ECONSTOR

WWW.ECONSTOR.EU

Der Open-Access-Publikationsserver der ZBW – Leibniz-Informationszentrum Wirtschaft
The Open Access Publication Server of the ZBW – Leibniz Information Centre for Economics

Winkelbach, Andreas; Walter, Achim

Working Paper

The More Learning, the Better? The Curvilinear Relationship between Technological Learning and New Product Commercialization

Arbeitspapiere des Instituts für Betriebswirtschaftslehre, CAU Kiel

Suggested Citation: Winkelbach, Andreas; Walter, Achim (2015) : The More Learning, the Better? The Curvilinear Relationship between Technological Learning and New Product Commercialization, Arbeitspapiere des Instituts für Betriebswirtschaftslehre, CAU Kiel

This Version is available at:
http://hdl.handle.net/10419/107018

Nutzungsbedingungen:
Die ZBW räumt Ihnen als Nutzerin/Nutzer das unentgeltliche, räumlich unbeschränkte und zeitlich auf die Dauer des Schutzrechts beschränkte einfache Recht ein, das ausgewählte Werk im Rahmen der unter
→ http://www.econstor.eu/dspace/Nutzungsbedingungen
nachzulesenden vollständigen Nutzungsbedingungen zu vervielfältigen, mit denen die Nutzerin/der Nutzer sich durch die erste Nutzung einverstanden erklärt.

Terms of use:
The ZBW grants you, the user, the non-exclusive right to use the selected work free of charge, territorially unrestricted and within the time limit of the term of the property rights according to the terms specified at
→ http://www.econstor.eu/dspace/Nutzungsbedingungen
By the first use of the selected work the user agrees and declares to comply with these terms of use.

ZBW Leibniz-Informationszentrum Wirtschaft
Leibniz Information Centre for Economics

Mitglied der Leibniz-Gemeinschaft

The More Learning, the Better?
The Curvilinear Relationship between Technological Learning and New Product Commercialization

Andreas Winkelbach and Achim Walter

Abstract

Managers entrusted with new product development (NPD) have to seek the optimal balance between prior competencies and learning activities to generate successful products. Yet prior NPD research has largely taken a positivistic view of learning despite an inkling that too much learning can lead to dysfunction. This study attempts to contribute the NPD literature by analyzing whether and, if so, when technological learning engenders shortcomings and affects new product commercialization.

We use a multi-informant longitudinal design combining unique survey and patent data on a multi-industry sample of about 163 product-based R&D collaborations in Germany. The results of a Cox regression reveal that prior technological knowledge is pervasively important for NPD and confirm that an inverted U-shaped relationship holds between the likelihood of commercialization and technological learning. The inverted U-shaped relationship supports the characterization of learning as a double-edged sword that helps overcome rigidities but also has downsides if taken too far. Exploitive learning, in particular, is the later of the two to incur downsides. This draws attention to the inherent uncertainty and costs of experimentation when learning is geared to exploration. As expected, technological progress determines NPD, but the influence is negligibly small. We argue that inertia dominates NPD projects, at least in the short-term.

Our findings mainly contribute to the NPD literature by demonstrating a differentiated learning-performance relationship. The results reveal whether and, if so, when, learning can become a drag to NPC and traps may occur. Managers are advised to ensure, at least, a fit between project requirements and prior competencies, but also to ensure adequate learning. Irrespective whether learning is geared to exploration or exploitation, it is advisable to maintain it at an appropriate level. This article suggests a patent-based instrument to monitor and manage learning efforts.

Introduction

New product development (NPD) gets caught between reliance on prior competencies and emphasis on learning activities. The latter is thought to avoid rigidity and help cope with change (Levitt and March 1988, Leonard-Barton 1992). Learning is mostly treated as an imperative (Flores *et al.* 2012) because NPD benefits from it (e.g., Michael and Palandjian 2004, Kim and Atuahene-Gima 2010), so its downside when pursued excessively has gone largely unnoticed. Some articles do relate excessive learning to firm performance (e.g., Uotila *et al.* 2009, Belderbos *et al.* 2010) and to innovation performance (Ahuja and Lampert 2001, Katila and Ahuja 2002, Atuahene-Gima and Murray 2007, Rothearmel and Alexandre 2009). For example, Levinthal and March (1993), in their seminal work, noticed that learning activities can exceed an optimum and lead to dysfunctional situations such as competency traps. These initial theoretical propositions concerning an optimal level of learning with respect to NPD and subsequent commercialization have been neither conclusively proved nor conclusively refuted. Given this indeterminacy, it remains crucial to empirically validate propositions about whether and – if so – when a firm's technological learning activities may impair NPD and affect new product commercialization (NPC).

Firm capabilities and environmental conditions are both critical to NPD (e.g., Cohen and Levinthal 1990, Leonard and Barton 1992). This article attempts to close the aforementioned information gap in the NPD literature while simultaneously analyzing prior technological knowledge and technological learning together with technological progress (Levitt and March 1988, Cohen and Levinthal 1990, Leonard-Barton 1992, Levinthal and March 1993).

Prior technological knowledge facilitates NPD and utilization of (external) knowledge (e.g., Cohen and Levinthal 1990, Bierly *et al.* 2009). However, situations in which competencies are quite narrow but their application has at the same time been quite successful may result in 'competency traps', in which unfamiliar developmental directions look less attractive and substantially affect the decision to commercialize (Levitt and March 1988, Leonard-Barton 1992).

Technological learning fosters NPD, as it is necessary to close knowledge gaps, perceive technological changes, and face competency traps (Levitt and March 1988, Levinthal and March 1993). Theory holds that learning activities can be geared to exploration or to exploitation, or to a mixture of both (March 1991). However, the positive influence of learning can eventually diminish, and firms that are tempted toward excessive learning may encounter failure and success (competency) traps, lowering the likelihood of commercialization (e.g., Levinthal and March 1993, Atuahene-Gima and Murray 2007). To date, almost no research has investigated a curvilinear effect of learning in connection with the likelihood of NPC. It is still debatable how technological learning affects NPD generally, and the question remains under what circumstances explorative versus exploitive learning might affect NPD more specifically. Even with respect to innovation performance, for instance, while a few studies have indeed proposed an inverted U-shaped effect of exploration and exploitation

learning, results have been mixed (Ahuja and Lampert 2001, Katila and Ahuja 2002, Atuahene-Gima and Murray 2007, Rothearmel and Alexandre 2009).

Given *high technological progress*, technologies may well obsolesce quickly, and knowledge stocks will erode (Tushman and Anderson 1986, Schoonhoven *et al.* 1990). These circumstances feed uncertainty as to an invention's value and technical feasibility and affect the decision to commercialize (Utterback 1994, Song and Montoya-Weiss 2001).

The theoretical development of our study draws on the knowledge based view (KBV), and since the KBV values renewing and maximizing the knowledge base, it draws as well on organizational learning (OL) theory. According to this perspective, a firm's competiveness is mainly based on the creation and application of knowledge (Grant 1996, Spender 1996, Levitt and March 1988). All knowledge-related resources, including a firm's knowledge base and learning capabilities, affect the efficient coordination and application of both internal and external knowledge (Cohen and Levinthal 1990, Grant 1996, Levitt and March 1988).

