly create competitive threats (Agarwal et al. 2004, Wezel et al. 2006). Firms thus rely on legal and retaliatory strategies to limit such competitive pressures, such as intellectual property rights (IPR) enforcement (Agarwal et al. 2009) or non-compete agreements (Marx 2011). These tensions generate adverse selection problems, which make parents' access to information about employee spinouts' technological achievements more problematic.

Second, parents have no managerial control over transferring their preferred routines and procedures to employee spinouts. Unlike CV spinouts, employee spinouts often feature projects with little complementarity with the parent firm's knowledge, so they likely fall outside consideration for incubation and formal support (Cassiman and Ueda 2006, Gambardella et al. 2014). A "selecting out" process thus arises,[1] such that parent firms provide corporate backing only to employee ventures that offer potential synergies with their own knowledge, routines, and procedures (Moore and Davis 2004). Non-backed spinouts tend to imply employees' misalignment with the strategic direction (Klepper 2007) and lack of socialization with the routines and procedures (Cirillo et al. 2014) of their parent firms. Employee spinouts also generate losses of firm-specific resources, routines, and procedures that are costly to replace (Philips 2001, Klepper and Sleeper 2005). If employee spinouts' social capital links and parental organizational imprinting are constrained (Mawdsley and Somaya 2016), parent firms may face more uncertainty when recombining unfamiliar components from their employee spinouts, as opposed to CV spinouts. On this basis, I offer the following hypothesis:

HYPOTHESIS 1B (H1B). *When exploring unfamiliar components, firm patents that cite its own CV spinouts produce higher quality than patents that cite its employee spinouts.*

If CV spinouts really do offer parent firms less uncertain external learning than CVC investments and alliances (H1A) and employee spinouts (H1B), due to their lower information asymmetry and higher control over transferring routines and procedures, the effects of these mechanisms also should vary according to whether the spun-out inventors possess a deep understanding of the parent's technological knowledge, routines, and procedures. That is, the benefits of using a CV spinout's unfamiliar components may be particularly relevant when the spun-out inventors' expertise matches that of the parent. Such expert inventors can negotiate better initial technological endowments and spin out with better

[1] I thank the senior editor for helping me articulate this thought.

complementary assets (Campbell et al. 2012). Furthermore, they are more likely to develop new knowledge that follows or parallels the parent's technological trajectory (e.g., Song 2003), facilitating greater understanding. These experts already have a better understanding of the procedural and strategic context of their parent firm, so they are more effective in transferring the key routines and procedure, or else redesigning them to eliminate inefficiencies (Cirillo et al. 2014). Therefore, the parent firm's inventors are more likely to understand the recombination of the inherited knowledge with new CV spinout's knowledge. They do not have to relearn the routines and procedures they already master, and thus can better learn how new CV spinout's knowledge can be recombined and what are the mechanisms behind cause and effect relationships.

This prediction is consistent with extant research on the role of employees' firm-specific expertise in organizational learning (Levitt and March 1993, March et al. 2000). In conditions of technological uncertainty, firms mostly rely on scientists who are both competent in their fields and experts on the firms' practices and idiosyncratic needs (Cohen and Levinthal 1990). Experts know which components and combinations are successful and likely understand the impetus for revising routines and procedures when feedback from new, valuable combinations becomes available (Levitt and March 1993). Exiting employees represent a valuable source of new information (Corredoira and Rosenkopf 2010, Kim and Steensma 2017), and their knowledge and expertise about their prior firm's practices is essential for effective communication and transmission of practices to that parent once they discover them (Levitt and March 1992, Song et al. 2003). Therefore, firms' ability to integrate new knowledge from external sources is highly idiosyncratic, according to exiting employees' firm-specific experience (Groysberg et al. 2008, Huckman and Pisano 2006). I hypothesize:

HYPOTHESIS 2 (H2). *Firm patents that cite its own CV spinouts produce higher patent quality when the CV spinouts employ inventors that hold parent-specific technological expertise.*

Data and Methodology

For the purposes of this study, I focus on a sample of U.S. firms operating in the information and communications technology (ICT) industry from 2000 to 2009. First, ICT is a knowledge-intensive industry (Almeida et al. 2002), for which access to external knowledge is critical to firm performance (Eisenhardt and Tabrizi 1995) and learning from external sources is very difficult (Cohen and Levinthal 1990). Second, firms in this industry use a plethora of strategic modes to explore external knowledge, such as CVC investments, alliances, and spinouts. Third, patents are an effective means to appropriate returns from ICT-related R&D (Arora et al. 2008), and patent citations provide a valid indicator of firms' attempts to integrate knowledge from external sources (Rosenkopf and Nerkar 2001). Thus, investigating this industry facilitates the collection of reliable data about inventions obtained through external knowledge searches. It also allows me to control for unobserved confounding factors at the industry (ease of learning) and country (IPR, legal appropriability regime) levels.

Sample of U.S. Corporate Spawned Ventures and Other Strategies

I started the data collection by identifying firms operating in ICT. Specifically, with the OECD (2002) definition of ICT, I found the largest public firms with primary activity in "office computing and accounting machines" (three-digit standard industrial code [SIC] 357), "communications equipment and electronic components" (three-digit SIC 365, 366, 367), and "measuring and controlling devices" (three-digit SIC 382). In this list, 20 leading U.S. corporations have used CV spinouts, alliances, and CVC investments as external learning strategies. For the purposes of this study, I focused on these 20 firms.

Next, I identified any ventures generated or spawned by founders formerly employed by these 20 corporations. To ensure data reliability and sampling that was as comprehensive as possible, I relied on different, complementary sources. I first searched for information about venture incubation and founding by the 20 firms during the 1990–2009 period in press releases and financial news available through Factiva Dow Jones, Google search, corporate websites, and academic sources (Chesbrough 2003). The keyword search algorithm included terms such as *spawned venture*, *spin-off*, *spinoff*, *spin-out*, and *spinout*,[2] along with the corporate names. With this keyword search, I screened more than 8,000 articles and news items. Then I searched for corporate employees' entrepreneurial activity by reviewing their curriculum vitae, available through LinkedIn and ZoomInfo. Specifically, I searched for persons who indicated an affiliation with any of the 20 firms and also cited *founder* as their job function in any record. This step involved reviewing about 26,900 curriculum vitae. Thus, I could control for the occurrence of a founding event right after the person's corporate employment.

I focused on employee ventures that earned at least one patent from the U.S. Patent and Trademark Office (USPTO) after their incorporation date. The resulting list of new ventures born out of employees' entrepreneurship includes both CV spinouts and employee spinouts. To distinguish between them, and thereby support tests of the precise effect of using CV spinouts as a strategy to enhance external learning, I searched for quantitative and qualitative information about each employee venture, including contingencies associated with the founding events or the ventures' governance, strategy, and objectives. In particular, I coded employee ventures as a *CV spinout* if any of the following criteria held: (1) It had received seed funds or other financial assets from the parent; (2) it had some ownership of parents' proprietary knowledge; and/or (3) it had signed either licensing[3] or supply[4] agreements with the parent. The resulting sample featured 142 employee ventures: 43 *CV spinouts* and 99 *employee spinouts*, incorporated in the United States between 1990 and 2009 by ex-employees of the 20 firms in the original list, which also earned patents from the USPTO after their incorporation date.

To support my theoretical claims with empirical evidence, I considered alternative strategic modes. First, I drew on VentureXpert data to construct a sample of *CVC portfolio ventures* that did not

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[2] Popular media and academic articles often use the terms spawned ventures, spinoffs, and spinouts synonymously, so the search included all of them, though for the purposes of this article, I distinguish them carefully.
[3] I detected two types of licensing agreements: At the founding date, a parent may agree to license one or more patents to its employee venture, or an employee venture may agree to (exclusively) license its future technological developments to its parent firm.
[4] These agreements include cases in which a spawning firm became the first customer of its spawned firm.

originate with corporate research.[5] This sample included 933 ventures that received CVC funds from the 20 firms between 1990 and 2009 and also earned patents from the USPTO. Second, I checked SDC Platinum data to construct samples of *alliances*. Following Rosenkopf and Almeida (2003), I assume that all alliances offer the potential for interorganizational learning. Thus the sample included all alliances completed by the 20 firms between 1990 and 2009 with 1,265 partners, all of which had patent records with the USPTO. Because different types of alliances may have different learning objectives, I ran robustness checks that distinguish equity vs. non-equity, technological vs. non-technological alliances.

Samples of Patents

This study seeks to examine the comparative advantages of alternative strategies—spinouts, CVC investments and alliances—on firms' invention quality. External knowledge can be sourced through several mechanisms, such as formal contractual arrangements, informal interactions among personnel, or integration of the knowledge source through formal acquisition. Consistent with research on firms' R&D and external learning (e.g., Almeida et al. 2002, Rosenkopf and Nerkar 2001) and interfirm knowledge transfers (Mowery et al. 1996), I rely on patent citation data to signal uses of other firms' knowledge. The primary source includes the USPTO patent data from 2000 to 2009 (Kaulagi and Fierro 2015), their backward citations to prior patents, and forward citations they received from subsequent patents up to 2014. With this information, I tabulated a list of cited patents and matched it with the list of patents granted to other firms. I constructed my sample of patents by first identifying 189 firm patents that cite the focal firm's CV spinouts' patents[6] and 393 patents that cite the firm's employee spinouts. Because firms' decisions to use spinouts' knowledge may be nonrandom (i.e., spinouts may be more likely to be cited by their parents than other firms, because of their greater proximity), I then selected control patents according to exact matches with the applicant name, application year, and technological category (NBER,

[5] Some ICT corporations—such as Xerox and Lucent Technologies—have incubated and backed spinouts through their CVC units. I consider these ventures CV spinouts but also control for their CVC seed funds. The list of CVC portfolio ventures includes startups that were not incubated by the corporation.

