LEADING INNOVATION:

How Top Managers Influence Technological Search and Innovation Performance of Firms

by

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LEADING INNOVATION:

How Top Managers Influence Technological Search and Innovation Performance of Firms

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ABSTRACT

Many top managers will agree that innovation is important to their company's success. Still there is little understanding of how top managers influence their company's innovation performance. This dissertation studies how top managers influence technological innovation at their firms. It consists of three empirical studies that provide valuable insights into the extent to which, in what specific ways, and under what conditions senior management influences firms' technological search behavior and how this behavior translates into innovation performance. Using micro-data on pharmaceutical firms and their subsidiaries, executives, and inventors, I examine how executives' knowledge, skills, abilities, and other characteristics affect firms' R&D investments and patent output. The first study investigates what CEO characteristics positively impact firms' innovation outcomes, and when and how they do so. The second study examines how managerial human capital that is available to the firm affects a firm's propensity to experiment with emerging and unfamiliar technologies. The third study investigates how the formal structure of a firm influences senior management's ability to coordinate among firms' inventors for the purposes of innovation performance. Overall, this dissertation results in a deeper and more comprehensive understanding of how the characteristics, strategic decisions, and actions of senior management explain the differences between firms in innovation performance. This dissertation also provides valuable insights into what corporate leaders can do to increase the likelihood of success in innovation.

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CHAPTER 1:
Introduction

Technological innovation and corporate leaders

Technological innovation is the lifeblood of organizations that compete in changing environments. New technologies not only play a key role in organizations' adaptation to shifting competitive landscapes but also bring about waves of "creative destruction" (Eggers & Park, 2018; Garcia-Macia, Hsieh, & Klenow, 2018; Schumpeter, 1934). These waves unleash bouts of major technological change in which new technologies replace older ones. The firms that set the wave in motion may have the opportunity to escape from competition, enter new markets, create new ones, and grow at a more rapid pace than rival firms do (Aghion, Akcigit, & Howitt, 2014; Christensen, 1997; Tushman & Anderson, 1986). More than five decades of empirical research shows that technological innovation is an important enabler of a competitive advantage that is associated with growth and superior financial performance for firms (Aghion & Howitt, 2008; Cohen, 2010; Kogan, Papanikolaou, Seru, & Stoffman, 2017), including during and following economic downturns (Flammer & Ioannou, 2018; Walrave, Romme, van Oorschot, & Langerak, 2017). Indeed, the world's most innovative companies are also the most valuable companies by market value (Ringel, Grassl, Möller, Zablit, & Manly, 2018). It comes as no surprise that most corporate leaders acknowledge that innovation is among their top three strategic priorities, and in fact, many believe that it is their firm's top driver of growth (Andrew, Manget, Michael, Taylor, & Zablit, 2010; Capozzi, Gregg, & Howe, 2010).

Although technological innovation is widely perceived as crucial to firms' continuing success, there are nonetheless major variations between corporations in terms of their innovative performance. The longstanding debate over why some firms succeed in innovation while others fail started with Schumpeter (1934). He initially argued that small, entrepreneurial firms are most likely to be the source of innovation. Later, he claimed that large, established firms were likely to be the driving force behind technological progress because they had greater incentive to invest in new technologies and superior access to financial and human capital (Schumpeter, 1950). They also have an ability to appropriate innovations from smaller firms (Teece, 1986). Subsequent research has been inconclusive on this debate (Cohen, 2010), but it does reveal that firm-specific attributes explain the large variety in firms' innovation success (Henderson & Cockburn, 1994). This latter finding resulted in the general understanding that differences between firms in terms of innovation performance can be explained by their different resources, routines, and capabilities and by differences in their internal organization,

such as organizational structure, incentive systems, culture, and search processes (Ahuja, Lampert, & Tandon, 2008; Teece, 1996).

Scholars have considerably advanced our current understanding of the organizational determinants of technological innovation. Relatively less attention has been given to the idea that differences between firms in innovation performance stem from the strategic choices and actions of their most powerful actors: their top executives (Talke, Salomo, & Rost, 2010). This is remarkable given the many anecdotal examples featured in the popular press that have strongly suggested a link between corporate leaders and innovation. Executives are the most influential actors in the strategic leadership of firms' innovation-related processes because they occupy a uniquely influential position within the firm (Burgelman et al., 2018; Simsek, Jansen, Minichilli, & Escriba-Esteve, 2015). A firm's senior management—that is, the team consisting of the firm's chief executive officer (CEO) and its other top executives—may directly influence innovation through top-down strategic planning and initiatives aimed at setting the innovation agenda (Barney, Foss, & Lyngsie, 2018). Yet, senior management more typically has an indirect influence on innovation by reacting to bottom-up initiatives advanced by other organizational members (Burgelman, 1983a, 1991; Day, 1994). Senior management indirectly influences others by establishing a context conducive to innovation. It creates this context through forming a vision for the future and communicating it to others, as well as through stimulating and motivating followers, the incentives that they put in place, and the other administrative arrangements that they adopt (Elenkov, Judge, & Wright, 2005). However, so far there is little understanding of how executives and their particular characteristics, strategic choices, and actions result in differences between firms in terms of innovation performance.

Key theoretical perspectives and research gaps

The key theoretical perspectives that help to explore how senior management influences technological innovation—a term defined in this dissertation as the discovery and development of new technology—originate in the strategy and innovation literature. This dissertation builds on the state of the art and contributes to the literature in the ways explained in this section.