This article adopts the perspective of a firm which has developed a product-based invention jointly with a public research organization (PRO). We perform a multi-informant longitudinal study combining for analysis unique survey and patent data on 163 R&D collaborations covering 20.774.130 patent families and 1031 observations. Applying techniques of survival time analysis (Cox regression) at the project-analytical level offers the possibility of investigating the likelihood of NPC and of finely dissecting the efficiency and limits of firms' capabilities in NPD projects (e.g., Hoang and Rothaermel 2010). In short, our study extends the literature on multiple fronts: first, it illuminates the influence of prior technological knowledge and technological learning on the likelihood of NPC in the context of a dynamic environment; second, it stresses the relative importance of explorative and exploitive technological learning for NPC; third, this article integrates the first and second points to provide a better understanding of how and when firms can find themselves caught in a competence trap. Overall, these findings ought to help firms optimize their commercialization strategies.

This paper is organized into four sections. First, we delineate the theoretical background and derive hypotheses. Then we introduce the study's central research design and briefly describe the methods. Following that we discuss the main results, and the paper concludes with a summary and implications for further research and for managerial practice.

Theoretical Background and Hypotheses

Following rationales of earlier studies that have examined the hazard of events in the context of product development projects (e.g. Kessler and Chakrabarti 1999, Hoang and Rothaermel 2010), we define NPC as time to market for product innovations based on inventions jointly developed with

PROs. Firm competency (or capability) refers to a bundle of complementary resources including knowledge, physical infrastructure, and organizational skills, routines, and processes (Day 1994, Miller 2003).[1] With respect to product development, managers are advised both to leverage existing competencies and to strive to renew them to avoid rigidity effects (Leonard-Barton 1992). According to KBV and OL theory, both kinds of effort are key to understanding and leveraging knowledge during value creation (i.a. Levitt and March 1988, Grant 1996).

Our definition of prior technological knowledge conforms to the concept of technological competency that includes all tangible and intangible technological-based resources (Danneels 2002). Based on this, prior technological knowledge essentially comprises distinct technological information plus experience about a specific subject domain (Grant 1996, Simonin 1999). It covers both elementary knowledge and the latest scientific knowledge, and it encompasses a form of know-how based on commercialization routines (Cohen and Levinthal 1990, Kogut and Zander 1992). A firm's prior technological knowledge is embedded in its products, machinery, processes, and people (Day 1994, Danneels 2002, Miller 2003).

Technological learning embraces organizational routines that ensure targeted knowledge development based on history or experience (Cohen and Levinthal 1989 1990, Levitt and March 1988, Argote 2012). An underlying theme of organizational learning is that firms' learning activities come in two forms: knowledge exploitation and knowledge exploration (March 1991). Firms that prefer exploitation learning activities invest in developing, standardizing, and refining the knowledge, skills, and processes they already possess. Exploration learning activities, by contrast, are those which pursue new knowledge (Levinthal and March 1993). We apply the exploitation-exploration framework at the project level (cf. Kim and Atuahene-Gima 2010) to examine the learning-NPC relationship.

Competency traps

Prior competency and organizational learning are both relevant to product development. However, the wrong balance between the two factors can lead to problems. One of these potential problems is known as a 'competency trap' (Levitt and March 1988, Levinthal and March 1993). If a firm has succeeded on its prior competency, it can become path-dependent, meaning that it is likely to continuously exploit the same competency because it has performed reliably and cost-effectively with it in the past (Hannan and Freeman 1984, Leonard and Barton 1992, Huff *et al.* 1992). Greater efficiency under the same circumstances thus immediately increases the firm's performance; and because the benefits of exploration are uncertain, managers tend to forego exploration and pursue exploitation (March 1991). It is a dynamic in which the experience of success tends to reinforce itself,

[1] Following other studies, the terms "capability" and "competence" are used synonymously (e.g., Day 1994; Grant 1996).

but which may at the same time enshrine dysfunctional rigidity effects. This has been called a 'capability-rigidity paradox' (Leonard-Barton 1992).

Firms at risk of falling into the competency trap are advised to pursue explorative as well as exploitive learning to overcome this kind of shortcoming (Levitt and March 1988, Cohen and Levinthal 1990, Leonard-Barton 1992). The general view represented in the literature is that both knowledge exploration and exploitation need to be kept in balance, maintaining the balance is called 'ambidexterity' (March 1991, p. 71, Cohen and Levinthal 1990, p. 133). If exploration is neglected, the firm's knowledge base will lose its value should competitiveness eventually require adapted knowledge resources (e.g. Sørensen and Stuart 2000, Michael and Palandjian 2004). Exploration activities enable a firm to respond better to innovation and changing conditions (e.g. March 1991, Ahuja and Lampert 2001). On the other hand, with a myopic focus on exploration, a firm incurs costs from experimentation. Exploitation helps maintain balance here because of its efficiency and value-creating quality (e.g. March 1991).

Much research has focused on this exploration/exploitation performance relationship; findings, however, have been mixed and show positive (e.g. Ahuja and Lampert 2001), non-significant (Jansen *et al.* 2006), and, sometimes, even negative (e.g. Lechner and Floyd 2012) effects. These inconsistent findings are not surprising given that learning has a downside that may offset its positive outcomes (Levinthal and March 1993). However, the curvilinear depreciation of exploration/exploitation and performance has rarely been investigated. Atuahene-Gima and Murray (2007), who employed a monetary new product performance measure, did find empirical evidence for U-shaped relationship between exploitative learning and (new product) performance (see also Rothaermel and Alexandre 2009, Uotila *et al.* 2009, Belderbos *et al.* 2010). The study by Katila and Ahuja (2002) reveals only the curvilinear relationship between exploitive learning and product innovation; its authors remarked that the proposed inverted U-shaped relationship between excessive learning and innovative outcomes might have been overstated.

Prior Technological Knowledge

According to the ground-breaking article by Cohen and Levinthal (1990), prior knowledge influences a firm's absorptive capacity in such a way that the evaluation, assimilation and transformation of external knowledge to commercial ends are largely functions of existing knowledge stocks. Experienced firms possess better information filters and iterative routines, and these enhance problem-solving mechanisms and skills arising out of development issues (see also Spender 1996, Argote 2012). In such cases, firms are able to see how knowledge sets are intertwined and are more competent in sourcing knowledge (Simonin 1999). The greater the similarity between or among knowledge domains, the more predictable and efficient the absorption process is (Makri *et al.* 2010),

and the easier it is to integrate new elements into the current technology base (Bierly *et al.* 2009) and to foresee more possibilities for technological development (Argote 2012). Mitchell (1989), for instance, observes that firms are more likely to commercialize new technologies within the very same industry in which they already possess specific capabilities. Similarly, Zander and Kogut (1995) point out that prior technological experience is a key factor in understanding new technologies. An improved understanding of causal relationships fosters product specification and developmental accuracy, and even lets firms define their commercialization strategy and strategic options more precisely (Rosenberg 1994, Simonin 1999). The overall effect is to lessen the uncertainty surrounding commercial success and technical feasibility. Value and commercialization ability are both perceived as greater, and this amounts to a positive influence on the likelihood of NPC (e.g. Wernerfelt and Karnani 1987, Cohen and Levinthal 1990).