[6] I only considered spinouts' patents applied for after the legal incorporation of the spun-out venture, not those started prior to that date—that is, while the spun-out inventors were still employed by the parent firm.

Marco et al. 2015) of patents in the spinout groups but that listed backward citations to patents owned by the firm (self-citations) or other U.S. firms.[7] Thus, the treated and control units were exposed to comparable learning environments. The sample of controls includes 9,600 patents that belong to the 20 firms, citing the firm's own patents and patents by the firm's CVC portfolio ventures, its allied partners,[8] and other U.S. firms with no apparent relationship to the focal firm. Table 1 shows the distribution of firms and patent observations.

[Insert Table 1 here]

Measures

The unit of analysis for this study is the parent firm's patents. For each patent in my samples, I measured several variables. For clarity, I refer to each focal patent as the *citing patent*, and thus, the patent's applicant is the *citing firm*. Likewise, I refer to the external source of knowledge as the *cited firm* and the sourced knowledge as the *cited patent*.

Dependent variable. Research on the economic importance of patented inventions has focused on different patent statistics to measure patent quality, such as forward citations (Harhoff et al. 1999, Rosenkopf and Nerkar 2001), backward citations (Hall et al. 2001), and patent claims (Nerkar 2003). Lanjouw and Schankerman (2004) show that the relative importance of each measure varies across technological categories. Following their approach, I measure the quality of the firm's invention by a weighted index of the number of claims awarded to the patent, forward citations the patent received in the five years after its granting, and the number of backward citations the patent made to prior patents. For each patent in my sample, I first used the data set developed by Marco et al. (2015) to identify the NBER technological categories to which the patent was assigned. Then I adopted the coefficients developed by Lanjouw and Schankerman (2004) for each technological category to weight the patent's claims, forward

[7] Patents may cite prior knowledge located in multiple locations. To identify the location of cited firms, I used patent data on the geographic location of the cited patents' assignees. To simplify the analyses, I considered only patents that list citations to U.S.-based firms exclusively.
[8] I considered a cited firm a partner if it had undergone an alliance with the focal firm within five years prior to the focal patent application year.

citations, and the inverse of its backward citations. *Patent quality index* is a linear combination of the three weighted indicators.

Citation counts. Consistent with prior research on external learning (e.g., Rosenkopf and Nerkar 2001), patent citation data indicate the firm's use of other firms' knowledge. For each patent, I tabulated the list of cited patents and counted the number of citations the patent made to prior patents[9] belonging to the firm's own patents (*self-citations*) and to external sources, such as CV spinouts, employee spinouts, CVC ventures, allied partners, and others. Citation count variables have a Poisson distribution, so in the main models I use their logarithmic transformation to correct for skewness.[10]

Unfamiliar components. Following Fleming (2001), I assessed whether a patent uses unfamiliar components, according to the extent to which its inventors recently and frequently recombined the set of components in the patent. For each patent, I first derived a list of all subclassifications assigned to the patent by the USPTO. Subclassifications proxy for knowledge components recombined in the focal patent (Fleming 2001). For each inventor listed in the patent, I measured his or her familiarity with the patent's components, based on the number of times he or she used such components in the past. Following Fleming (2001), I multiplied this count by a decay coefficient over five years, to account for time-constant knowledge loss. Next, I derived the average component familiarity of all inventors listed in the patent. This measure shows overdispersion around the mean and is highly skewed to the left (zeroes) and right (high values) sides of its distribution. I therefore transformed it into a dummy variable, equal to 1 if the average component familiarity in the patent was null, such that the patent recombined components unfamiliar to its inventors, and 0 otherwise.

Outbound mobility of parent's experts. In line with prior research on knowledge workers' mobility (Palomeras and Melero 2010, Song et al. 2003), I assessed the extent to which exiting inventors hold expertise on the parent's knowledge, routines and procedures by matching their technological

[9] For this study, I exclude repeated citations, such as citations to patents that already have been cited by the firm in its prior patents.
[10] Robustness checks using regression models with count citation variables (not reported due to space limitations) led to similar results.

expertise (prior mobility) with the area of technological expertise of the parent. For each firm–year item in my sample, I identified the firm's core U.S. patent classifications (USPC), according to classifications in which the firm's patenting frequency was higher than its mean patenting frequency in all other USPCs. For each patent, I derived a list of inventors who moved from the citing firm to the cited CV spinouts and counted the number of patents these spun-out inventors applied for in the parent's most frequent USPCs during their corporate employment. This count is highly skewed to both the left and right sides of its distribution, so I transformed it into a dummy variable too, equal to 1 if the focal patent cites CV spinouts that employ inventors with any experience in the parent's most frequent USPCs, and 0 otherwise. Accordingly, I adopted subgroup analyses (Venkatraman 1989), instead of testing linear interactions.

Spinouts are important drivers of their industry's rate of technological change (Klepper and Sleeper 2005), so their chances of being cited by incumbents might be higher than that of other firms, simply because of the intrinsic differences that mark CV spinouts' strategies. In particular, it may be difficult to compare CV spinouts with other strategies with different learning objectives. To account for these caveats, I considered several covariates in my analysis.

Cited patents' impact. Parent firms should recognize or be aware of the value of their spinouts' projects, which could guide them to select the best options. To control for this possibility, I measured the impact of cited patents in a field as the average number of forward citations that these cited patents received in the five years after their application date (Fleming 2001).

Ownership and assignments. Patent citation data cannot reveal instances in which firms' collaboration on a project led to higher interfirm cross-citation rates (Mowery et al. 1996, Hagedoorn 2003). Spinout strategies also may be associated with different costs; for example, parent firms might engage in common R&D projects with their CV spinouts, which would encourage selections with a high cross-citation rate (Mowery et al. 1996) and potentially explain higher quality outcomes, because of the parent's incentives to protect the spinouts' inventions. Therefore, I considered two proxies. First, I measured the citing firm's equity *ownership* of cited firms, which prior research identifies as an explanatory variable for interfirm cross-citation patterns (Mowery et al. 1996). Second, I considered *patent assignments*. When two firms collaborate on a project that results in a patent application, they rarely appear as coapplicants (Hagedoorn 2003). Instead, one company applies, then transfers the patent rights, through licensing or IPR transfer, to the collaborator. This tactic is particularly common for CV spinouts. Thus, IPR transfers constitute a necessary control to compare CV spinouts with other strategies.

The transfer of patent ownership must be filed with the USPTO to be legally binding (Serrano 2010). Patent assignments describe the rationale for a transfer, the names of the buyers and sellers, patent numbers, and the date the parties signed the private agreement. Using the USPTO Patent Assignment Database, I extracted all patent assignments involving the 20 corporations in the sample. For each citing patent, I derived a list of assignments between the citing and cited firms, prior to the citing patent's application year. Then I selected those that indicated either outright sale or license of patents. *Patent assignments* thus equaled 1 if the citing and cited firms had signed patent assignments in the past.

Temporal exploration. Research has argued that the longer knowledge is in use or available, the more inventors can select the best recombinant solutions that have emerged over time (Nerkar 2003). Parent firms could better recognize and be inclined to cite their spinouts' knowledge because of a higher temporal awareness of their spinout projects. Therefore, it is meaningful to include a temporal exploration measure (the mean age of the cited patents) as a control.

Geographical proximity. Parent firms may be more aware of technological developments by their spinouts than by other firms, because the former tend to locate in the parent firms' geographical areas (Klepper and Sleeper 2005). I computed a *geographical proximity* measure with an approach similar to Corredoira and Rosenkopf's (2010). For each citing firm–cited firm pair, I coded a dummy index, equal to 1 if the two firms located in the same U.S. state, and 0 otherwise. Geographical proximity thus is the average of the dummy index, collapsed to the level of the citing patent.

Technological distance. Spinouts' knowledge may be in closer proximity to the parent firm's than is other firms' knowledge in the parent firm's technological search space. I therefore included a measure of *technological distance* as a control, which required two steps. First, for each citing patent, I prepared lists of all USPCs to which the citing patent was assigned, or citing classes, and of all USPCs to which the cited patents were assigned, or cited classes. Second, similar to Breschi et al. (2003), for each possible pair of citing class–cited class, I computed a cosine similarity index to measure the angular separation between the vectors that represent recombinations of the citing and the cited classes with all other USPCs in a moving time window of five years from t – 5 to t – 1.[11] Its value ranges between 0 (citing and cited classes are in completely different fields) and 1 (citing and cited classes are similarly recombined across technological areas). For each citing patent, I computed the index average across all pairs of citing–cited classes, and I subtracted it from 1, so that high values indicated greater technological distance.

Workers' mobility. Literature on external learning (Corredoira and Rosenkopf 2010, Song et al. 2003) suggests that the interorganizational mobility of workers facilitates interorganizational learning. Relevant knowledge developed by CV spinouts is more likely to be cited than knowledge developed by other firms, because of their relevant worker mobility patterns. Accordingly, I controlled for the number of inventors that moved from the citing firm to cited firms in the last five years (*OutMobility5*) and for the number of inventors hired by the citing firm away from cited firms in the last five years (*InMobility5*). To further reduce the bias that might result from workers' mobility, I included two measures of the strength of prior interactions between inventors in the citing and the cited firms. *Prior co-tenure* is the mean number of years spent simultaneously in the organizations by inventors of citing and cited firms. *Prior collaborations* is the mean number of inventions co-patented by inventors of citing and cited firms.

Industry proximity. I have suggested that information asymmetry may derive from competition dynamics between a firm and its CVC ventures, allied partners and employee spinouts. To control for this possibility, I computed the measure *same industry*. First, I collected information on the primary SIC codes of cited CV spinouts, employee spinouts, CVC ventures, and allied partners. Second, for each citing firm–cited firm pair, I coded a dummy index, equal to 1 if the two firms declared the same SIC code, and 0 otherwise. The measure is thus the average of the dummy index, collapsed to the level of the citing patent.