The strategy literature aims to explain why some firms succeed while other fails by identifying the drivers of organizational performance. It shows that the fates and fortunes of firms hinge on the strategic decisions and actions taken by the people who lead them (Wowak, Gomez-Mejia, & Steinbach, 2017). A strand of the literature that has played a longstanding role in the study of the impact of managers on firms is that based on the upper echelons perspective. Building on the premise of bounded rationality (Cyert & March, 1963)—"the idea that informationally complex, uncertain situations are not objectively knowable, but, rather,

are merely interpretable" (Hambrick, 2007, p. 334)—the central argument of this perspective is that executives' experiences, values, and personalities greatly influence their personal interpretations of the strategic situations faced by the firm and that, in turn, these factors affect their strategic choices (Hambrick & Mason, 1984). As a result, organizational outcomes—at the levels of both strategy and performance—are to some extent a reflection of the characteristics of a firm's top executives (Finkelstein, Hambrick, & Cannella, 2009).

More recently, the resource-based view has offered an alternative perspective that firms create a competitive advantage through their possession of valuable, rare and costly-to-imitate resources and capabilities, and their organization to exploit them (Barney, 1991, 1995). These resources and capabilities can be viewed as bundles of tangible and intangible assets, including a firm's managerial human capital (Nyberg, Moliterno, Hale, & Lepak, 2014). Managerial human capital underpins the "capabilities with which managers build, integrate, and reconfigure organizational resources and competencies" (Adner & Helfat, 2003, p. 1012). Managers make different strategic decisions because they have varying levels and combinations of "dynamic managerial capabilities," even when the conditions in the external environment of their firms are similar (Kor & Mesko, 2013). As a result, this perspective shows that heterogeneity in managerial resources and capabilities explain the differences between firms in strategic behavior and performance (Adner & Helfat, 2003; Helfat & Martin, 2015).

Upper echelons researchers emphasize that executives' experiences, values, and personalities, which are almost always proxied by demographic characteristics, result in personalized lenses that shape their strategic choices (Hambrick, 2007). By contrast, researchers in the resource-based tradition stress that managers' knowledge, skills, and abilities gained through education and work experience shape the managerial capabilities that provide the capacity to direct innovation and performance (Helfat & Martin, 2015). In addition, most upper echelons studies tend to treat senior management characteristics as independent of one another (Carpenter, Geletkancz, & Sanders, 2004). However, resource-based view researchers have called this practice into question. They cite executives' tendency to embody a "bundle" of characteristics, and they suggest that a firm's decision-making process is more likely to reflect the interaction or configuration of multiple characteristics than it is individual characteristics in isolation (Kor, 2003).

Researchers in both streams, however, have seldom directly linked senior management characteristics to organizational performance because of the complex causal chain that runs from the executive to eventual performance (Liu, Fisher, & Chen, 2018). Instead, they have associated those characteristics with specific strategic choices and initiatives, such as resource

allocation to research and development (R&D) and the initiation of new strategic technological initiatives (Gerstner, Konig, Enders, & Hambrick, 2013; Kor, 2006). In doing so, they have made the implicit assumption that these strategic choices and actions have implications for organizational performance. Yet to study the underexamined causal chain between senior management characteristics and firms' innovation performance, it is necessary to build a comprehensive model that accounts both for the mediation mechanisms that connect senior management characteristics to innovation performance and for contingency (moderating) mechanisms related to the functioning of senior management (Liu et al., 2018).

Meanwhile, the innovation literature has focused mainly on the execution-oriented aspects of innovation management. In line with this focus, this literature attributes differences in innovation performance to underlying differences in how firms execute innovation activities at the project level (Hoisl, Gruber, & Conti, 2017; Talke et al., 2010).[1] A complementary body of research that suggests that innovation performance results from strategic and organizational factors remains largely neglected (Ahuja et al., 2008; O'Reilly & Tushman, 2013). This set of studies adopts two main theoretical perspectives that differentiate between a firm's ability to innovate and its motivation to do so. Concerning the former, the organizational perspective argues that variations in innovation performance between firms can be understood through differences in their ability to innovate, which are based upon their existing knowledge, capabilities, and other organizational attributes (Ahuja & Katila, 2001; Henderson & Cockburn, 1994; Leonard-Barton, 1992; Nelson & Winter, 1982; Teece, 1996). With respect to the latter, the economic perspective argues that firms have different motivations, as past performance and commitment to current profit streams affect their incentives to pursue innovation (Christensen & Bower, 1996; Greve, 2003; Henderson, 1993). Furthermore, the emerging behavioral perspective explains differences in firms' technological innovation by pointing out that the same factors that motivate firms to pursue new technologies also impact the success of such endeavors. The fundamental mismatch between the drivers of motivation and those of ability is what results in firms' behavioral tendencies to under- or overinvest in technological innovation (Eggers & Kaul, 2017).

Although these are important insights, the role of a firm's senior management as a key driver of innovation performance is still not adequately understood (Li, Maggitti, Smith, Tesluk, & Katila, 2013; Simsek et al., 2015). This is surprising in view of the growing evidence that innovation activities and processes do need strategic leadership from the top (Barney et

[1] For an extensive review on the best practices for new product development and innovation execution processes, see the series by Kahn, Barczak, and colleagues (2006; 2009; 2012; 2016).

al., 2018; Talke et al., 2010; Yadav, Prabhu, & Chandy, 2007). Especially when ambiguity between means and ends exists, as is particularly the case when it comes to innovation processes (Garud, Tuertscher, & Van de Ven, 2013), the role of a firm's top managers becomes highly salient (Hambrick, 2007). Executives' strategic choices and actions may impact not only the ways in which a firm executes innovation activities but also its ability and motivation to innovate (Ahuja et al., 2008). A firm's senior management therefore might well be one of the deeper but still unobserved sources that explains the remarkable presence of persistent firm heterogeneity in relation to innovation performance.