Another perspective, however, emphasizes the ways in which more experienced firms are prone to competency traps such that they are likely to overestimate the potential value of an invention. Such firms may be predisposed to reward R&D projects that are close to their prior activities unjustifiably and without objective proof (Cohen and Levinthal 1989 1990, Leonard-Barton 1992). Prior success colors their expectations, and they may rely on leveraging knowledge and become attached to prior commitments to specific actors and technologies (Huff *et al.* 1992, Christensen 1997). In such cases, a firm can be said to have fallen into a competency trap to the detriment of its innovation performance (e.g. Michael and Palandjian 2004). Crucially, however, the antecedents of such regrettable innovation decisions do not look like essential flaws at the time. Firms cannot know beforehand when they have crossed the line. When capabilities have become rigid, R&D projects in familiar domains are prioritized, at least in the lifespan of a single project (Leonard-Barton 1992). Organizational politics and pressures can significantly reinforce such traps (Levinthal and March 1993, Michael and Palandjian 2004). Opportunism prevails as individual actors must take responsibility for new R&D projects. Managers encounter a tension between new, risky projects as opposed to well-known, quick-start projects; but with regard to the latter, the direct effects on an individual's career seem more tangible (Lampert 1986, Huff *et al.* 1992). Higher rewards may encourage engagement in a risky project, but a firm in a competency trap or a firm focused on short-term success will neglect such incentives (Lampert 1986, March 1991, Leonard-Barton 1992). Essentially, this kind of biased commitment toward an NPD project might be another factor predisposing firms to decide to commercialize.

Based on the foregoing, we argue that a higher degree of congruence between firms' prior technological knowledge and a given invention will increase the likelihood of NPC.

Hypothesis 1: There is a positive relationship between firms' prior technological knowledge and the likelihood of new product commercialization.

Technological Learning

Generally, NPD benefits from learning (e.g. Michael and Palandjian 2004), and learning appears to be an appropriate means of avoiding rigidities (e.g. Levitt and March 1988, Leonard and Barton 1992, Bierly and Chakrabarti 1996). However, excessive learning activities may engender dysfunctionality inhibitive to NPD (Cohen and Levinthal 1990, Levinthal and March 1993).

The beginnings of every NPD project may be dominated by ambiguity anyway, but high technological and market uncertainty on one hand, paired with a firm not knowing how to address these problems on the other, mean that that firm cannot evaluate an invention's potential for commercial success or its technological feasibility (Cohen and Levinthal 1990, Folta 1998, Song and Montoya-Weiss 2001). In general, learning helps firms cope with unforeseen events and obstacles and fill knowledge gaps (Levitt and March 1988, Levinthal and March 1993). It provides for greater assessment capacity, lowering initial uncertainty and better revealing the outlines of the NPD task. Learning thus influences the likelihood of NPC in a positive manner (Song and Montoya-Weiss 2001, Levinthal and March 1993).

Irrespective of whether NPD is geared toward explorative or exploitive learning, another current in the literature assumes that while both kinds of learning may have a tipping point, each incurs the risk of a different type of trap (Levinthal and March 1993). Firms who focus predominately on knowledge exploration in NPD projects continuously generate new knowledge. Confusion and information overload can result, and lead to two phenomena which both decrease the likelihood of NPC: failure traps and over-engineering (e.g. Levinthal and March 1993, Ahuja and Lampert 2001). Reconfiguring existing knowledge and searching for complementary knowledge is even more complex and challenging than integrating familiar knowledge (Grant 1996). Ongoing experimentation can run into a dynamic of failure, the costs to a firm of experimentation being that results are less tangible and, often, negative. Although failure may prompt continued knowledge exploration, if it proceeds in an endless cycle, it results in an unrewarding change, and the NPD process may be prolonged (Levinthal and March 1993).

A different potential technological learning problem is over-engineering. As new market conditions, product requirements, or production improvements turn up during explorative learning, uncertainty remains high (March 1991). Not knowing what to expect amounts to a threatening situation when several application possibilities may be being benchmarked against each other. It does not matter whether a firm's R&D is in line with market needs or the firm's goals; in either case, over-engineering prolongs commercialization time.

Focusing on exploitative activities increases the efficiency of current competencies and, in turn, fosters commercialization. A dose of exploitation is necessary to overcome potential failure traps and apply new knowledge to commercial ends (Cohen and Levinthal 1990, March 1991). However,

excessive knowledge exploitation may lead to repeated success (competency) traps with self-reinforcing tendencies. As firm experience in existing competency grows, creativity drops, and changes appear less rewarding (Cohen and Levinthal 1990, Levitt and March 1988, Levinthal and March 1993). With respect to market entry, excessive exploitative learning may lead to shortfalls as considerable knowledge gaps and problems of access to product specification market information are overlooked or ignored (Atuahene-Gima and Murray 2007, Ahuja and Lampert 2001). To the extent that salient information escapes notice, firms risk repeatedly getting into development loops, for which reason excessive exploitation learning arguably decreases the likelihood of NPC (Levinthal and March 1993). All the arguments indicate that explorative and exploitive learning both may accelerate NPC, but we assume a tipping point at which subsequent technological learning begins to lower the likelihood of NPC. This gives rise to the following hypothesis:

Hypothesis 2a: There is an inverted U-shaped relationship between firms' technological learning and the likelihood of new product commercialization.

In general, firms are advised to strike a balance between keeping existing competencies and renewing responsively through exploration (e.g. March 1991). However, the extent to which explorative or exploitive learning respectively supports or inhibits development and launch of innovative products remains unclear.

Firms geared toward knowledge exploitation utilize existing technologies and build rigid relationships with external entities such as suppliers and customers, which leads to the institutionalization of reputation and commitment (Levinthal and March 1993, Christensen 1997). From this perspective, knowledge exploitation appears to limit the likelihood of commercialization, because such circumstances mean that markets are restricted. Danneels' (2007) case study underscores how firms often fail at leveraging technological resources in new markets. Moreover, knowledge exploitation might limit the learning curve because it can lead to a one-dimensional focus on specific technologies and markets. The fact that learning results from experience can constrain further learning; again we have a path-dependency effect – a familiarity trap – in which the only solutions pursued or even sought after are close to those already known (Levitt and March 1988, Levinthal and March 1993, Ahuja and Lampert 2001). The other side of this, of course, is that truly relevant problem-solving information, facts, and trends may be overlooked with respect to NPD. This is supported by Michael and Palandjian (2004), who demonstrate that organizational learning diminishes as firm experience grows.

On the other hand, exploitation does have a positive effect on information-based controllability and efficiency, so it contributes to the certainty, cost efficiency, and success of NPD. These results arrive more quickly and tangibly (March 1991, Levinthal and March 1993, Kim and Atuahene-Gima 2010). Sørensen and Stuart (2000), for instance, suggest that firms following mostly

well-worn paths generate more innovations; at the same time, however, such innovations are less influential.