[11] Robustness checks (e.g., with a time window of ten years) led to similar results.

No forward citations. About 28% of patents in the sample received no forward citations in the five years after their grant date. Because the dependent variable is an index that includes forward citations, I included a dummy to capture when the observation belongs to a group of patents with zero forward citations, to control for unobserved differences among patents in the sample.

Finally, I controlled for technological categories and for firm and year effects. Table 2 contains a description of the variables and the descriptive statistics.

[Insert Table 2 here]

Results

Regression Analysis

The main model for the analysis is an ordinary least squares specification that regresses the dependent variable, *patent quality index*, on citation counts and other controls. Table 3 contains the regression estimates. Venkatraman (1989) posits that subgroup analysis can offer a better estimate of the different effects of certain strategies across contexts, so I distinguish patents using *familiar components* and *unfamiliar components*, then run separate models for the split samples. Column 2 of Table 3 offers evidence that firm patents that cite the firms' CV spinouts are associated with a higher patent quality index than other patents that cite other sources. The coefficient estimate for CV spinouts is significantly higher than those for CVC ventures ($p < 0.001$) and alliances ($p < 0.01$), in support of H1A. In addition, the coefficient for CV spinouts in the case of unfamiliar components is significantly higher than in the case of familiar components ($p < 0.001$; one-sided Wald test, not shown here), where I observe no statistical difference between CV spinouts and CVC ventures and alliances ($p > 0.1$).

Firm patents that cite the firm's own CV spinouts produce a higher patent quality index than those that cite the firm's employee spinouts. This result holds when the patent recombines unfamiliar components (Column 2, Table 3; $p < 0.05$, one-sided test), in line with H1B. This difference is not significant when the patent recombines familiar components (Column 1).

To test H2, in Columns 3 and 4 of Table 3, I split the citation variable for CV spinouts into *with parent expert* and *without parent expert* categories. The coefficient for CV spinouts with parent experts is significantly higher than that without parent experts ($p < 0.05$, one-sided tests) and other strategies (all $p < 0.001$, one-sided tests) in the case of unfamiliar components, in support of H2. The coefficient for CV spinouts without experts also is higher than CVC ventures and alliances in the case of unfamiliar components. Yet this difference is not significant when comparing CV spinouts without parent experts with employee spinouts (Column 4), which is congruent with the observed importance of social and human capital in the spinout effect.

[Insert Table 3 here]

Robustness Checks

Matching estimators. The composition of my sample makes it difficult to generalize the results. Citations to CV spinouts are relatively rare, and they may be associated with different learning objectives than other strategies. To address this bias and check the robustness of my results, I used a quasi-experimental research design and compared the effects of citing different sources of (similar) knowledge on patent quality index. That is, let Y_{i1} be the outcome of patent quality index when patent i is subject to the treatment (i.e., it cites a CV spinout) and Y_{i0} be the value of the same variable when the unit reflects a control condition (i.e., does not cite a CV spinout). The effect of citing a CV spinout is $e_i = Y_{i1} - Y_{i0}$, and the expected effect on the treated sample is:

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

where $T = 1$ (= 0) if patent i cites (does not cite) a CV spinout. Because we cannot directly observe $\mathrm{E}(Y_{i0} \,|\, T_i = 1)$, we lack counterfactual evidence about what would happen if a treated patent did not cite a CV spinout. If treated and control patents differ systematically (i.e., decisions to cite CV spinouts rather than other firms are not random), then $\mathrm{E}(Y_{i0} \,|\, T_i = 0)$ offers a biased estimator of $\mathrm{E}(Y_{i0} \,|\, T_i = 1)$.

Econometrics literature offers several models to assess treatment effects with observational data without random assignments to different groups, such as sample selection models, propensity score matching, or matching estimators (for a discussion, see Guo and Fraser 2010). Each model involves different features and different assumptions that the data must meet. For the current research, matching estimators provide the most appropriate statistical method. As Dehejia and Wahba (2002) demonstrate, when the selection of control units is valid and based on observable covariates, matching estimators produce unbiased estimates of the treatment effect. They impute the missing outcomes Y_{i0} of treated units, using the outcomes for units with *similar* values of relevant covariates that had not been exposed to the treatment. I adopted the nearest-neighbors matching procedure proposed by Abadie et al. (2004) and estimated the average treatment on the treated, adjusted for heteroskedasticity-consistent standard errors across four observations at the same treatment level, to compare the variability of the dependent variable in observations with approximately the same covariate values. With the small treated group, perfect matching could lead to biased estimates (Abadie and Imbens 2002), so I designed a matching structure with replacement and four matched controls, as well as exact matching on the firm, technological class, components familiarity and outbound mobility of parent's experts. The latter condition produces a better test of the role of parent's experts in CV spinouts, as compared to parent's experts in other firms. The results (Table 4) are in line with the idea that CV spinouts provide better outcomes in uncertain technological areas if they hire parent experts. In contrast, CVC ventures, alliances and employee ventures do not exert the same effect.

[Insert Table 4 here]

Supplemental Analyses

Non-compete employee spinouts. If firms can better learn from their CV spinouts because of organizational imprinting, but this effect is mitigated in employee spinouts due to competitive pressures, we also should observe variance among employee spinouts depending on the extent to which they occupy overlapping industry segments with the parent. I therefore estimated models that split the sample of employee spinouts into those that entered the same industry as their parent (three-digit SIC code) and those that did not. When using unfamiliar combinations, citing employee spinouts that enter other industries does not produce a statistically significant effect on patent quality index. Yet employee spinouts, absent competitive pressures, provide slightly better learning opportunities than CVC (p = 0.06), which instead lack the social ties. This effect also is not statistically different from the influence of CV spinouts, unless the latter employ the parent's experts (Column 4, Table 5; $p > 0.01$, one-sided test). Thus, the results are consistent with the effects of spinout imprinting and parent managerial control on routines and procedures transfer: Spinouts can provide parents with better opportunities to learn unfamiliar component combinations than other strategies when they benefit from corporate backing and they hire experts on their parent's knowledge, routines and procedures.

[Insert Table 5 here]

Own vs. others' CV spinouts. Although a firm's citations to its CV spinouts indicate a higher patent quality index, this result may arise because spinouts tend to be more explorative than other firms (Klepper and Sleeper 2005). I therefore estimated another model in which I compared citations to the firm's own CV spinouts with the firm's citations to other firms' CV spinouts. The results in Table 6 support the previous hypotheses test results.

[Insert Table 6 here]

Alliances. Prior research has argued that any kind of alliance yields the potential for external learning (Rosenkopf and Almeida 2003). Yet contractual agreements may differ in terms of learning objectives (Koza and Lewin 1998), which may bias the results. I therefore estimated other models to compare the effects of citing equity and non-equity alliances, and those of citing technological and non-technological alliances. Results (Tables 6 and 7) highlight the stronger effect of technological and equity alliances, compared with other types of alliances when the patent recombines unfamiliar components, and they confirm the highest effects of CV spinouts with parent experts ($p < 0.05$, one-sided tests).

[Insert Tables 7 and 8 here]

Mean and Standard Deviation. Firms may confront less uncertainty when they use unfamiliar components produced by their CV spinouts, which should be associated with less variance in patent quality index. To investigate this premise, I conducted additional analyses of the predicted mean and standard deviation of patent quality index, using a linear regression log-likelihood evaluator by Gould et al. (2006) for Stata, which models the standard deviation σ as it varies over the data. Formally,

$$\ln \mathrm{l}_i = \ln \phi \ \{(y_i - \theta_{1i})/ \ \theta_{2i}\} - \ln \theta_{2i}$$

$$\theta_{1i} = \mu_i = \mathrm{x}_i \boldsymbol{\beta}$$

$$\theta_{2i} = \sigma_i = \mathrm{x}_i \boldsymbol{\beta}$$

where $\ln \mathrm{l}_i$ fills in the log-likelihood values for each patent; θ_{1i} contains the values of the regression equation; and θ_{2i} is the variable that contains the values of the standard deviation. Table 9 provides the findings of the maximum likelihood estimation. In line with my predictions, when parents use unfamiliar components developed by their CV spinouts that employ parent experts (Column 4), they produce inventions with higher expected mean quality ($p < 0.05$, one-sided tests) and lower expected standard deviations ($p < 0.01$, one-sided tests). The effect of CV spinouts with parent experts on the expected standard deviation of patent quality index also is not statistically different from that of self-citations ($p = 0.068$, one-sided tests). Using other external knowledge sources does not prompt similar effects. The importance of this result is even more notable with the recognition that, due to a pure statistical artifact, variance always increases with a greater mean. The same differences do not hold when firms use familiar components. Thus, this analysis supports the idea that using CV spinouts' unfamiliar knowledge helps parents produces higher outputs than using other internal and external learning strategies, and these outputs are as certain as those of using firm's internal knowledge.

[Insert Table 9 here]

Knowledge flows. I argued that thanks to lower information asymmetry and similar procedural environments with their CV spinouts, parents should enjoy a greater probability of selecting high quality, impactful knowledge when using their CV spinouts' unfamiliar components, as opposed to other strategies. To test this premise I estimated a model that predicts knowledge flows between external sources and parents. First, for each patent in my sample, I tabulated a list of cited patents and obtained 156,790 pairs of citing–cited patents ($y = 1$). To improve estimation efficiency, for each citing–cited pair, I also constructed a set of control pairs (i.e., $y = 0$), which include all patents that were not cited by the firm and belong to the same NBER technological subcategory (Marco et al. 2015) and geographical area (U.S. state) and application year as those in the treated group. Following this approach I obtained 342,657 citing–cited pairs, including treated and control conditions. Second, I determined whether cited (treated and control) patents produced impactful knowledge. That is, following prior literature on breakthrough inventions (Ahuja and Lampert 2001), for each citing–cited pair, I coded a dummy variable that takes a value of 1 if the cited patent is in the top 5% of the distribution of USPTO patents invented in the same year and NBER technological subcategory. Finally, for each citing–cited pair, I identified the original assignee of the cited patent and coded dummy variables for CV spinouts and other groups of firms.