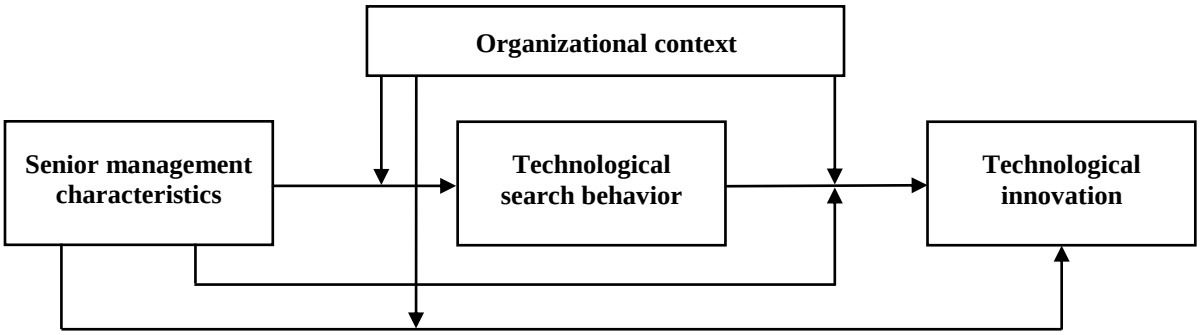
Moreover, the strategy and innovation literatures have for the most part developed independently from each other but much can be gained from combining them. The strategy literature has mainly focused on how senior management characteristics relate to firms' strategic behavior and performance. The innovation literature has investigated how innovation management and organizational attributes affect firms' success in technological innovation. Combining the two creates scope for considering the entire causal chain that connects senior management to actual innovation performance. In examining this causal chain, it is important to acknowledge the influence of the organizational context in the theoretical and empirical framework of this dissertation's studies because a firm's senior management and innovation processes are embedded in the wider organizational context (Simsek et al., 2015; Van de Ven, 1986). The failure of prior research to do so has meant that many aspects of what, how, and why different organizational conditions may shape executive behavior and the management of innovation have been left unexplored. This results in an incomplete understanding of how executives influence innovation performance (Busenbark, Krause, Boivie, & Graffin, 2016; Van de Ven, Ganco, & Hinings, 2013). Examining senior management characteristics, organizational context, and technological innovation jointly matters because it can help us to better understand why senior management influences innovation performance by teasing out the theoretical mechanisms at play throughout the causal chain. It also makes it possible to isolate the effect of each characteristic and context and to examine the interplay between them to learn what organizational conditions strengthen or weaken senior management's influence on innovation. This will result in a more comprehensive perspective on how senior management influences firms' technological innovation.

Overview of the three studies in the dissertation

This dissertation aims to develop a deeper and more comprehensive understanding of to what extent, in what specific ways, and under what conditions senior management influences firms' technological search behavior, as well as of how this behavior translates into technological

innovation. Studying how top managers shape search behavior and subsequent innovative performance is a challenging task: technological innovation is a distal organizational outcome; there are several ways in which senior management can influence technological innovation; and executives operate in different organizational contexts. This dissertation addresses these challenges by incorporating three distinct features in its comprehensive conceptual framework (presented in Figure 1.1).

Figure 1.1: Conceptual framework of this dissertation



First, the dissertation's overarching framework focuses on the specific link between the characteristics of senior management and firms' strategic decisions on the one hand, and the translation of these into concrete search processes and innovation outcomes on the other hand. This approach addresses the causal gap that exists between executives' behavior and firms' innovation performance. Second, the framework explicitly considers how senior management influences technological innovation directly through its strategic choice of specific search activities and processes (i.e., the direct and indirect effects of senior management characteristics on technological innovation), as well as indirectly through the implementation of these choices (i.e., the moderation effects of senior management characteristics and firms' formal structural attributes related to senior management). Third, the framework differentiates between two levels of analysis: (1) the role of organizational context for innovation; and (2) the processes of strategic leadership and innovation execution embedded within this context. This allows for a detailed examination of the interdependencies between senior management and its organizational context in shaping innovation strategies and performance of firms.

The framework as a whole makes it possible to explore to what extent and in what specific ways senior management is important to technological innovation at different stages of the causal chain and under different organizational conditions. I conduct three separate but highly complementary studies to cover the different stages through which, ways in which, and conditions under which senior management influences technological innovation.

Chapter 2: CEO research orientation, organizational context, and innovation

While there has been a dramatic increase in CEOs with "general skills" (as opposed to ones who have context-specific skills) in recent decades, the steady decline in R&D intensity and firms' innovation outcomes is no less remarkable. These circumstances prompt the question: What CEO characteristics positively impact firms' innovation outcomes, and when and how do they do so? The first study in this dissertation provides an answer to this question by examining how, as chief decision makers in a corporation, CEOs with a research orientation—those with aptitude and motivation in relation to science and technology—increase their firms' innovation outcomes. This study not only hypothesizes a direct association between CEO research orientation and firms' innovation outcomes but also offers an in-depth examination of three contextual organizational factors that determine CEOs' managerial discretion in influencing innovation (i.e., CEO duality, slack resources, and firm age) and of two specific ways in which research-oriented CEOs influence innovation (i.e., strategic choice of an R&D-intensive investment strategy and the implementation of such a strategy).