Knowledge exploitation operates at the cost of good information. This is a drag on NPC, especially since pioneering firms are advised to detect novel technological and social circumstances (Williamson 1975). Without explorative learning, crucial information eludes decision makers until just before market entry, forcing repeated developmental stages and lowering any ability to adapt to the bandwidth of environmental changes (Leonard-Barton 1992, March 1991). Conversely, broadening a firm's knowledge base increases strategic flexibility (Volberda 1996). In particular, commercial ends benefit even from just a modicum of new, external knowledge (Cohen and Levinthal 1990). Still, whenever NPD proceeds in an exploratory mode, experimentation with novelties or surprises beyond the current knowledge horizon can be unpredictable and often comes with intangible results and negative feedback ("*experimentation with new alternatives that have returns that are uncertain, distant, and often negative*" Levinthal and March 1993, p. 105). The fact that these downsides of explorative learning are inherent and pervasive (March 1991) makes them more likely to crop up than the downsides of exploitive learning. This is especially salient with respect to NPC as opposed to innovativeness or new product success (Ahuja and Lampert 2001, Rothaermel an Alexandre 2009). Essentially, knowledge exploration exceeds the optimum at a lower level than knowledge exploitation does. Therefore, we hypothesize the following:

Hypothesis 2b: *The tipping point, at which the likelihood of new product commercialization decreases, is later for technological exploitation learning than for technological exploration learning.*

Technological Progress

One can expect the likelihood of commercialization to decrease in an environment characterized by high technological progress for several reasons. For one, technological progress means high uncertainty about market conditions and evolving technology (Anderson and Tushman 1990, Song and Montoya-Weiss 2001). New technologies in such an environment are continually generated, and they replace existing ones for reasons related to function and resources. Numerous commercialization possibilities arise; these are relatively easy to detect. Moreover, existing knowledge stocks and technologies may erode or even enter the market as obsolete products (Anderson and Tushman 1990, Schoonhoven *et al.* 1990). Hence, it is very difficult ex ante to assess an invention's value or gauge its development process, and firms' perceptions and beliefs with respect to commercialization may be affected accordingly (Song and Montoya-Weiss 2001). The development processes under such conditions are characterized by sizeable managerial effort manifesting in excessive resource consumption in terms of time spent continuously forecasting around imponderables or gathering pertinent facts (Miliken 1987). And conversely, timely commercialization is more easily achieved in

stable and predictable environments (Eisenhardt and Tabrizi 1995, Bstieler 2005). The aforementioned phenomena lead us to hypothesize that technological progress may lower the likelihood of NPC. Therefore,

Hypothesis 3: The greater the technological progress, the lower the likelihood of new product commercialization.

Method

Sample and Procedure

Analysis is directed at focused NPD projects in German firms that built on inventions developed jointly with a German PRO. A project-based analysis is useful in situations in which either innovation speed or the likelihood of NPC is in focus, as only NPD can be "*accelerated, not individuals or organizations*" (Kessler and Chakrabarti 1999, p. 236). To address the proposed hypotheses, we make use of a Cox Regression combining unique survey and patent data on 163 R&D collaborations.

Identifying the relevant R&D projects:

Having no comprehensive list, we compiled our own initial list from the EPO Worldwide Patent Statistical Database (PATSTAT) of patented science-industry R&D collaborations pursued between 2007 and 2011 in which both partners held IP rights. We used different database versions to minimize the problems of changing property rights in patents. We gathered contact information on all inventors mentioned in the patent family, and our multi-respondent firm and project specific information was gathered by trained interviewers (>50) who conducted face-to-face interviews using a standardized questionnaire during 2012 and 2013. All interviewed representatives were actively involved in their respective projects, so they were the most qualified survey respondents and could be designated as key informants (Campbell 1955, Simonin 1999). During the pre-test phase, respondents emphasized that their respective projects were unique in a way that made them the subject of detailed recollection, which in turn did not indicate any serious hindsight bias. Social desirability bias was reduced by the questionnaire being self-administrated with an emphasis both on anonymity and on the provision of honest, dependable answers (Nederhof 1985). The calculated inter-rater reliability (Cohens's Kappa, $\varkappa$) revealed a substantial strength of agreement ($\varkappa$=0.754) (Landis and Koch 1977).

We identified 250 knowledgeable project participants on the technology recipients' side (firms). Of these, 212 respondents agreed to participate. In 4.80% of them, potential contacts refused to participate for reasons of secrecy (N=12), had no interest (N=16, 6.40%) or lack of capacity (N=10, 4.00%). 61 respondents participated in the second survey. Due to missing data and with focus on product-based projects; 163 of all 212 identified product- and process-based projects constituted to our final sample. The resulting overall response rate was 65.2%. 79% of all interviewees held a senior position as manager or division head and had been employed for an average of 14 years and 7 months.

This indicates that we managed to gather accurate data on factors such as market entry time. The total firm size in terms of numbers of employees at the beginning of the project ($X \leq 10$ = 20.25%, $11 \leq X \leq 50$ = 19.63%, $51 \leq X \leq 250$ = 15.95%, $251 \leq X \leq 10000$ = 20.25%, $X > 10000$ = 23.93%) and the industry breakdown (electronics 22%, instruments 23%, chemistry 22%, mechanical engineering 25% and others 9%) were evenly spread across the sample, indicating no industry bias. The average geographical distance between the PRO and the firm was 183 km (mean = 183.62, median = 117.43, sd =184.17). A non-response bias can be ruled out with high confidence because the distribution of potential and actually participating firms corresponded to the population in terms of research institutions, industry, and years ($p>0.10$).

Identifying the relevant patents:

We started by matching every survey with patent data based on the focal invention. To do this we gathered all patent data on (1) the firm's patent portfolio (N=15.376 applied patent families within the International Patent Classification (IPC) of the focal invention, i.e., 94 adequate applied patent families for each firm on average during the period under review) and (2) technological progress (N=20.758.754 applied patent families worldwide within the IPC of the focal invention, i.e., 127.519 adequate applied patent families worldwide for each NPD project, on average, during the period under review). The patent portfolio by firm was analyzed at the smallest business-unit level (the same approach as that used in our survey).

Measures

Measures were developed following standardized processes (Churchill 1979). All measures are adapted from established studies or are objectified to the greatest extent possible to ensure a high degree of objectivity and generality (Nederhof 1985, Podsakoff *et al.* 2003).[2] The survey was pilot-tested in six pre-tests. After a third round, no changes or adjustments in wording were found to be necessary.

Dependent variable. The study's dependent variable refers to the hazard rate for NPC. It incorporates information on event occurrence and on the time interval between the initiation of the R&D collaboration and eventual market entry (for a similar approach, see e.g. Hansen 1999). The number of months assessed by key informants served as a proxy for this interval. We have validated this measure for 35 NPD projects according to the triangulation principle. To this end we used publicly available data about every R&D collaboration including its cooperation agreement, any press releases about the

[2] As we conducted a survey in Germany, the item translation and back-translation from English into German was carried out twice under the control of a native speaker.

time of market launch, and patent data such as filing dates. All our validation steps lead us to believe that this measure is not biased, as we found no discrepancies.

Independent variables. Prior technological knowledge was captured by adapting Simonin's (1999) experience measure to the present research context. Moreover, we added one item that refers to the matching R&D resources invested in the focal NPD project (e.g. Danneels 2002). Using a non-reverse-coded 7-point interval scale ranging from 1 („strongly disagree") to 7 („strongly agree"), the respondents were asked to evaluate (1) their level of experience, (2) their level of knowledge, and (3) the match between the project's requirements and their existing R&D resources including machinery and equipment (e.g. Simonin 1999, Danneels 2002). All items showed a high degree of covariance, indicating high internal consistency reliability (CA = 0.79)). The inter-rater reliability for all the experts proved satisfactory ($\varkappa$ = 0.754) (Landis and Koch 1977). Our decision to measure prior knowledge subjectively rather than through patent data is rooted in the premise that patents reveal no details about internal resources such as infrastructure.