Table 10 shows three probit estimations.[12] The first specification (Column 1) includes all citing–cited pair observations. The second (Column 2) estimates the probability of a citation on a subset of breakthrough innovations (top 5%), and the last specification (Column 3) estimates this probability for a subset of breakthrough innovations for which the cited patents pertain to USPC subcategories that were previously unused, unfamiliar to the citing firm (Fleming 2001). *Ceteris paribus*, firms in this sample do not cite their CV spinouts' patents significantly more than CVC ventures' patents. Yet the likelihood that a firm will cite an external breakthrough in unfamiliar technological areas is higher when the invention is produced by the firm's CV spinouts. This effect is stronger than those associated with CVC investments and alliances (all $p < 0.001$, one-sided test) and employee ventures ($p < 0.05$, one-sided test). These results suggest that parents can leverage more valuable knowledge flows from their CV spinouts than from other strategic formats.

[Insert Table 10 here]

Discussion and Conclusion

Extant literature emphasizes CV spinouts as strategies to commercialize untapped corporate technology (Chesbrough 2003). The present article highlights another compelling facet: CV spinouts enrich the

[12] Other studies of the determinants of knowledge flows (e.g., Singh 2005) match treated citing–cited pairs with a limited set of control pairs, then use weighted, exogenous sampling, maximum likelihood estimators to predict the likelihood of patent citations. The sampling strategy in this study includes *all* control conditions based on perfect matches, so I instead opted for a probit specification.

external recombinant opportunities of their parents with new sets of unfamiliar knowledge components, such that firm inventors can draw on the experiences of spun-out inventors and reduce uncertainty in their invention outputs. To establish empirical support for these theoretical claims, I considered the CV spinout effect in comparison with alternative strategies for external learning. Due to corporate venturing incubation, the parent firm can gain social capital links with its spun out employees, such as formal and informal relations, which persist after the spinout event. CV spinout strategies thus can reduce information asymmetry in their parents' external learning. Parent–spinout organizational imprinting also promotes similarities between procedural environments. The same effect does not materialize in the absence of formal agreements or spinout incubation, because of no control on routines and procedures transfers, lack of knowledge complementarity, or tensions that likely arise in the relational ties of employee spinouts with parents as a result of competitive behaviors too. Parent firms thus can gain substantial awareness of the value of CV spinouts' projects when they explore unfamiliar knowledge and when spun-out inventors hold parent-specific expertise, so parents can learn better from them than they can from other firms about impactful external technological developments.

Several limitations hinder the generalizability of these results though. First, CV spinout strategies may differ intrinsically from other strategies. Each strategy has unique strategic intents that coevolve with the firm's institutional, organizational, and competitive environment, with different search and learning objectives at any point in time (for a discussion of alliance strategies, see Koza and Lewin 1998). The higher patent quality index in the treated group might result endogenously from the spinout strategy, because CV spinouts may be selected based on potential synergies with the capabilities of the parent firm. In this respect, as prior literature notes (e.g., Chesbrough 2006, Christensen 1997), the rationale for initiating CV spinouts is usually not to patent other inventions but rather to exploit commercial technologies previously developed by the parent firm. The 20 firms in this sample do not exhibit significant differences in their propensities to generate spinouts compared with CVC investments or alliances. Also, CV spinouts in my sample show variance in their exploratory performance. Even if CV spinouts are endogenously intended to be explorative or develop complementary technologies, other strategies could be devoted to the same aims; the quasi-experimental research design of this study is meant to control for—and match—observable strategic differences.

Second, I did not consider parent firm's and employees' motivations to initiate spinouts or the cost associated with CV strategies. In this respect, it was not my purpose to prove causality, or to estimate the overall effect of spinout strategies on corporate inventions. Rather, my sampling strategy and analyses aimed to show that, considering and possibly correcting for dissimilarities in strategies, significant differences exist between the use of CV spinouts and that of other strategies. In particular, after accounting for observable differences and *ceteris paribus*, inventions that build on CV spinouts' unfamiliar knowledge induce higher quality, and CV spinouts offer a compelling, valuable strategy for external learning in uncertain technological areas.

Third, different knowledge search mechanisms exist, but I focus on just one, patent citations, to show that, conditional on one mechanism, important differences appear between CV spinouts and other strategies. The empirical focus on ICT, a setting in which patents are effective means to appropriate value from R&D (Arora et al. 2008) and patent citations offer a valid indicator of the use of external knowledge (Rosenkopf and Nerkar 2001), sought to reduce this potential bias.

Despite these limitations, this study makes several contributions. First, to the best of my knowledge, this study is among the first to explore differences between CV spinouts (Chesbrough 1998, 2003) and employee spinouts (Agarwal et al. 2004) empirically, as well as to compare them with alternative strategic modes for external learning. In turn, the evidence from this study adds robustness to Agarwal et al.'s (2007) intuition that parents can strategically manage knowledge spill-ins from their employee ventures. By focusing on patent quality, this study also sheds a light on the economic importance of knowledge spill-ins. In addition, it provides insights about the underlying mechanisms and boundary conditions for this effect. It shows that spill-ins are significant only from unfamiliar technological areas and from CV spinouts that hire experts on the parent's knowledge, routines and procedures. Therefore, spill-ins are not necessarily driven by parents' investments and managerial control in their spinouts (e.g., Kim and Steensma 2017).

Second, these results inform research into the effects of interfirm mobility on knowledge flows (e.g., Corredoira and Rosenkopf 2010, Song et al. 2003). My results suggest that mobility to spinouts is a necessary but insufficient condition to generate invention quality through external knowledge search. The evidence is consistent with the idea that not all mobility events to spinouts are equally beneficial in generating valuable knowledge spill-ins; CV spinouts by workers with firm-specific expertise appear to provide better external learning opportunities than otherwise.

Third, this study provides evidence about and insights into CV spinouts as important, overlooked, strategic mechanisms for enhancing external learning capabilities. In doing so, this study complements prior research on external learning strategies by adopting a comparative lens to examine spinouts, CVC investments and alliances together. Thus, my results offer guidelines for managerial practice; as Chesbrough recommends,

> “instead of looking to them primarily for near term revenue that would be incremental to the current business, [CV spinouts] could be managed as long-term options on new future markets. This would free [CV spinouts] from the tyranny of supporting only the existing businesses and could provide [the parent] with a platform for building future businesses” (Chesbrough 2002: 835-836).

Previous studies have focused on CV spinouts as technological exits or strategies to market existing, untapped technology owned by the parent (Chesbrough 2002). The current study suggests that CV spinouts also provide parents less uncertain external learning opportunities. Firms may spin out their innovation assets and grow their ecosystems of spinout ventures, to nurture the development of risky projects that are not strategic for the parent firm. By operating as independent subsystems within the corporation (Christensen 1997), spinouts bear the costs and risks of exploration. The technological developments achieved by spinouts thus can help parents learn about unfamiliar knowledge, and the parent-specific expertise of spun-out workers can help the parent leverage the capabilities of the spinouts it has spawned (Agarwal et al. 2007).

Thus, CV spinouts provide viable opportunities to reconfigure parent firms' knowledge bases. Still, much work remains to be done to explain CV spinouts' contributions to a fundamental issue for strategy research, namely, identifying the drivers of strategic change and renewal.

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Table 1 Distribution of Firms and Patent Observations

Firms	Patents	Firms	Patents
Advanced Micro Devices, Inc.	155	LSI Logic Corporation	396
Agilent Technologies, Inc.	46	Lucent Technologies, Inc.	480
Analog Devices, Inc.	57	Motorola, Inc.	444
Apple, Inc.	833	Qualcomm, Inc.	524
Cirrus Logic, Inc.	95	Scientific-Atlanta, Inc.	11
Cypress Semiconductor	39	Sun Microsystems, Inc.	865
Fairchild Semiconductor	48	Tektronix, Inc.	44
Harris Corporation	23	Texas Instruments, Inc.	53
Hewlett-Packard Company	1,587	Xerox Corporation	1,452
Intel Corporation	2,671	Xilinx, Inc.	359
		Total observations	10,182

Table 2 Main Variables and Descriptive Statistics (N = 10,182)