In this study, the heterogeneity of different CEOs' research orientations is observed through a handcrafted sample that encompasses an array of CEO career experiences in the domains of research, science, and technology. Empirical evidence from 109 CEOs from 87 U.S.-based pharmaceutical firms over the period 2001–2013 provides support for most of the hypotheses. This study contributes to the longstanding debate over whether and to what extent CEOs impact organizational performance, such as firms' innovation outcomes. It even moves beyond this debate by explicitly addressing what kinds of CEOs impact firms' innovation outcomes, as well as how and when they do so. Another notable contribution is its argument that CEOs constitute, through their research orientation and innovation-strategy choices, a key factor that explains variation between different firms' abilities and motivations to innovate.

Chapter 3: Managerial human capital, diversification, and exploratory search

A second study further explores the strategic decisions and actions of senior management that underpin one of the key strategic behaviors for innovation, namely a firm's search behavior. It is seldom disputed that the search for new technologies is a vital activity for the creation of technological innovations that contribute to future growth and firms' survival in the long run. Comparatively, much less is known about why firms differ in their decisions as to where to search for new technologies. This is a process that involves a fundamental trade-off between local and exploratory search. This study examines the role played by senior management in bringing about the widely observed differences between firms' propensities for exploratory search by considering the question: How does the managerial human capital that is available

to a firm affect its propensity for exploratory search? The study's focus on the availability of managerial human capital emphasizes that, considering that the organizational context in which top managers operate may result in managerial complexity and the placing of competing demands on those managers, it is imperative to examine the interplay between managerial human capital and this context in explaining differences in exploratory search by firms. This rationale results in the hypothesis that the positive association between managerial human capital and a firm's exploratory search behavior is negatively moderated by a firm's degree of diversification.

The results of an analysis of a longitudinal sample consisting of 133 U.S. public pharmaceutical firms show that managerial human capital—which in the study encompasses generic, industry-specific, and firm-specific skills—increases firms' propensity to explore emerging technologies. This relation weakens with a firm's diversification of its business over product and geographical markets, which indicates that diversification diverts managerial resources away from exploratory search. No such evidence is found in the study's analyses that predict firms' propensity for unfamiliar technologies. These findings shed new light on an antecedent of firms' search behavior that helps to explain why some firms overcome learning traps and inertia that prevents them from engaging in exploratory search. This study also suggests that a firm's search processes are a useful way to account for the mechanisms that link senior management's characteristics and strategic choices with performance outcomes. In doing so, it underscores the fundamental trade-off nature of strategic choice that managers face, and it highlights how this trade-off is influenced by managers' skills, knowledge, and experience as well as by the organizational context.

Chapter 4: Knowledge diversity, innovation, and the moderating role of formal structure

A firm's engagement in search and innovation activities such as those discussed in the previous chapters likely results in knowledge diversity among that firm's inventors, as the search for new technologies is conducted by inventors who need to specialize in one or a few technological domains. While the literature has predominantly focused on how innovation activities that increase knowledge diversity improve chances for technological innovation, the increasing need for coordination of knowledge exchange and combination when inventors possess diverging knowledge remains a relatively neglected issue. The third and final study addresses the question: How does the formal structure of a firm influence senior management's ability to coordinate diverse knowledge for innovation? This study develops rival hypotheses in relation to three structural attributes of firms that are related to top management teams

(TMTs) and that capture important aspects of both horizontal and vertical organizational structure.

By means of a fine-grained dataset focused on 119 pharmaceutical firms between 2000 and 2011, empirical evidence indicates that administrative intensity, hierarchical structure in TMTs, and functional structure in TMTs determine the extent to which a firm's senior management can effectively intervene in the firm's innovation process by coordinating and facilitating knowledge exchange and combination. The results highlight how a company's formal structure can enable or constrain its senior management's ability to achieve the coordination required to benefit from knowledge diversity for the purposes of bringing about innovation. This study complements the literature on organizing for innovation by emphasizing the need for coordination in a firm's pursuit of technological innovation through knowledge recombination.

Research setting and data

The research setting of this dissertation is the U.S. pharmaceutical industry. Technological innovation is vital in the pharmaceutical industry, where the rate of new drug discovery typically determines whether a company thrives or dies (Pisano, 2006). This sector's relentless focus on innovation has made the role of a firm's senior management critically important (Gerstner et al., 2013; Schneider et al., 2012). This focus has also contributed to some of the most important successes in modern medicine. Examples here include aspirin's working compound, salicylic acid, which is used to treat pain, fever, or inflammation; the antibiotic penicillin, which is used to treat bacterial infections; and insulin, which is used to treat diabetes. Two main approaches to drug development are (traditional) pharmaceutical R&D, which is based on chemical synthesis and trial-and-error screening of potential compounds, and biotechnology R&D, which revolves around the understanding of living organisms, requires deep expertise in molecular biology, and enables targeted identification of drug candidates (Hughes, Rees, Kalindjian, & Philpott, 2011; Munos, 2009). Both approaches are costly and time consuming, and they involve extremely high risks (Scannell, Blanckley, Boldon, & Warrington, 2012). This makes the pharmaceutical industry an R&D-intensive industry in which the total R&D costs per employee are more than twice those of any other industry (Lakdawalla, 2018).