Technological learning describes the extent to which learning activities in certain knowledge areas concerning the focal invention took place during the NPD (Levitt and March 1988, Atuahene-Gima and Murray 2007). As learning is cumulative and has to be examined longitudinally (Cohen and Levinthal 1990, Miner and Mezias 1996), we make use of objective patent data. This guarantees that our criterion is objective and repeatable and varies with time. Since every patented invention must exceed the state of the art and describe an inventive step, patents are suitable to reveal organizational learning (i.a. Katila and Ahuja 2002). Technological learning is captured through the absolute annual growth of patent applications (consolidated on patent family level) by each firm within the 4-digit IPC of the focal invention. Larger firms are likely to generate greater numbers of patent applications in same IPC than are smaller firms, but this need not reflect more cumulative learning, since the researchers who generate them often do not know each other. To account for this fact, we normalized by firm size to eliminated the expected skewing of the data.

We subscribe to Atuahene-Gima and Murray's (2007) way of differentiating between *exploitive* and *explorative technological learning*. They define exploitive learning as the discovery and use of knowledge related to existing competency and explorative learning as the same but unrelated to existing competency. Building on this operationalization, we divided the sample at the median of prior knowledge. If a firm possessed, e.g., low prior competency with respect to a patented invention characterized by specific IPCs, we measured the growth of patent applications within these IPCs. We argue that, in such unfamiliar settings, explorative learning dominates as firms acquaint themselves with new contexts and information. Exploitive learning takes place in familiar settings, which means that a firm's level of prior technological knowledge is higher than the median.

Technological progress refers to the advancement of technological knowledge within a certain area and represents the changing opportunity pool (Kortum 1993). Patent data is adequate for evaluating the technological environmental development because the path of technological progress is reflected in patent applications. We assess technological progress by the absolute annual growth of applied patents worldwide (consolidated on the patent family level) within the 4-digit IPC of the focal invention (for a similar approach, see Levitas *et al.* 2006).

Control variables. We incorporate several variables that may influence the likelihood of new product commercialization.[3] We created *industry dummies* to control for industry sectors and estimate potential confounding effects (Nerkar and Shane 2007). *Firm age* is included and calculated as the number of months, at the beginning of R&D collaboration, since the firm's foundation. We posit that older firms capture value from external knowledge in different ways than younger firms do (Hannan and Freeman 1984). *Project year* is incorporated to control for year effects and for right-censoring (Hoang and Rothaermel 2010). Projects initiated later in our sample might be less likely to have been commercialized. By incorporating a binary variable for *prior patent applications*, we were able to take the firms' familiarity with patents as well as new technological developments into consideration. *Tie strength* refers to the degree of social interaction and accompanying facilitation of NPD as dyadic communication and knowledge transfer between the PRO and the firm improves (Hansen 1999). To eliminate subjective influences, we asked for the number of employees temporarily exchanged between the firm and the PRO and the number of long-term employee exchanges over the course of the R&D collaboration. *Prior partnership experience* was measured as a binary variable to control for organizational similarity and relationship capital between the PRO and the firm; these factors facilitate knowledge transfer (Gulati 1995, Hansen 1999). Because *technological characteristics* influence NPD (Nerkar and Shane 2007), we included patent-based controls for technological characteristics such as *patent scope*, *radicalness* and *science-link* (Lerner 1995, Bierly and Chakrabarti 1996, Ahuja and Lampert 2001).

[3] Firm size is not incorporated as a control variable on account of the fact that technological learning is normalized by firm size.

Results

Descriptive statistics and Cox regression analysis

For the first part of the analysis, Table 1 depicts the descriptive statistics and the bivariate correlation matrix. To analyze our hypotheses, we used a Cox proportional hazard regression with a robust specification, entering the controls, main effects, and interactions (Cox 1972). Following Grambsch and Therneau's (1994) tests of PH assumption and our theoretical arguments, we treated technological learning, technological progress, and firm age as time-dependent variables. As for the regression model itself, its results appear in Table 2. All models are highly significant ($p<0.01$-0.001), with the model significance (χ^2) increasing as additional variables are incorporated. This suggests that all independent variables and proposed moderations are explanatory of how and when new products are commercialized. The significant Model 1 ($\chi 2 = 30.86$, $p < 0.0035$) reports the model's baseline, including all control variables. Model 2 adds firms' prior technological knowledge, technological learning, and technological progress ($\chi 2 = 42.56$, $p < 0.0003$). Into Model 3 we inserted the squared term of the firms' technological learning ($\chi 2 = 52.72$, $p < 0.0000$). As Hypothesis 1 predicts, Models 2, and 3 provide evidence that firms with a higher degree of prior technological knowledge are more likely to commercialize inventions ($\beta_{PK} = 0.45$, $p < 0.001$). It becomes obvious that an increase of one point on the 1-7 rated prior knowledge scale increases the hazard of new product commercialization by 34.3% ($\exp^{0,272}$). Hypothesis 2a is supported on the fact that the technological learning coefficients of the linear term and the squared term are significant and move in the hypothesized directions; the hazard ratios of the linear term is less than 1, whereas the square terms have hazard ratios greater than 1 ($\beta_{TL} = 0.461$, $p < 0.01$; $\beta_{TLxTL} = -0.717$, $p < 0.05$) in model 3. The inflection point, at which the likelihood of NPC starts to deteriorate, occurs at a ratio of annual technological learning per firm employees of 2.90 patent applications at family-level. Hypothesis 2b proposes that the tipping point, at which the likelihood of commercializing an invention decreases, comes later for technological exploitation learning than for technological exploration learning. Turning now to the results, it is obvious that the technological learning coefficients of the linear term and the squared term are repeatedly highly significant both for model 'Explor-3' and for model 'Exploi-3', and are highly significant in the hypothesized directions (Explor-3: $\beta_{TL} = 1.345$, $p < 0.001$; $\beta_{TLxTL} = -3.760$, $p < 0.001$; Exploi-3: $\beta_{TL} = 0.648$, $p < 0.01$; $\beta_{TLxTL} = -0.892$, $p < 0.01$). The tipping point associated with explorative learning comes sooner than that associated with exploitive learning, which provides evidence for hypothesis 2b (Explor-3 shows a ratio of annual technological learning per firm employees of 2.30, the same ratio in Exploi-3 is 3.20). The resultant data in model 3 make clear that technological progress is significant, but also that an annual increase of one percent of patent applications worldwide in the focal IPC only lowers the hazard of invention commercialization by 0.002 % ($\beta_{TP} = -0{,}002$, $p < 0.05$). Hypothesis 3a is therefore supported by the data-based analysis; but from a practical point of view the effect of technological progress seems to be negligible.

Post-hoc Analysis: Robustness Checks and Endogeneity

To verify our results, we conducted several robustness checks. For one, we recast all the calculations shown in Table 2 following the exploration and exploitation measures of Jansen *et al.* (2006) and split them on their median. The results were identical to those of our patent-based approach ($p<0.001$). Our model specification and longitudinal design, based on survey and patent data, were conceived so as to largely preclude simultaneous causality, hindsight-bias, and common method bias (i.a. Podsakoff *et al.* 2003).