Variable	Description	Mean	SD	Min	Max
Patent quality index	Lanjouw and Schankerman's (2004) weighted index with claims, forward (5 years) and backward citations	9.326	5.22	0.37	81.23
ln(*CV spinouts*)	ln(1 + # citations to the focal firm's CV spinouts)	0.008	0.07	0	1.60
ln(*Employee spinouts*)	ln(1 + # citations to the focal firm's employee spinouts)	0.016	0.11	0	3.55
ln(*CVCs*)	ln(1 + # citations to the focal firm's allied firms)	0.019	0.12	0	2.39
ln(*Alliances*)	ln(1 + # citations to the focal firm's CVC portfolio ventures)	0.013	0.09	0	1.60
ln(*Self-citations*)	ln(1 + # citations to the focal firm's own patents)	0.150	0.35	0	3.36
ln(*Others*)	ln(1 + # citations to the other firms)	2.225	0.99	0	6.99
Cited patents' impact	*Mean*(# of citations [Forw5] received by cited patents)	21.03	16.89	0	227
Ownership	*Mean*(% ownership of citing firm in cited firms)	0.094	0.18	0	1
Patent assignments	1{prior patent assignments from/to citing to/from cited firms}	0.077	0.26	0	1
Temporal exploration	*Mean*(Δ citing-cited patents application year)	6.040	3.04	0	32
Geographical proximity	*Mean*(1{citing-cited firms locates in the same U.S. state})	0.242	0.24	0	1
Technological distance	*Mean* cosine similarity index between recombination vectors of classes *i* and *j* at year *t*, ∀ citing–cited classes (*i*, *j*)	0.640	0.28	0	1
ln(*InMobility5*)	ln(*Mean*(Σ prior mobility from cited to citing firm))	2.442	1.67	0	6.80
ln(*OutMobility5*)	ln(*Mean*(*Σ* prior mobility from citing to cited firm))	0.841	1.37	0	6.90
Prior co-tenure	Years spent in the same firm by inventors of the citing and those of the cited firms	0.132	0.47	0	12
ln(*Prior collaborations*)	ln(1 + # citations to former co-inventors in the cited firms)	0.042	0.19	0	2.63
Industry proximity	*Mean*(1{citing firm has same SIC code as cited firm})	0.248	0.32	0	1
No forward citations	1{Citing patent received no forward citations in [t_1, t_5]}	0.282	0.45	0	1
Component familiarity	1{Fleming's (2001) component familiarity > 0}	0.310	0.46	0	1
Outbound mobility of parent's experts	1{Cited outbound inventors were expert with the parent firm's core technological areas during their stay at the parent}	0.379	0.49	0	1

Table 3 Linear Regressions on Patent Quality Index

Split sample:	*Familiar components*		*Unfamiliar components*		*Familiar components*		*Unfamiliar components*	
	1		2		3		4	
Variables:	*Coef.*	*Std.err.*	*Coef.*	*Std.err.*	*Coef.*	*Std.err.*	*Coef.*	*Std.err.*
ln(*CV spinouts*)	- 0.207	(0.95)	2.114***	(0.51)				
with parent expert					- 0.922	(0.60)	3.986***	(0.88)
w/o parent expert					- 0.064	(1.15)	1.655*	(0.72)
ln(*Employee spinouts*)	- 0.079	(0.49)	0.492	(0.73)	- 0.076	(0.49)	0.485	(0.73)
ln(*CVC ventures*)	0.300	(0.27)	- 1.035***	(0.26)	0.297	(0.27)	- 1.059***	(0.26)
ln(*Alliances*)	0.782	(0.70)	- 0.098	(0.44)	0.789	(0.70)	- 0.091	(0.44)
ln(*Self-citations*)	0.664*	(0.23)	- 0.004	(0.37)	0.663*	(0.23)	- 0.001	(0.36)
ln(*Other firms*)	0.396*	(0.16)	0.305	(0.16)	0.396*	(0.16)	0.307	(0.16)
Cited patents' impact	0.019*	(0.00)	0.024*	(0.01)	0.019*	(0.00)	0.024*	(0.01)
Ownership	- 0.400	(0.39)	- 1.606*	(0.66)	- 0.398	(0.39)	- 1.591*	(0.67)
Patent assignments	0.774**	(0.24)	1.041	(0.96)	0.773**	(0.24)	1.041	(0.95)
Temporal exploration	- 0.032	(0.04)	- 0.016	(0.04)	- 0.032	(0.04)	- 0.015	(0.04)
Geographical proximity	0.371	(0.25)	- 0.355	(0.51)	0.371	(0.25)	- 0.340	(0.51)
Technological distance	0.252	(0.17)	- 0.157	(0.25)	0.250	(0.17)	- 0.150	(0.25)
ln(*InMobility5*)	- 0.026	(0.03)	- 0.154*	(0.06)	- 0.026	(0.03)	- 0.153*	(0.06)
ln(*OutMobility5*)	- 0.125**	(0.03)	0.021	(0.08)	- 0.125**	(0.03)	0.018	(0.08)
Prior co-tenure	0.088	(0.12)	0.093	(0.25)	0.088	(0.12)	0.094	(0.25)
ln(*Prior collaborations*)	- 0.158	(0.33)	- 0.927	(0.83)	- 0.158	(0.33)	- 0.928	(0.83)
Industry proximity	- 0.670*	(0.29)	0.340	(0.32)	- 0.670*	(0.29)	0.328	(0.31)
No forward citations	- 1.267***	(0.13)	- 1.396***	(0.16)	- 1.267***	(0.13)	- 1.401***	(0.16)
Firm dummies (20)	9 firms***		7 firms***		9 firms***		7 firms***	
Application year dummies (10)	2 years**		1 year**		2 years**		1 year**	
NBER Technology subcategory dummies (16)	5 technologies***		1 technology***		5 technologies***		1 technology***	
Constant	8.232***	(0.40)	9.136***	(0.57)	8.232***	(0.39)	9.129***	(0.57)
Observations	7,024		3,158		7,024		3,158	
R-squared	0.137		0.168		0.137		0.168	
	One-sided test p-values for linear combinations of coefficients							
β(*CV spinouts*) - β(*Emp. spinout*) = 0	p = 0.454		**p = 0.044**					
β(*CV spinouts*) - β(*CVC ventures*) = 0	p = 0.321		**p = 0.000**					
β(*CV spinouts*) - β(*Alliances*) = 0	p = 0.200		**p = 0.003**					
β(*CV spinouts*) - β(*Self-citations*) = 0	p = 0.202		**p = 0.000**					
β(*CV spinouts*) - β(*Other firms*) = 0	p = 0.279		**p = 0.003**					
β(*CV spin. with*) - β(*CV spin. w/o*) = 0					p = 0.239		**p = 0.037**	
β(*CV spin. with*) - β(*Emp. spinout*) = 0					p = 0.173		**p = 0.001**	
β(*CV spin. with*) - β(*CVC ventures*) = 0					**p = 0.042**		**p = 0.000**	
β(*CV spin. with*) - β(*Alliances*) = 0					**p = 0.039**		**p = 0.001**	
β(*CV spin. with*) - β(*Self-citations*) = 0					**p = 0.008**		**p = 0.001**	
β(*CV spin. with*) - β(*Other firms*) = 0					**p = 0.025**		**p = 0.000**	
β(*CV spin. w/o*) - β(*Empl. spin.*) = 0					p = 0.497		p = 0.158	
β(*CV spin. w/o*) - β(*CVC ventures*) = 0					p = 0.389		**p = 0.001**	
β(*CV spin. w/o*) - β(*Alliances*) = 0					p = 0.264		**p = 0.028**	
β(*CV spin. w/o*) - β(*Self-citations*) = 0					p = 0.280		**p = 0.005**	
β(*CV spin. w/o*) - β(*Other firms*) = 0					p = 0.354		p = 0.060	

Note. Dependent variable is *Patent Quality Index*. Robust standard errors (in parentheses) are clustered by firm.
* $p < .05$; ** $p < .01$; *** $p < .001$.

Table 4 Matching estimators: Average Treatment Effect for the Treated (ATT) on Patent Quality Index

Treated group: **CV spinouts**	*Control groups:* **CVC investments**		**Alliances**		**Employee spinouts**		**Corporate patents (self-citations)**	
Split sample: **Familiar components**	*Coef.*[a]	*Std.err.*[b]	*Coef.*[a]	*Std.err.*[b]	*Coef.*[a]	*Std.err.*[b]	*Coef.*[a]	*Std.err.*[b]
ATT(*CV spinout without parent experts*)	-0.424	(0.70)	-2.542*	(1.00)	-0.881	(0.69)	-0.896	(0.89)
ATT(*CV spinout with parent experts*)	1.777†	(0.92)	-0.214	(1.42)	-0.151	(0.93)	1.871†	(1.08)
	One-sided test p-values for coefficients differences							
β(*without*) - β(*with*) = 0	***p* = .000**		***p* = .000**		***p* = .003**		***p* = .000**	

Treated group: **CV spinouts**	*Control groups:* **CVC investments**		**Alliances**		**Employee spinouts**		**Corporate patents (self-citations)**	
Split sample: **Unfamiliar components**	*Coef.*[a]	*Std.err.*[b]	*Coef.*[a]	*Std.err.*[b]	*Coef.*[a]	*Std.err.*[b]	*Coef.*[a]	*Std.err.*[b]
ATT(*CV spinout without parent experts*)	0.152	(1.16)	2.708*	(1.11)	-0.291	(1.52)	1.366	(1.36)
ATT(*CV spinout with parent experts*)	3.585*	(1.68)	3.754*	(1.53)	3.048*	(1.42)	3.577*	(1.55)
	One-sided test p-values for coefficients differences							
β(*without*) - β(*with*) = 0	***p* = .000**		***p* = .014**		***p* = .000**		***p* = .001**	

Note. The dependent variable is *Patent quality index*.

[a] Bias adjusted nearest neighbor matching estimation for average treatment effect for the treated (ATT). The covariates included for matching are *Cited patents' impact*, *Patent assignments*, *Temporal exploration*, *Geographical proximity*, *Technological distance*, *OutMobility5*, *Prior co-tenure*, *Prior collaborations*, *Industry proximity*, *Citations to other firms*, fixed effects for *firm*, *application year* and *NBER technology subcategory*. Four comparison units per treated unit.

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

† $p < .1$; * $p < .05$; ** $p < .01$; *** $p < .001$.