An innovating pharmaceutical company often patents its newly discovered drugs because if it does not do so, the underlying technology can be copied by other firms with relative ease. This implies that the firm's rivals will be able to benefit from the innovation at a substantially lower cost. In a study conducted across thirty-four different industries, Cohen, Nelson, and

Walsh (2000) found that the pharmaceutical industry ranks second only to the medical device industry in terms of the effectiveness that it attributes to patents as a mechanism for protecting intellectual property. This makes the pharmaceutical industry an appropriate research setting, in which firms' innovation activities and outcomes can be observed in a detailed and reliable way. While researchers acknowledge that patent data do not provide a perfect measurement (e.g., new technologies may be protected by trade secrets), they are the most widely used source for empirical research on technological innovation (Cohen, 2010). Hall, Jaffe, and Trajtenberg (2005), for instance, illustrate that citations are a good measure of innovative quality and economic importance. Specifically, they find that an extra citation per patent boosts a firm's market value by 3 percent.

A key part of this dissertation was the extensive data collection conducted across different data sources and the construction of a unique microlevel and longitudinal dataset of 195 publicly listed U.S.-based pharmaceutical companies. According to Compustat, those firms were among the hundred largest employers in the pharmaceutical industry—this industry being defined as being covered by Standard Industrial Classification (SIC) codes 2833, 2834, 2835, and 2836—at any time during the 2000–2014 period and for which data were available in the BoardEx database. This focus made it possible to observe substantial innovation activity as well as the personnel and assets of small-, medium-, and large-sized firms in the pharmaceutical industry, and, at the same time, it facilitated the data collection process across multiple databases. The following data types and sources were consulted: (1) patent information from the United States Patent and Trademark Office (USPTO) and disambiguated inventor data from the FUNG database over the 1976–2015 period; (2) data on CEOs, other top executives, and board directors from BoardEx (1999–2014) and Execucomp (1992–2014); (3) data on each firm's subsidiaries and historical names, which were extracted from SEC filings (10-K filings, Exhibit 21 section) from the 1994–2015 period; (4) historical shareholdings data from Thomson Reuters Eikon (1996–2015) and the Thomson Reuters Institutional Holdings (13F) database (1980–2016); (5) records on divestitures, strategic alliances, joint ventures, and mergers and acquisitions from Thomson Reuters Securities Data Company (SDC) platinum data in relation to the 1962–2016 period; (6) accounting information from Compustat North America (1950–2016) and Compustat Segments (1976–2016); and (6) extensive manual searches of and extractions from online resources, such as annual reports, company websites, SEC filings, FDA filings, Lexis Nexis, Marquis Who's Who, Bloomberg Executive Profile and Biography, and Equilar.

Observations across these databases were merged over two steps. First, the observations across databases of parent firms were merged using commonly used identifiers (e.g., GVKEY and CUSIP). Second, to correctly match USPTO and SDC records to both parent firms and their wholly owned subsidiaries, detailed family trees of all 195 focal firms were constructed. These family trees contained yearly varying data on the start and end date of each parent-subsidiary relationship, the percentage of ownership by parent firm, each entity's country or state of incorporation, each entity's legal form, and each entity's historical names and alternative name formats (e.g., abbreviations). A custom-designed computer algorithm was developed to match company names (USPTO assignee and applicant names or SDC entity name), legal form, and country data to the company info in each firm's family tree (for more details, see Appendix 1.1). Eventually, all unique records that matched with the 195 focal firms and their wholly owned subsidiaries were aggregated at the ultimate parent level to capture each focal firm's full patent output, external R&D activity, and financials. The resulting dataset included detailed data on 95,142 patent applications, 11,298 inventors, and 9,281 managers related to 195 firms and their 12,375 subsidiaries.

It is important to note that this sample mutates over time as firms were delisted or acquired by other firms. During the total study period covered by the three studies in this dissertation, which runs from 2000 to 2014, there were three spinoffs of focal firms that resulted in new focal firms (e.g., Abbott Laboratories and Abbvie in 2013) and fourteen (reverse) mergers and acquisitions between sampled firms (e.g., Merck & Co. merged with Schering-Plough in 2009). Those fourteen cases were treated as separate firms before the merger and as a single entity after the merger using the GVKEY of the firm that continued to file financial statements. Moreover, although the United States is the largest market for pharmaceuticals worldwide, this sample does neglect some important pharmaceutical companies based in continental Europe and Japan.

CHAPTER 2:
CEO Research Orientation, Organizational Context, and Innovation

This study develops and tests a comprehensive framework that explains what, when, and how CEO characteristics influence firms' innovation outcomes in R&D-intensive industries. Empirical evidence from 109 CEOs from 87 U.S.-based pharmaceutical firms over the period 2001–2013 reveals that research-oriented CEOs—those with an aptitude and motivation for science and technology—increase their firms' innovation outcomes. The results indicate that the CEO-innovation relationship strongly depends on the extent of CEOs' managerial discretion, which is shaped by the organizational context. A more detailed analysis shows that research-oriented CEOs influence innovation through an R&D-intensive strategy. These insights contribute to a more comprehensive understanding of CEO strategic choices and processes that result in firms' innovation outcomes, and they allow for a better understanding of why firms differ in their innovation performance.