Over-specified and underspecified models are another general source of endogeneity. With regard to over-specification, we find confirmation of our model specification in two facts: one, that each model shows a higher significance than Model 1, and two, that the full model shows both the highest significance and the best fit. By plotting the Nelson-Aalen cumulative hazard function against Cox-Snell residuals and comparing the jagged line to the reference line, we also deem the models to be fitting. Some degree of deviation for large values of time (right tail) is normal for models with censored data (Cleves *et al.* 2008).

We countered the possibility of under-specification of the model by considering additional control variables. First, since one may suppose an interaction to arise between firm age and radicalness, we tested for whether new firms more often commercialize radical inventions (Nerkar and Shane 2007). Second, we incorporated a variable for marketing-related capabilities (Song *et al.* 2005). Third, since sufficient financial funds importantly minimize the risk of project failure (Laursen and Salter 2004), we tested for the firms' finances by integrating the number of researchers at the firm, as stated on the patent, as a proxy for their financial support. It turns out that all variables were insignificant, and inclusion of the foregoing did not change the pattern of our original findings. All in all, the results lead us to assume we have a well-fitted model.

Tab. 1: Descriptive statistics and correlations (N = 1031)

	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Electrical engineering [b]	0.26	0.44	1															
2. Instruments [b]	0.26	.44	-.07	1														
3. Chemistry [b]	0.29	0.45	-.25	.09	1													
4. Mechanical engineering [b]	0.35	0.48	-.21	-.30	-.35	1												
5. Other fields	0.11	0.32	-.09	-.14	.01	-.14	1											
6. Firm age	43.37	63.11	-.16	-.18	.21	-.06	.08	1										
7. Patenting experience [b]	0.69	0.46	-.22	-.15	.11	-.02	-.06	.34	1									
8. Tie strength	2.13	3.33	.04	-.15	-.10	.06	.02	.04	.10	1								
9. Prior partnership [b]	0.79	0.41	.00	-.07	.04	-.07	-.08	.04	.04	.05	1							
10. Project year	2006	2.75	.10	.10	-.01	-.12	-.09	.07	-.01	-.37	.12	1						
11. Patent scope	2.45	1.52	-.17	.15	.24	-.13	.05	.06	.08	-.02	.04	.06	1					
12. Radicalness	5.43	4.87	-.06	.05	.18	-.10	.01	-.03	.14	-.09	.01	.04	.36	1				
13. Science-link	4.03	11.09	-.05	.06	.22	-.17	-.04	-.04	.02	-.03	-.06	.03	.23	.12	1			
14. Prior technological knowledge	4.36	1.55	-.07	.18	.09	-.14	-.22	-.12	.02	-.05	.12	.14	-.06	.10	.05	1		
15. Technological learning [a]	0.02	0.13	.08	.03	.01	.02	-.06	-.07	.03	-.02	.06	-.01	.04	.07	-.01	.01	1	
16. Technological progress [a]	8.19	3.43	-.02	.08	.06	-.05	-.07	-.04	.02	.06	-.01	-.19	.19	.01	.01	.01	.11	1

Notes:

[a] Log-transformed. [b] Dummy variable.

Number of observations (R&D collaborations, events) = 1031 (163, 71).

All correlation coefficients above 0.05 are significant at $p < 0.05$.

Tab. 2: Model results

Independent variable [a]	Model 1	Model 2	Model 3	Model Explor-3	Model Exploi-3
Prior Technological Knowledge (PTK)	#	0.271 ** (0.093)	0.265 ** (0.093)	0.515 * (0.255)	-0.021 (0.421)
Technological Learning (TL) [c]	#	0.017 (0.021)	0.467 ** (0.168)	1.345 *** (0.317)	0.648 ** (0.238)
TL x TL	#	#	-0.733 † (0.412)	-3.760 *** (0.853)	-0.892 ** (0.318)
Technological Progress (TP) [c]	#	-0.002 * (0.001)	-0.002 ** (0.001)	-0.002 * (0.001)	-0.001 (0.001)
Controls:					
Electrical engineering [a]	0.356 (0.285)	0.544 † (0.289)	0.615 * (0.289)	0.365 (0.521)	0.343 (0.511)
Instruments [a]	0.576 † (0.321)	0.551 † (0.323)	0.689 * (0.319)	0.976 (0.629)	0.926 † (0.515)
Chemistry [a]	-0.121 (0.327)	-0.170 (0.331)	-0.202 (0.327)	-0.986 (0.870)	0.302 (0.430)
Mechanical engineering [a]	-0.370 (0.304)	-0.300 (0.295)	-0.188 (0.292)	-0.466 (0.559)	0.140 (0.424)
Other fields [a]	0.268 (0.425)	0.676 (0.420)	0.787 † (0.417)	0.193 (0.754)	1.126 * (0.54)
Prior patents [a]	-0.704 * (0.314)	-0.637 * (0.318)	-0.619 * (0.311)	-1.059 * (0.514)	-0.798 (0.574)
Tie strength	-0.013 (0.049)	-0.001 (0.040)	0.006 (0.039)	-0.398 * (0.176)	0.359 *** (0.086)
Prior partnership [a]	-0.388 (0.29)	-0.380 (0.272)	-0.351 (0.273)	-0.715 (0.464)	-0.666 (0.484)
R&D collaboration year	0.011 (0.084)	0.075 (0.083)	-0.074 (0.084)	-0.274 * (0.125)	0.300 * (0.134)
Patent scope	0.231 * (0.104)	0.315 ** (0.102)	0.324 ** (0.104)	0.542 ** (0.197)	0.26 † (0.148)
Radicalness	-0.076 * (0.033)	-0.096 ** (0.036)	-0.099 ** (0.036)	-0.104 (0.065)	-0.121** (0.045)
Science-link	-0.077 * (0.038)	-0.069 * (0.031)	-0.071 * (0.029)	-0.048 (0.036)	-0.144 * (0.057)
Firm age	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Log-pseudo-likelihood	-287.72	-280.22	-276.34	-94.36	-117.08
χ^2	30.86 **	42.56 ***	52.72 ***	82.09 ***	68.51 ***

Notes:
[a] Unstandardized regression coefficients are reported with robust standard errors in parentheses.
[b] Dummy variable. [c] Log-transformed. Number of observations (R&D collaborations, events) = Model 3: 1031 (163, 71), Model Explor-3: 581 (89, 32), Model Exploi-3: 450 (74, 39).
Significant at: *** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.05$, † $p \leq 0.10$ level.
#: variable not included in the regression.

Summary and Implications

Research to date has focused on the learning-performance relationship but for the most part neglected a possible curvilinear influence of learning activities related to the development and launch of new products (e.g. Levinthal and March 1993). The present study illuminates the interrelationship of prior technological knowledge, technological learning, and technological progress alongside dyadic factors and technological characteristics with respect to the likelihood of NPC. Our findings provide valuable insights into NPD with nuanced possibilities for ways to think about it, make it more manageable, and define optimized commercialization strategies.

Our Hypothesis 1 proposes that prior technological knowledge is an essential factor that increases the likelihood of NPC, and our findings of a Cox regression confirm that it is so. Moreover, the study reveals that technological learning is beneficial up to a certain optimum at which the hazard of NPC decreases (Hypothesis 2a). However, if we distinguish exploitive from explorative learning, it turns out that NPD characterized by explorative technological learning reaches this apex sooner than its counterpart (Hypothesis 2b). Put differently, our results indicate that the costs of experimentation associated with explorative learning become dominant relatively quickly. On the whole one can assume that firms that exceed this learning ceiling are prone to fail and to fall into competency traps. This conclusion, however, should not be interpreted only in a negative sense as a kind of proscription, because it is conceivable that firms tempted toward explorative learning may discover an even better invention or innovative quality. Future research is necessary to tackle the question of when it might be smart to terminate or delay an NPD project mired in excessive learning.