Table 5 Linear Regressions on Patent Quality Index: Competing vs. Non-competing Employee Spinouts

Split sample:	*Familiar components*		*Unfamiliar components*		*Familiar components*		*Unfamiliar components*	
	1		2		3		4	
Variables:	*Coef.*	*Std.err.*	*Coef.*	*Std.err.*	*Coef.*	*Std.err.*	*Coef.*	*Std.err.*
ln(*CV spinouts*)	- 0.207	(0.94)	2.147***	(0.52)				
with parent expert					- 0.947	(0.63)	4.002***	(0.89)
w/o parent expert					- 0.060	(1.15)	1.691*	(0.74)
ln(*Employee spinouts*)								
same industry as parent	- 0.279	(0.52)	0.351	(0.95)	- 0.283	(0.52)	0.347	(0.95)
other industry	0.228	(0.76)	0.653	(0.90)	0.239	(0.76)	0.644	(0.90)
ln(*CVC ventures*)	0.301	(0.26)	- 1.031**	(0.27)	0.298	(0.26)	- 1.055**	(0.27)
ln(*Alliances*)	0.774	(0.70)	- 0.130	(0.45)	0.781	(0.70)	- 0.123	(0.45)
ln(*Self-citations*)	0.666**	(0.23)	- 0.019	(0.35)	0.665**	(0.23)	- 0.015	(0.35)
ln(*Other firms*)	0.397*	(0.16)	0.298	(0.17)	0.397*	(0.16)	0.301	(0.17)
Cited patents' impact	0.019*	(0.00)	0.024*	(0.01)	0.019*	(0.00)	0.024*	(0.01)
Ownership	- 0.404	(0.39)	- 1.615*	(0.65)	- 0.402	(0.39)	- 1.600*	(0.66)
Patent assignments	0.773**	(0.24)	1.028	(0.96)	0.773**	(0.24)	1.027	(0.96)
Temporal exploration	- 0.032	(0.04)	- 0.015	(0.04)	- 0.032	(0.04)	- 0.014	(0.04)
Geographical proximity	0.371	(0.25)	- 0.364	(0.52)	0.370	(0.25)	- 0.350	(0.52)
Technological distance	0.253	(0.17)	- 0.154	(0.25)	0.252	(0.17)	- 0.147	(0.25)
ln(*InMobility5*)	- 0.026	(0.03)	- 0.155*	(0.06)	- 0.026	(0.03)	- 0.154*	(0.06)
ln(*OutMobility5*)	- 0.125**	(0.03)	0.016	(0.08)	- 0.125**	(0.03)	0.014	(0.08)
Prior co-tenure	0.088	(0.12)	0.089	(0.25)	0.088	(0.12)	0.090	(0.24)
ln(*Prior collaborations*)	- 0.105	(0.20)	- 0.264	(0.31)	- 0.105	(0.20)	- 0.264	(0.31)
Industry proximity	- 0.666*	(0.29)	0.337	(0.33)	- 0.667*	(0.29)	0.325	(0.33)
No forward citations	- 1.266***	(0.13)	- 1.401***	(0.16)	- 1.266***	(0.13)	- 1.407***	(0.16)
Firm dummies (20)	9 firms***		7 firms***		9 firms***		7 firms***	
Application year dummies (10)	2 years**		1 year**		2 years**		1 year**	
NBER Technology subcategory dummies (16)	5 technologies***		2 technologies***		5 technologies***		2 technologies***	
Constant	8.226***	(0.40)	9.155***	(0.55)	8.227***	(0.40)	9.148***	(0.55)
Observations	7,024		3,158		7,024		3,158	
R-squared	0.137		0.168		0.137		0.168	

	One-sided test p-values for linear combinations of coefficients			
β(*Emp. spin. same*) - β(*Emp. spin. other*) = 0	p = 0.298	p = 0.419	p = 0.294	p = 0.416
β(*Emp. spin. same*) - β(*CV spinout*) = 0	p = 0.472	**p = 0.048**		
β(*Emp. spin. same*) - β(*CV spin. with*) = 0			p = 0.216	**p = 0.001**
β(*Emp. spin. same*) - β(*CV spin. w/o*) = 0			p = 0.427	p = 0.142
β(*Emp. spin. same*) - β(*CVC ventures*) = 0	p = 0.148	p = 0.090	p = 0.147	p = 0.078
β(*Emp. spin. same*) - β(*Alliances*) = 0	p = 0.123	p = 0.327	p = 0.120	p = 0.331
β(*Emp. spin. same*) - β(*Self-citations*) = 0	p = 0.067	p = 0.362	p = 0.066	p = 0.374
β(*Emp. spin. other*) - β(*CV spinout*) = 0	p = 0.364	p = 0.100		
β(*Emp. spin. other*) - β(*CV spin. with*) = 0			p = 0.146	**p = 0.008**
β(*Emp. spin. other*) - β(*CV spin. w/o*) = 0			p = 0.414	p = 0.217
β(*Emp. spin. other*) - β(*CVC ventures*) = 0	p = 0.454	p = 0.061	p = 0.463	p = 0.060
β(*Emp. spin. other*) - β(*Alliances*) = 0	p = 0.221	p = 0.248	p = 0.223	p = 0.251
β(*Emp. spin. other*) - β(*Self-citations*) = 0	p = 0.316	p = 0.267	p = 0.322	p = 0.271

Note. Dependent variable is *Patent Quality Index*. Robust standard errors (in parentheses) are clustered by firm.
* $p < .05$; ** $p < .01$; *** $p < .001$.

Table 6 Linear Regressions on Patent Quality Index: Own vs. Others' CV Spinouts

Split sample:	*Familiar components*		*Unfamiliar components*		*Familiar components*		*Unfamiliar components*	
	1		2		3		4	
Variables:	*Coef.*	*Std.err.*	*Coef.*	*Std.err.*	*Coef.*	*Std.err.*	*Coef.*	*Std.err.*
ln(*CV spinouts*)	- 0.212	(0.95)	2.139***	(0.52)				
with parent expert					- 0.932	(0.60)	4.004***	(0.89)
w/o parent expert					- 0.069	(1.15)	1.681*	(0.74)
ln(*Other firms' CV spinouts*)	- 0.162	(0.18)	- 0.000	(0.22)	- 0.162	(0.18)	0.008	(0.21)
ln(*Employee spinouts*)	- 0.070	(0.50)	0.515	(0.73)	- 0.067	(0.50)	0.508	(0.73)
ln(*CVC ventures*)	0.327	(0.26)	- 1.021**	(0.27)	0.324	(0.26)	- 1.046**	(0.27)
ln(*Alliances*)	0.817	(0.72)	- 0.122	(0.45)	0.824	(0.72)	- 0.116	(0.45)
ln(*Self-citations*)	0.669**	(0.23)	- 0.018	(0.35)	0.668**	(0.23)	- 0.015	(0.34)
ln(*Other firms*)	0.401*	(0.15)	0.300	(0.17)	0.401*	(0.15)	0.303	(0.17)
Cited patents' impact	0.019*	(0.00)	0.024*	(0.01)	0.019*	(0.00)	0.024*	(0.01)
Ownership	- 0.421	(0.39)	- 1.609*	(0.66)	- 0.419	(0.39)	- 1.593*	(0.66)
Patent assignments	0.773**	(0.25)	1.029	(0.96)	0.772**	(0.25)	1.029	(0.96)
Temporal exploration	- 0.033	(0.04)	- 0.015	(0.05)	- 0.033	(0.04)	- 0.014	(0.04)
Geographical proximity	0.384	(0.25)	- 0.367	(0.52)	0.383	(0.25)	- 0.353	(0.53)
Technological distance	0.252	(0.17)	- 0.152	(0.24)	0.250	(0.17)	- 0.144	(0.25)
ln(*InMobility5*)	- 0.024	(0.03)	- 0.155*	(0.06)	- 0.024	(0.03)	- 0.154*	(0.06)
ln(*OutMobility5*)	- 0.125**	(0.03)	0.017	(0.08)	- 0.125**	(0.03)	0.014	(0.08)
Prior co-tenure	0.087	(0.12)	0.088	(0.25)	0.087	(0.12)	0.089	(0.25)
ln(*Prior collaborations*)	- 0.106	(0.20)	- 0.265	(0.31)	- 0.106	(0.20)	- 0.265	(0.31)
Industry proximity	- 0.667*	(0.29)	0.327	(0.32)	- 0.667*	(0.29)	0.315	(0.32)
No forward citations	- 1.266***	(0.13)	- 1.404***	(0.16)	- 1.266***	(0.13)	- 1.409***	(0.16)
Firm dummies (20)	8 firms***		7 firms***		8 firms***		7 firms***	
Application year dummies (10)	2 years**		1 year**		2 years**		1 year**	
NBER Technology subcategory dummies (16)	5 technologies***		2 technologies***		5 technologies***		2 technologies***	
Constant	8.234***	(0.40)	9.155***	(0.56)	8.234***	(0.39)	9.148***	(0.56)
Observations	7,024		3,158		7,024		3,158	
R-squared	0.137		0.168		0.137		0.168	
	One-sided test p-values for linear combinations of coefficients							
β(*Own CV spinouts*) - β(*Others firms'*) = 0	p = 0.480		$\boldsymbol{p}$ **= 0.001**					
β(*Own CV spin. with*) - β(*Others firms'*) = 0					p = 0.126		$\boldsymbol{p}$ **= 0.001**	
β(*Own CV spin. w/o*) - β(*Others firms'*) = 0					p = 0.469		$\boldsymbol{p}$ **= 0.014**	

Note. Dependent variable is *Patent Quality Index*. Robust standard errors (in parentheses) are clustered by firm. * $p < .05$; ** $p < .01$; *** $p < .001$.