Introduction

Understanding how CEOs influence firm strategies and outcomes has received much research interest in recent decades (Burgelman et al., 2018; Liu et al., 2018). A rise in the importance of CEOs' general managerial skills has been observed as one of the most striking trends in the past half century (Bertrand, 2009; Crossland, Zyung, Hiller, & Hambrick, 2014), and stemming from this observation, recent research has shown that S&P 1500 firms that have "generalist" CEOs exhibit higher innovation outcomes (Custódio, Ferreira, & Matos, 2017). Simultaneously, however, many firms have shifted from a strategic orientation of "R&D as a driver of growth" to "R&D as an expense". This is exemplified by a steady decline in R&D intensity, a corresponding decline in firms' R&D capability, and, subsequently, reduced innovation outcomes (Cummings & Knott, 2018). This decrease in firm innovation may be explained by a lack of CEOs with context-specific skills (Cummings & Knott, 2018; Simsek et al., 2015) such as technological domain expertise in R&D-intensive industries (Felix & Bistrova, 2015).

Indeed, the pharmaceutical industry has experienced a decline in innovation outcomes (Munos, 2009; Scannell et al., 2012), even though the development of cutting-edge technology is critical to a firm's sustained profits and even existence (Roberts, 1999). The innovation literature has addressed the struggles to innovate predominantly from a competence perspective, by attributing performance differentials to differences in firms' underlying

innovation capabilities (Ahuja et al., 2008; Henderson & Cockburn, 1994). This literature offers no explanation, however, as to why firms make different innovation strategy choices in the first place (Ahuja & Lampert, 2001). In this respect, the innovation literature misses out on the role of critical strategic and organizational conditions in which such innovation capabilities reside (Talke et al., 2010). While van de Ven (1986) has already argued that strategic leadership is crucial in the organization and management of innovation at firms, many innovation scholars have failed to effectively consider the role of guidance and leadership from the top (Simsek et al., 2015; Yadav et al., 2007). As a result, we lack a comprehensive understanding of the strategic choices and processes through which CEOs influence firms' innovation outcomes.

To advance our understanding of the strategic implications of CEO characteristics on corporate innovation in R&D-intensive industries, I study what, when, and how CEO characteristics impact firms' innovation outcomes in the pharmaceutical industry. Drawing on upper echelons theory (Hambrick, 2007; Hambrick & Mason, 1984), I first argue that CEOs exhibit considerable heterogeneity in their ability and motivation in relation to science and technology. This aids me in explaining differences between firms in innovation outcomes. A comparison of former Genentech CEO Arthur Levinson, who enjoyed a distinguished career in scientific research and in the development of biotechnology, and Robert Hugin, an MBA graduate who specialized in corporate finance in emerging technologies before becoming Celgene's CEO, illustrates the diversity between CEOs that exists in this area. To capture such heterogeneity among CEOs and show what CEO characteristics impact firms' innovation outcomes in R&D-intensive industries, I introduce the notion of CEO research orientation, which I define as the array of career experiences in the domains of research, science, and technology that an executive had prior to becoming a CEO.

To assess when CEOs with a research orientation influence firms' innovation outcomes, I argue that the organizational context in which CEOs operate determines their managerial discretion or latitude for action (Busenbark et al., 2016; Hambrick & Finkelstein, 1987). Specifically, I examine whether CEOs' structural power as a board chairperson, the availability of slack resources for experimentation, and presence of inertial forces in older firms affect the extent to which a CEO's research orientation spurs a firm's innovation (Krause, Semadeni, & Cannella, 2014; Nohria & Gulati, 1996; Sorensen & Stuart, 2000). To detail one mediating mechanism for how research-oriented CEOs influence innovation, I argue that those CEOs who strategically choose an R&D-intensive investment strategy and who have a better understanding of how to effectively implement such a strategy affect their firms' innovation outcomes (Bromiley & Rau, 2016; Finkelstein et al., 2009; Liu et al., 2018). Taken together,

this study proposes a comprehensive framework that indicates that through their research orientation, and operating in a given context, CEOs shape their firms' strategic choice of R&D resource allocation and attendant innovation outcomes. I find considerable support for my model by utilizing a panel dataset involving 109 CEOs from 87 U.S. pharmaceutical firms over the period 2001 to 2013.

This study adds to upper echelons theory by explaining and testing the complex causal chain between CEOs and firms' innovation outcomes. This study moves beyond merely observing a direct relationship between CEO characteristics and innovation (Balsmeier & Buchwald, 2014; Cummings & Knott, 2018; Custódio et al., 2017; Wu, Levitas, & Priem, 2005). Instead, it explicitly examines when and how CEO strategic choices fuel subsequent processes that result in firms' innovation outcomes. I thereby respond to recent calls by developing and testing comprehensive models that examine CEO influence on firm outcomes such as innovation (Busenbark et al., 2016; Liu et al., 2018). Through the introduction of CEO research orientation, I provide a new and more advanced conception of executive "makeup" that is salient to the prediction of firms' innovation outcomes (Ahuja et al., 2008; Gerstner et al., 2013). This study also contributes to the innovation literature by shedding important new light on the role of the CEO as an important yet often overlooked factor that influences firms' innovation outcomes (Talke et al., 2010). It thereby develops a more profound understanding of firm heterogeneity in innovation performance, and one that moves beyond a mere competence perspective on innovation capability (Ahuja et al., 2008).