When it comes to technological progress, it seems that rapid change does not exert a major influence on the likelihood of commercialization. Contrary to our expectations (Hypothesis 3), the effect of technological progress on NPD, while significant, is quite low. This holds especially with respect to familiar NPD projects. One explanation for these findings seems especially plausible: firms that succeeded competitively based on prior competencies may be prone to competency traps. Decision-making about a familiar NPD project, in other words, is most likely biased. We would therefore assume firms tend to pursue familiar NPD projects without objective proof or due consideration of technological progress, at least in the short term. When competency become rigidity, it is usually updated or replaced, as rigidity may inhibit the performance of subsequent projects. However, this does not happen over the lifespan of a single project (Leonard-Barton 1992). It would be crucial to get to the bottom of this situation, so this is an exciting avenue for further research.

Theoretical Contributions

This article's various analyses contribute to the NPD literature mainly with respect to the learning-performance relationship, with a series of contributions for both theory and practice. As all findings

emphasize the importance of knowledge based resources alongside organizational learning for NPC, the KBV and OL theories receive empirical support. Simultaneously, the results enrich the KBV and OL literature because they speak to a major critique of the KBV: that more knowledge always leads to greater success. Technological knowledge and technological learning indeed appear to be key drivers of NPD. However, in a project-driven view learning shows a certain optimum beyond which the likelihood of NPC decreases.

This study also enhances the NPD literature in bringing the two (often disparate) currents of prior technological knowledge and technological learning together. The results suggest that both approaches should be utilized in parallel. In a similar vein, Zander and Kogut (1995) note how improbable it would be if preexisting firm competencies correspond with the competencies required for any given NPD project. Conceivably, prior technological knowledge and technological learning must both be considered and tracked in their respective influence on NPD. However, the imbalanced or excessive execution of learning can lead to the formation of competency traps, which brings us to this study's next contribution:

The study reveals an effect of learning that advances both theoretical and empirical understanding about the if-and-when of learning becoming a drag on NPC. Thinking about a tipping point at which learning exceeds its utility and takes on the qualities of a trap goes back to Levinthal and March (1993). Obviously, technological learning, whether of the explorative or exploitive variety, governs innovation; but each type pursued excessively can lead into a specific kind of trap. Our results suggest that too much explorative learning likely increases failure traps, whereas excessive exploitive learning leads into familiarity traps. As far as we know, this is the first study to provide empirical evidence for the theorized curvilinear relationship between technological learning and commercialization likelihood. These findings have been enabled in no small measure by an improved methodology and improved data, and this calls for continued applications of such validated and integrated longitudinal methodologies for a deeper understanding of reality.

Managerial Implications

This study provides some practical assistance for managers entrusted with NPD. At first glance it might seem trivial that prior technological knowledge (as compared to a lack of such knowledge), enhances the likelihood of NPC (Argote 2012). However, this is actually not as self-evident as it sounds. Management needs to evaluate the goodness of fit prior to NPD in order to assess time to market and avoid illusory thinking. Less experienced or younger firms must pay extra heed to this finding. Unlike better established firms, they have fewer capital reserves, and so much as a delay in market entry could have fatal consequences.

Managers handling NPD are additionally advised to strive to develop knowledge to face changes and avoid rigidities (Levitt and March 1988, Leonard-Barton 1992). In this respect, firms, and in particular their human resource departments, ought to create and maintain a working environment where employees can flourish in terms of flexibility, social interaction, and communication, without which learning processes may be limited. Orchestrating learning may confront management with at least two issues: first, managers need to appreciate the differences between the two types of technological learning. Explorative learning, for instance, furthers the innovation degree, while its counterpart can have cost advantages (e.g. March 1991, Kim and Atuahene-Gima 2010). Second, learning comes at a cost in any case (e.g. Levinthal and March 1993), so managers must watch for suboptimal learning ratios. This article provides a patent-based instrument to monitor deviation from optimal learning levels, which in turn should help manage learning efforts in the spirit of ensuring NPD success.

Organizational inertia and a decision-making bias toward commercialization at the project-level can be counteracted by managerial action. Management can forestall some common pitfalls by implementing foresight control instances to observe the environment and obtain objective data.

Limitations and Avenues for Future Research

This study should be interpreted with specific limitations in mind, and these offer several avenues for future research. First, our conclusions might be valid only for certain projects and actors in Germany. It will be worthwhile for future research to apply our analytical framework in other national contexts and in other collaborative settings among customers, suppliers or other firms.

Second, this study is silent on the extent to which prior technological knowledge influences NPD primarily via a distorted level of commitment to an invention or, alternatively, via an actual improvement in the ability to commercialize. It would be valuable to scrutinize the detailed mechanisms underlying these adverse effects in further research.

Third, we have been focused on prior technological knowledge and technological learning. Market-related knowledge and market-related learning may affect product development in different ways. Although our study reveals no significant influence of prior market-related capabilities on NPC, studies that integrated market-related knowledge would be pertinent to establishing clearer theoretical boundaries.

References

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

Anderson, P., and Tushman, M. L. (1990). Technological discontinuities and dominant designs: A cyclical model of technological change. *Administrative Science Quarterly,* 35 (4): 604-633.

Argote, L (2012). *Organizational learning: Creating, retaining and transferring knowledge*. Springer.

Atuahene-Gima, K., and Murray, J. Y. (2007). Exploratory and exploitative learning in new product development: A social capital perspective on new technology ventures in China. *Journal of International Marketing,* 15 (2): 1-29.

Belderbos, R., D. Faems, B. L., and Looy, B. V. (2010). Technological activities and their impact on the financial performance of the firm: Exploitation and exploration within and between firms. *Journal of Product Innovation Management,* 27 (6): 869-882.

Bierly, P., and Chakrabarti, A. (1996). Generic knowledge strategies in the US pharmaceutical industry. *Strategic Management Journal,* 17 (2): 123-135.

Bierly, P. E., Damanpour, F. and Santoro, M. D. (2009). The application of external knowledge: organizational conditions for exploration and exploitation. *Journal of Management Studies,* 46 (3): 481-509.

Bstieler, L. (2005). The moderating effect of environmental uncertainty on new product development and time efficiency. *Journal of Product Innovation Management,* 22 (3): 267-284.

Campbell, D. T. (1955). The informant in quantitative research. *American Journal of Sociology,* 60 (1): 339-342.

Chesbrough, H. W. (2003. *Open innovation: The new imperative for creating and profiting from technology*. Boston, MA: Harvard Business School Press.

Churchill, G. A. (1979). A paradigm for developing better measures of marketing constructs. *Journal of Marketing Research,* 16 (1): 64-73.

Cleves, M., W. Gould, Gutierrez, R., and Marchenko, Y. (2008). *An introduction to survival analysis using Stata (2nd ed.).* College Station, USA: Stata Press.

Cohen, W. M., and Levinthal, D. A. (1989). Innovation and learning: the two faces of R&D. *The Economic Journal,* 99 (397): 569-596.