Table 7 Linear Regressions on Patent Quality Index: Equity vs. Non-equity Alliances

Split sample:	*Familiar components*		*Unfamiliar components*		*Familiar components*		*Unfamiliar components*	
	1		2		3		4	
Variables:	*Coef.*	*Std.err.*	*Coef.*	*Std.err.*	*Coef.*	*Std.err.*	*Coef.*	*Std.err.*
ln(*CV spinouts*)	- 0.213	(0.94)	2.146***	(0.52)				
with parent expert					- 0.988	(0.65)	4.005***	(0.89)
w/o parent expert					- 0.059	(1.15)	1.690*	(0.74)
ln(*Equity alliances – including JVs*)	- 2.839**	(0.78)	1.579	(0.93)	- 2.848**	(0.78)	1.574	(0.93)
ln(*Non-equity alliances*)	1.518*	(0.57)	- 0.570	(0.73)	1.528*	(0.56)	- 0.562	(0.73)
ln(*Employee spinouts*)	- 0.044	(0.48)	0.512	(0.72)	- 0.040	(0.48)	0.506	(0.72)
ln(*CVC ventures*)	0.295	(0.27)	- 1.026**	(0.27)	0.293	(0.27)	- 1.049**	(0.27)
ln(*Self-citations*)	0.658*	(0.23)	- 0.019	(0.36)	0.656*	(0.23)	- 0.016	(0.35)
ln(*Other firms*)	0.399*	(0.16)	0.303	(0.17)	0.399*	(0.16)	0.306	(0.17)
Cited patents' impact	0.019*	(0.00)	0.024*	(0.01)	0.019*	(0.00)	0.024*	(0.01)
Ownership	- 0.390	(0.39)	- 1.601*	(0.66)	- 0.388	(0.39)	- 1.586*	(0.66)
Patent assignments	0.790**	(0.24)	1.023	(0.95)	0.789**	(0.24)	1.023	(0.95)
Temporal exploration	- 0.032	(0.04)	- 0.016	(0.04)	- 0.032	(0.04)	- 0.015	(0.04)
Geographical proximity	0.370	(0.25)	- 0.374	(0.52)	0.369	(0.25)	- 0.360	(0.52)
Technological distance	0.253	(0.17)	- 0.156	(0.25)	0.251	(0.17)	- 0.149	(0.25)
ln(*InMobility5*)	- 0.028	(0.03)	- 0.155*	(0.06)	- 0.028	(0.03)	- 0.154*	(0.06)
ln(*OutMobility5*)	- 0.126**	(0.03)	0.016	(0.08)	- 0.126**	(0.03)	0.013	(0.08)
Prior co-tenure	0.086	(0.12)	0.091	(0.25)	0.086	(0.12)	0.092	(0.25)
ln(*Prior collaborations*)	- 0.102	(0.20)	- 0.265	(0.31)	- 0.102	(0.20)	- 0.265	(0.31)
Industry proximity	- 0.673*	(0.28)	0.325	(0.32)	- 0.674*	(0.28)	0.313	(0.32)
No forward citations	- 1.265***	(0.13)	- 1.402***	(0.16)	- 1.264***	(0.13)	- 1.408***	(0.16)
Firm dummies (20)	9 firms***		7 firms***		9 firms***		7 firms***	
Application year dummies (10)	2 years**		1 year**		2 years**		1 year**	
NBER Technology subcategory dummies (16)	5 technologies***		1 technology***		5 technologies***		1 technology***	
Constant	8.216***	(0.39)	9.165***	(0.55)	8.216***	(0.39)	9.158***	(0.55)
Observations	7,024		3,158		7,024		3,158	
R-squared	0.137		0.168		0.137		0.168	
	One-sided test p-values for linear combinations of coefficients							
β(CV spinout) - β(Equity alliances) = 0	***p* = 0.024**		*p* = 0.304					
β(CV spinout) - β(Non-equity alliances) = 0	*p* = 0.079		***p* = 0.004**					
β(CV spin. *with*) - β(Equity alliances) = 0					***p* = 0.027**		***p* = 0.033**	
β(CV spin. *with*) - β(Non-equity alliance) = 0					***p* = 0.003**		***p* = 0.001**	
β(CV spin. *w/o*) - β(Equity alliances) = 0					***p* = 0.032**		*p* = 0.462	
β(CV spin. *w/o*) - β(Non-equity alliance) = 0					*p* = 0.124		***p* = 0.021**	

Note. Dependent variable is *Patent Quality Index*. Robust standard errors (in parentheses) are clustered by firm.
* $p < .05$; ** $p < .01$; *** $p < .001$.

Table 8 Linear Regressions on Patent Quality Index: Technological vs. Non-technological Alliances

Split sample:	*Familiar components*		*Unfamiliar components*		*Familiar components*		*Unfamiliar components*	
	1		2		3		4	
Variables:	*Coef.*	*Std.err.*	*Coef.*	*Std.err.*	*Coef.*	*Std.err.*	*Coef.*	*Std.err.*
ln(*CV spinouts*)	- 0.216	(0.94)	2.143***	(0.52)				
with parent expert					- 0.984	(0.64)	4.003***	(0.89)
w/o parent expert					- 0.063	(1.15)	1.687*	(0.74)
ln(*Technological alliances*)	- 2.378**	(0.64)	0.745	(0.97)	- 2.387**	(0.64)	0.739	(0.97)
ln(*Non-technological alliances*)	1.455***	(0.35)	- 0.433	(0.85)	1.465***	(0.34)	- 0.424	(0.85)
ln(*Employee spinouts*)	- 0.053	(0.48)	0.507	(0.73)	- 0.049	(0.48)	0.500	(0.73)
ln(*CVC ventures*)	0.296	(0.27)	- 1.022**	(0.27)	0.293	(0.27)	- 1.045**	(0.27)
ln(*Self-citations*)	0.664**	(0.23)	- 0.020	(0.35)	0.662**	(0.23)	- 0.017	(0.35)
ln(*Other firms*)	0.397*	(0.16)	0.301	(0.17)	0.397*	(0.16)	0.304	(0.17)
Cited patents' impact	0.019*	(0.00)	0.024*	(0.01)	0.019*	(0.00)	0.024*	(0.01)
Ownership	- 0.392	(0.39)	- 1.605*	(0.66)	- 0.390	(0.39)	- 1.589*	(0.66)
Patent assignments	0.776**	(0.24)	1.026	(0.96)	0.776**	(0.24)	1.026	(0.96)
Temporal exploration	- 0.032	(0.04)	- 0.016	(0.04)	- 0.033	(0.04)	- 0.014	(0.04)
Geographical proximity	0.371	(0.25)	- 0.369	(0.52)	0.371	(0.25)	- 0.354	(0.52)
Technological distance	0.257	(0.17)	- 0.151	(0.25)	0.255	(0.17)	- 0.144	(0.25)
ln(*InMobility5*)	- 0.027	(0.03)	- 0.156*	(0.06)	- 0.027	(0.03)	- 0.154*	(0.06)
ln(*OutMobility5*)	- 0.125**	(0.03)	0.017	(0.08)	- 0.125**	(0.03)	0.014	(0.08)
Prior co-tenure	0.085	(0.12)	0.089	(0.25)	0.085	(0.12)	0.090	(0.25)
ln(*Prior collaborations*)	- 0.102	(0.20)	- 0.266	(0.31)	- 0.103	(0.20)	- 0.266	(0.31)
Industry proximity	- 0.676*	(0.29)	0.327	(0.32)	- 0.676*	(0.29)	0.315	(0.32)
No forward citations	- 1.265***	(0.13)	- 1.402***	(0.16)	- 1.265***	(0.13)	- 1.408***	(0.16)
Firm dummies (20)	9 firms***		7 firms***		9 firms***		7 firms***	
Application year dummies (10)	2 years**		1 year**		2 years**		1 year**	
NBER Technology subcategory dummies (16)	5 technologies***		1 technology***		5 technologies***		1 technology***	
Constant	8.225***	(0.39)	9.160***	(0.55)	8.225***	(0.39)	9.153***	(0.56)
Observations	7,024		3,158		7,024		3,158	
R-squared	0.137		0.168		0.137		0.168	
	One-sided test p-values for linear combinations of coefficients							
β(CV spinout) - β(Tech. alliances) = 0	***p* = 0.024**		*p* = 0.119					
β(CV spinout) - β(Non-tech. alliance) = 0	*p* = 0.076		***p* = 0.009**					
β(CV spin. *with*) - β(Tech. alliances) = 0					*p* = 0.068		***p* = 0.014**	
β(CV spin. *with*) - β(Non-tech. alliance) = 0					***p* = 0.001**		***p* = 0.001**	
β(CV spin. *w/o*) - β(Tech. alliances) = 0					***p* = 0.034**		*p* = 0.225	

Note. Dependent variable is *Patent Quality Index*. Robust standard errors (in parentheses) are clustered by firm. * $p < .05$; ** $p < .01$; *** $p < .001$.