Theory and hypotheses

CEO research orientation and firms' innovation outcomes

People's career paths provide much insight with respect to their ability and motivation in general as well as with regard to their preferences, beliefs, skillsets, values, goals, and search for meaning in particular (Arthur, Khapova, & Wilderom, 2005; Judge, Cable, Boudreau, & Bretz, 1995; Sullivan & Baruch, 2009). In a similar vein, CEOs' careers reflect their unique abilities and motivations (Busenbark et al., 2016; Crossland et al., 2014). The core of the upper echelons theory holds that, faced with competing tasks and limited attentional resources (Cyert & March, 1963), CEOs make strategic choices through highly personalized lenses that arise from their experiences, motives, and personalities (Hambrick, 2007; Hambrick & Mason, 1984). Much research has subsequently shown that the specific "orientations" that CEOs bring to the firm shape strategic decision making and organizational outcomes (Finkelstein et al., 2009, p. 49). In this study, I argue that CEOs have a certain level of research orientation—that is, aptitude and motivation for science and technology. This is revealed by their career

experiences in the domains of research, science, and technology prior to their becoming a CEO. Specifically, I postulate that CEOs who (1) have a PhD degree in science or engineering, (2) have academic experience, (3) have R&D experience, and (4) hold patents are likely to exhibit higher ability and motivation in relation to science and technology.

Prior research has related these CEO characteristics to ability and motivation in relation to science and technology. More specifically, highly educated CEOs are more receptive to new ideas and innovation (Barker & Mueller, 2002; Hambrick & Mason, 1984). The cognitive ability and technological expertise that are associated with a PhD enable and motivate CEOs to have a higher awareness of technological developments and more capacity to process technological information (Brown & Eisenhardt, 1997; Roach & Sauermann, 2010). Finally, CEOs with extensive technology-related work experience are likely to have developed a substantial professional network and be better able to absorb knowledge from more or other technological domains (Katila, Thatchenkery, Christensen, & Zenios, 2017). This increases their cognitive ability in and awareness of science and technology (Dietz & Bozeman, 2005). In sum, CEO research orientation represents the motivation and ability required to provide strategic guidance in research that breaks scientific boundaries and to engage in leadership focused on applying new research techniques in the most promising technological areas.

I expect that CEOs affect innovation strategies and outcomes because they are among the most influential actors in their organizations (Bromiley & Rau, 2016). CEOs influence organizational outcomes by shaping firms' strategic actions, endorsing employee proposals, and establishing a context that steers organizational behavior. They create this context through (re)structuring the firm's structure, systems, and processes, and through the recruitment, promotion, compensation, and training of employees (Chin, Hambrick, & Trevino, 2013). For instance, CEOs can create a supportive environment for experimentation and failure (e.g., through incentive structures). This, in turn, affects the likelihood of innovation outcomes (Wu et al., 2005). CEOs are also in the position to evaluate and promote the value and potential application of novel technological ideas and proposals (Brown & Eisenhardt, 1997; Burgelman, 1983a).

Three mechanisms explain why research-oriented CEOs are more likely to create a supportive organizational context for innovation. First, their experience in research, science, and technology provides them with complex "cognitive schemas" that enable them to develop a more comprehensive awareness of new opportunities and to better understand new technologies at earlier stages of development and in times of technological uncertainty (Nadkarni & Chen, 2014; Yadav et al., 2007). As a result, CEOs with a research orientation

are better able to discover and comprehend technological opportunities and subsequently develop a clearer vision for technological advancement (Kaplan & Tripsas, 2008; Shane, 2000). In this respect, research demonstrates that successful executives with technological expertise had a strong vision for their firms' future and were able to detect links among innovation projects because they had a simultaneous awareness of the present and the future (Brown & Eisenhardt, 1997; Eisenhardt, 1989).

Second, recent studies show that CEO personality and strategic leadership behaviors influence innovation through the development of a socio-cultural context (Elenkov & Manev, 2005; O'Reilly III, Caldwell, Chatman, & Doerr, 2014). Here, research-oriented CEOs are likely to create a context of shared norms, values, and beliefs that are supportive of an innovation culture (Berson, Oreg, & Dvir, 2008; Giberson et al., 2009). For instance, they can create and foster such a culture through leadership activities, standard operating procedures, reward systems, and evaluation criteria, all of which can be used to steer, reward, and control innovation activities (Wu et al., 2005).

Finally, research-oriented CEOs are likely to hire and attract like-minded personnel who share their technological vision and skills. As (intellectual) human capital is a key element of innovation, the selection and retention of research-oriented people are paramount (Tyler & Steensma, 1998; Zucker, Darby, & Brewer, 1998). The resulting innovation culture not only stimulates innovation activity (as discussed) but also strengthens the attraction, selection, and departure of organizational members on the basis of their fit with a socio-cultural context focused on innovation (Berson et al., 2008; Elenkov & Manev, 2005). Combined, these three mechanisms explain why research-oriented CEOs are more likely to enable firms' innovation outcomes, which results in the following hypothesis:

Hypothesis 1: CEO research orientation is positively related to firms' innovation outcomes.

Organizational context, managerial discretion, and CEO influence

The extent to which CEOs are able to influence their firms' strategies and outcomes depends on the organizational context in which CEOs operate (Busenbark et al., 2016; Narayanan, Zane, & Kemmerer, 2011). That context is shaped by firm-level factors related to organizational structures, resources, and routines that enhance or hinder CEOs' managerial discretion or latitude for action (Hambrick & Finkelstein, 1987; Liu et al., 2018). Therefore, I consider three contextual factors that determine managerial discretion and thus explain when CEOs can influence firms' innovation outcomes: CEO formal power, availability of slack resources, and organizational age.