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

Cox, D. R. (1972). Regression models with life tables (with discussion). *Journal of the Royal Statistical Society,* 34 (2): 187-220.

Day, G. S. (1994). The capabilities of market-driven organizations. *Journal of Marketing, 58:* 37-52.

Danneels, E. (2002). The dynamics of product innovation and firm competences. *Strategic Management Journal,* 23 (12): 1095-121.

Danneels, E. (2007). The process of technological competence leveraging. *Strategic Management Journal,* 28 (5): 511-533.

Eisenhardt, K. M., and Tabrizi, B. N. (1995). Accelerating adaptive processes: Product innovation in the global computer industry. *Administrative Science Quarterly,* 40 (1): 84-110.

Flores, L. G., Zheng, W., Rau, D., and Thomas, C. H. (2012). Organizational learning subprocess identification, construct validation, and an empirical test of cultural antecedents. *Journal of Management,* 38 (2): 640-667.

Folta, T. B. (1998). Governance and uncertainty: The tradeoff between administrative control and commitment. *Strategic Management Journal,*19 (11): 1007-1028.

Grambsch, P., and Therneau, T. M. (1994). Proportional hazards tests and diagnostics based on weighted residuals. *Biometrika,* 81 (3): 515-26.

Grant, R. M. (1996). Toward a knowledge-based theory of the firm. *Strategic Management Journal,* 17 (2): 109-122.

Gulati, R. (1995). Does familiarity breed trust? The implications of repeated ties for contractual choice in alliances. *Academy of Management Journal,* 38 (1): 85-112.

Hannan, M. T., and Freeman, J. (1984). Structural inertia and organizational change. *American Sociological Review,* 49 (2): 149-164.

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

Hoang, H., and Rothaermel, F. T. (2010). Leveraging internal and external experience: Exploration, exploitation, and R&D project performance. *Strategic Management Journal,* 31 (7): 734-58.

Huff, J. O., Huff, A. S., and Thomas, H. (1992). Strategic renewal and the interaction of cumulative stress and inertia. *Strategic Management Journal* 13 (1): 55-75.

Jansen, J. J., Van Den Bosch, F. A., and Volberda, H. W. (2006). Exploratory innovation, exploitative innovation, and performance: Effects of organizational antecedents and environmental moderators. *Management Science,* 52 (11): 1661-1674.

Kessler, E. H., and Chakrabarti, A. K. (1999). Speeding up the pace of new product development. *Journal of Product Innovation Management*, 16 (3): 231-247.

Kim, N. and Atuahene-Gima, K. (2010). Using exploratory and exploitative market learning for new product development. *Journal of Product Innovation Management* 27 (4): 519-536.

Kortum, S. (1993). Equilibrium R&D and the patent-R&D ratio: US evidence. *American Economic Review: Papers and Proceedings*, 83 (2): 450-457.

Lambert, R. A. (1986). Executive effort and selection of risky projects. *The Rand Journal of Economics,* 17 (1): 77-88.

Landis. J. R., and Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics,* 33 (1): 159-174.

Laursen, K., and Salter, A. (2004). Searching high and low: What types of firms use universities as a source of innovation? *Research Policy,* 33 (8): 1201-1215.

Lechner, C., and Floyd, S. W. (2012). Group influence activities and the performance of strategic initiatives. *Strategic Management Journal,* 33 (5): 478-495.

Lee, L. (1983). Generalized econometric models with selectivity. *Econometrica,* 51 (2): 507-12.

Leonard-Barton, D. (1992). Core capabilities and core rigidities: A paradox in managing new product development. *Strategic Management Journal,* 13 (S1): 111-125.

Lerner, J. (1995). Venture capitalists and the oversight of private firms. *The Journal of Finance,* 50 (1): 301-318.

Levinthal, D. A., and March, J. G. (1993). The myopia of learning. *Strategic Management Journal,* 14 (2): 95-112.

Levitas, E. F., McFayden, M. A., and Loree, D. (2006). Survival and the introduction of new technology: A patent analysis in the integrated circuit industry. *Journal of Engineering and Technology Management,* 23 (3): 182-201.

Levitt, B., and March, J. G. (1988). Organizational learning. *Annual Review of Sociology,* 14: 319-340.

Makri, M., Hitt, M. A., and Lane, P. J. (2010). Complementary technologies, knowledge relatedness, and invention outcomes in high technology mergers and acquisitions. *Strategic Management Journal,* 31 (6): 602-628.

March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization Science,* 2 (1): 71-87.

Michael, S. C., and Palandjian, T. P. (2004). Organizational learning and new product introductions. *Journal of Product Innovation Management,* 21(4): 268-276.

Miller, D. (2003. An asymmetry-based view of advantage: towards an attainable sustainability. *Strategic Management Journal,* 24 (10): 961-976.

Miner, A. S., and Mezias, S. J. (1996). Ugly duckling no more: Pasts and futures of organizational learning research. *Organization Science,* 7 (1): 88-99.

Nederhof, A. J. (1985). Methods of coping with social desirability bias: A review. *European Journal of Social Psychology,* 15 (3): 263-280.

Nerkar, A., and Shane, S. (2007. Determinants of invention commercialization: An empirical examination of academically sourced inventions. *Strategic Management Journal,* 28 (11): 1155-1166.

Podsakoff, P. M., MacKenzie, S. B., Podsakoff, N. P., and Lee, J. Y. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology,* 88 (5): 879-903.

Rosenberg, N. (1994). *Exploring the Black Box: Technology, Economics, and History.* Cambridge: Cambridge University Press.

Rothaermel, F. T., and Alexandre, M. T. (2009). Ambidexterity in technology sourcing: The moderating role of absorptive capacity. *Organization Science,* 20 (4): 759-780.

Schoonhoven, C. B., Eisenhardt, K. M., and Lyman, K. (1990). Speeding products to market: Waiting time to first product introduction in new firms. *Administrative Science Quarterly,* 35 (1): 177-207.

Simonin, B. L (1999). Ambiguity and the process of knowledge transfer in strategic alliances. *Strategic Management Journal,* 20 (7): 595-623.

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

Song, M., C. Droge, Hanvanich, S., and Calantone, R. (2005). Marketing and technology resource complementarity: An analysis of their interaction effect in two environmental contexts. *Strategic Management Journal,* 26 (3): 259-276.

Song, M., and Montoya-Weiss, M. M. (2001). The effect of perceived technological uncertainty on Japanese new product development. *Academy of Management Journal*, 44 (1): 61-80.

Spender, J. C. (1996). Making knowledge the basis of a dynamic theory of the firm. *Strategic Management Journal*, 17 (2): 45-62.

Uotila, J., Maula, M., Keil, T., and Zahra, S. A. (2009). Exploration, exploitation, and financial performance: analysis of S&P 500 corporations. *Strategic Management Journal*, 30 (2): 221-231.

Wernerfelt, B., and Karnani, A. (1987). Competitive strategy under uncertainty. *Strategic Management Journal*, 8 (2): 187-194.

Kogut, B., and Zander, U. (1992). Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization Science*, 3 (3): 383-397.

Zander, U., and Kogut, B. (1995). Knowledge and the speed of the transfer and imitation of organizational capabilities: An empirical test. *Organization Science*, 6 (1): 76-92.