Table 9 Maximum Likelihood Estimation of the Effects on Mean (μ) and Standard Deviation (σ) of Patent Quality Index

Split sample:	*Familiar components*		*Unfamiliar components*		*Familiar components*		*Unfamiliar components*	
	1		2		3		4	
Variables:	*Coef.*	*Std.err.*	*Coef.*	*Std.err.*	*Coef.*	*Std.err.*	*Coef.*	*Std.err.*
Effects on μ								
ln(*CV spinouts*)	- 0.418	(0.72)	2.069*	(0.97)				
with parent expert					- 0.258	(1.09)	2.461*	(0.99)
w/o parent expert					- 0.272	(0.96)	1.536	(1.07)
ln(*Employee spinouts*)	0.153	(0.28)	1.030	(0.70)	0.166	(0.28)	1.115	(0.79)
ln(*CVC ventures*)	0.047	(0.24)	0.382	(0.55)	0.086	(0.24)	0.297	(0.54)
ln(*Alliances*)	0.971	(0.61)	0.327	(0.57)	0.970	(0.52)	0.359	(0.57)
ln(*Self-citations*)	0.567*	(0.24)	- 0.129	(0.28)	0.566*	(0.25)	- 0.143	(0.26)
ln(*Other firms*)	0.197***	(0.05)	0.285*	(0.12)	0.194***	(0.05)	0.293*	(0.12)
Cited patents' impact	0.014*	(0.00)	0.015	(0.00)	0.014*	(0.00)	0.014*	(0.00)
Ownership	- 0.714	(0.53)	- 1.046	(0.64)	- 0.723	(0.52)	- 1.069	(0.67)
Patent assignments	0.993***	(0.26)	1.008	(0.94)	1.006***	(0.26)	1.023	(0.95)
Temporal exploration	- 0.018	(0.02)	- 0.012	(0.02)	- 0.018	(0.02)	- 0.008	(0.02)
Geographical proximity	0.387	(0.21)	- 0.361	(0.55)	0.404*	(0.18)	- 0.321	(0.48)
Technological distance	- 0.015	(0.17)	- 0.240	(0.24)	- 0.056	(0.20)	- 0.278	(0.28)
ln(*InMobility5*)	- 0.055	(0.02)	- 0.114*	(0.05)	- 0.051	(0.04)	- 0.120*	(0.05)
ln(*OutMobility5*)	- 0.091***	(0.02)	- 0.067	(0.06)	- 0.090***	(0.02)	- 0.062	(0.06)
Prior co-tenure	- 0.040	(0.12)	0.037	(0.14)	- 0.042	(0.12)	0.050	(0.14)
ln(*Prior collaborations*)	- 0.145	(0.23)	- 0.578	(0.30)	- 0.140	(0.23)	- 0.535	(0.32)
Industry proximity	- 0.278	(0.16)	0.498*	(0.24)	- 0.281	(0.15)	0.436	(0.28)
No forward citations	- 1.076***	(0.15)	- 1.042***	(0.14)	- 1.071***	(0.16)	- 1.069***	(0.14)
Firm, year and technology dummies	Included		Included		Included		Included	
Constant	10.260***	(0.93)	9.090***	(0.45)	10.358***	(0.92)	9.346***	(0.31)
Effects on σ								
ln(*CV spinouts*)	1.322	(2.28)	- 0.411	(1.08)				
with parent expert					- 3.230	(1.87)	- 1.582**	(0.56)
w/o parent expert					1.782	(2.57)	- 0.163	(1.32)
ln(*Employee spinouts*)	- 0.112	(0.35)	0.777	(0.66)	- 0.110	(0.35)	0.776	(0.58)
ln(*CVC ventures*)	1.033	(0.76)	- 0.122	(0.16)	1.025	(0.75)	- 0.189	(0.17)
ln(*Alliances*)	0.099	(0.70)	- 0.620	(0.36)	0.062	(0.71)	- 0.613	(0.38)
ln(*Self-citations*)	0.358	(0.22)	- 0.465*	(0.22)	0.353	(0.21)	- 0.507*	(0.21)
ln(*Other firms*)	0.197***	(0.05)	0.096	(0.10)	0.199***	(0.05)	0.089	(0.11)
Cited patents' impact	0.019**	(0.00)	0.003	(0.00)	0.018**	(0.00)	0.003	(0.00)
Ownership	- 0.029	(0.33)	0.505	(0.92)	- 0.022	(0.34)	0.555	(0.98)
Patent assignments	0.740*	(0.31)	1.191	(1.29)	0.747*	(0.30)	1.196	(1.28)
Temporal exploration	0.024*	(0.01)	0.024	(0.04)	0.024*	(0.01)	0.022	(0.04)
Geographical proximity	- 0.010	(0.15)	- 0.460	(0.44)	0.017	(0.15)	- 0.450	(0.43)
Technological distance	0.220	(0.20)	0.409	(0.28)	0.206	(0.19)	0.394	(0.31)
ln(*InMobility5*)	- 0.042	(0.04)	- 0.032	(0.05)	- 0.038	(0.05)	- 0.025	(0.04)
ln(*OutMobility5*)	- 0.034	(0.03)	- 0.002	(0.15)	- 0.038	(0.04)	- 0.007	(0.15)
Prior co-tenure	0.030	(0.19)	0.071	(0.17)	0.027	(0.19)	0.073	(0.17)
ln(*Prior collaborations*)	0.164	(0.37)	- 0.146	(0.76)	0.191	(0.39)	- 0.154	(0.72)
Industry proximity	- 0.348***	(0.10)	- 0.338	(0.33)	- 0.356***	(0.09)	- 0.326	(0.35)
No forward citations	- 0.372***	(0.09)	- 0.569***	(0.15)	- 0.369***	(0.08)	- 0.563***	(0.12)
Firm, year and technology dummies	Included		Included		Included		Included	
Constant	4.082***	(0.40)	4.751***	(0.69)	4.095***	(0.42)	4.772***	(0.72)
Observations	7,024		3,158		7,024		3,158	
Log-likelihood	-19,971		- 9,237		-19,971		- 9,237	

Note. Dependent variable is *Patent Quality Index*. Robust standard errors (in parentheses) are clustered by firm.
* $p < .05$; ** $p < .01$; *** $p < .001$.

Table 9 (cont'd)

	1	2	3	4
	One-sided test p-values for linear combinations of coefficients (effects on σ)			
β([σ]*CV spinouts*) - β([σ]*Emp. spinout*) = 0	p = 0.270	p = 0.220		
β([σ]*CV spinouts*) - β([σ]*CVC ventures*) = 0	p = 0.445	p = 0.390		
β([σ]*CV spinouts*) - β([σ]*Alliances*)= 0	p = 0.261	p = 0.419		
β([σ]*CV spinouts*) - β([σ]*Self-citations*) = 0	p = 0.344	p = 0.481		
β([σ]*CV spinouts*) - β([σ]*Other firms*) = 0	p = 0.312	p = 0.320		
β([σ]*CV spin. with*) - β([σ]*Emp. spinout*) = 0			p = 0.054	***p* = 0.002**
β([σ]*CV spin. with*) - β([σ]*CVC ventures*) = 0			***p* = 0.006**	***p* = 0.004**
β([σ]*CV spin. with*) - β([σ]*Alliances*) = 0			***p* = 0.026**	***p* = 0.047**
β([σ]*CV spin. with*) - β([σ]*Self-citations*) = 0			***p* = 0.035**	p = 0.068
β([σ]*CV spin. with*) - β([σ]*Other firms*) = 0			***p* = 0.035**	***p* = 0.001**

Table 10 Probit on Source Patents' Citation: Estimation of Knowledge Flows

Sample:	*All Source Patents*		*Only Top 5% Source Patents (Breakthroughs)*			
Source components:	*Familiar & Unfamiliar Source Components*		*Familiar & Unfamiliar Source Components*		*Only Unfamiliar Source Components*	
	1		2		3	
Variables:	*Coef.*	*Std.err.*	*Coef.*	*Std.err.*	*Coef.*	*Std.err.*
Self-citation	0.910*	(0.43)	1.517***	(0.26)	1.715***	(0.28)
CV spinout	0.807	(0.45)	2.001***	(0.59)	2.342***	(0.49)
Employee spinout	0.880	(0.52)	1.083**	(0.39)	1.318***	(0.35)
CVC investment	0.172	(0.20)	0.225	(0.18)	0.181	(0.19)
Alliance	0.090	(0.40)	0.620***	(0.12)	0.789***	(0.15)
Other firm	- 0.198	(0.42)	0.505*	(0.20)	0.772**	(0.24)
Source patent's impact	0.080	(0.04)	- 0.020	(0.05)	- 0.010	(0.04)
Ownership	0.013	(0.06)	- 0.116	(0.06)	- 0.188***	(0.05)
Patent assignments	0.003	(0.02)	- 0.078*	(0.03)	0.059	(0.04)
Temporal exploration	- 0.012	(0.00)	0.007	(0.01)	0.001	(0.01)
Geographical proximity	- 0.131	(0.07)	- 0.251***	(0.05)	- 0.198**	(0.07)
Technological distance	- 1.310***	(0.03)	- 1.120***	(0.05)	- 1.222***	(0.05)
ln(*InMobility5*)	- 0.112*	(0.04)	- 0.292***	(0.08)	- 0.225**	(0.08)
ln(*OutMobility5*)	- 0.299***	(0.04)	- 0.276***	(0.04)	- 0.271***	(0.04)
Prior co-tenure	- 0.040**	(0.01)	- 0.031*	(0.01)	- 0.023	(0.01)
ln(*Prior collaborations*)	- 0.282	(0.19)	1.489***	(0.36)	1.234**	(0.45)
Industry proximity	0.290***	(0.03)	0.262***	(0.02)	0.225***	(0.02)
Firm, year and technology dummies	included		included		included	
Constant	- 0.207	(0.43)	- 0.353	(0.22)	- 1.096***	(0.31)
Observations (citing-cited pairs)	342,657		29,444		19,593	
Log Likelihood	- 181,084		- 16,091		- 10,525	
	One-sided test p-values for linear combinations of coefficients					
β(*CV spinout*) - β(*Self-citation*) = 0	p = 0.251		p = 0.149		***p* = 0.048**	
β(*CV spinout*) - β(*Employee spinout*) = 0	p = 0.408		***p* = 0.029**		***p* = 0.019**	
β(*CV spinout*) - β(*CVC investment*) = 0	p = 0.082		***p* = 0.001**		***p* = 0.000**	
β(*CV spinout*) - β(*Alliance*) = 0	***p* = 0.000**		***p* = 0.004**		***p* = 0.000**	
β(*CV spinout*) - β(*Other firm*) = 0	***p* = 0.000**		***p* = 0.001**		***p* = 0.000**	

Note. Dependent variable is *Citation*. Robust standard errors (in parentheses) are clustered by firm.
* $p < .05$; ** $p < .01$; *** $p < .001$.