With regard to the first of these factors, the amount of formal power that a CEO has is an important predictor of a CEO's influence on organizational activities and outcomes. Here, the CEO's structural position relative to the board effectively reflects such structural (i.e., formal) power (Chin et al., 2013; Finkelstein et al., 2009). Specifically, CEO-chair duality has been consistently found to raise such CEO power (Krause et al., 2014). It effectively determines how (un)constrained a CEO is in shaping strategy. Hence, I expect that research-oriented CEOs who also chair the board are more able to formulate an innovation strategy that is in line with personal aspirations.

Hypothesis 2a: CEO duality positively moderates the positive relationship between CEO research orientation and firms' innovation outcomes.

Second, slack resources may offer CEOs more leeway in steering the organization in line with personal preferences (Jensen and Meckling, 1976; Wasserman et al., 2010). In this respect, slack resources may free up managerial resources (e.g., time, effort and attention). This may facilitate experimentation and increase the ability to pursue risky innovation projects (Chen, 2008; Nohria & Gulati, 1996). Slack also decreases the pressure for short-term performance from shareholders (Walrave, van Oorschot, & Romme, 2011). As a result, CEOs with a research orientation and slack resources are better able to pursue their preferred innovative ideas and research. I therefore expect that the relation between CEO research orientation and firms' innovation outcomes is positively influenced by the availability of slack resources.

Hypothesis 2b: Firm slack resources positively moderates the positive relationship between CEO research orientation and firms' innovation outcomes.

Finally, firm age affects the influence that CEOs have on their firms' activities and outcomes. As firms develop specific routines, competences, and norms over time (Hannan & Freeman, 1984; Henderson & Cockburn, 1996), R&D processes, incentive systems, and resource-allocation processes tend to become increasingly routinized and therefore difficult to change (Kapoor & Klueter, 2015)—even by the CEO. An older firm's innovation activities, such as the search for new technological knowledge, are therefore often constrained by its own imprinted processes, cultures, and capabilities (Leonard-Barton, 1992; Sorensen & Stuart, 2000). In addition, research shows that the influence that the CEO can exert over firm behavior and subsequent outcomes decreases with firm age (Beckman & Burton, 2008). In this respect, a CEO's prior career experiences are found to have a particularly strong influence on explorative activities when a firm is founded (Beckman, 2006). Compared to younger firms, older firms have more inert routines, competences, and norms that may reduce the potential

impact CEOs have on their firms. Therefore, I expect that the influence of CEO research orientation on innovation outcomes will be weaker for older firms.

Hypothesis 2c: Firm age negatively moderates the positive relationship between CEO research orientation and firms' innovation outcomes.

CEOs' strategic choices and allocation of resources to R&D.

To examine in more detail how research-oriented CEOs' strategic influence fuels subsequent organizational processes and ultimately innovation outcomes, I argue here that resource allocation to R&D partially mediates the CEO-innovation relationship. CEOs have significant control over their firms' strategy formulation processes and R&D resource-allocation processes (Bromiley & Rau, 2016; Gerstner et al., 2013; Narayanan et al., 2011). Prior research shows that CEOs who have advanced science-related degrees and extensive experience in engineering and technology spend more R&D dollars per employee (Barker & Mueller, 2002). CEOs with technological domain expertise have a tendency to use R&D and science as a universal response to organizational failure and to achieve corporate growth objectives (Cummings & Knott, 2018; Felix & Bistrova, 2015). They are also more likely to be inclined to employ more people with a high level of education and a technical background (Tyler & Steensma, 1998; Zucker et al., 1998). This may lead research-oriented CEOs to choose an R&D-intensive investment strategy to pursue their technological vision for innovation.

While investment in R&D is not a guarantee of innovation success, it certainly is an important input. It helps firms to attract, train, and retain R&D employees as well as to acquire other R&D resources that are required to develop an absorptive capacity and innovation capability (Cohen & Levinthal, 1994; Zucker et al., 1998). Especially in technology-intensive industries, R&D investments are a primary source of innovation output (Hagedoorn & Cloodt, 2003). Studies show that R&D intensity positively impacts patent output or related types of innovation outcomes (e.g., Griliches, 1990; Hall, Griliches, & Hausman, 1986). Hence, I argue that one of the mechanisms through which research-oriented CEOs influence firms' innovation outcomes is through intensifying R&D investments. Specifically, I hypothesize that R&D intensity partially mediates the relationship between CEO research orientation and firms' innovation outcomes.

Hypothesis 3: Firm R&D intensity partially mediates the positive relationship between CEO research orientation and firms' innovation outcomes.

The CEO's role in the implementation of an R&D-intensive investment strategy

Another explanation for how research-oriented CEOs spur firms' innovation outcomes is through effective strategy implementation. Successful implementation of a firm's strategy through daily leadership activities is one of a CEO's primary tasks (Burgelman et al., 2018; Simsek et al., 2015). Prior research shows that R&D-intensive firms achieve higher productivity and economic returns when they are managed by CEOs with technical expertise and a propensity for innovation (Beal & Yasai-Ardekani, 2000; Pan, 2015). This can be explained by the fact that these firms require higher levels of information processing, decision-making speed, and technological know-how (Eisenhardt, 1989; Gupta & Govindarajan, 1984). In this respect, research-oriented CEOs can effectively steer the implementation of an R&D-intensive strategy. They are able to process more technical information and they are motivated to solve complex research-related problems, which facilitates fast strategic decision making (Barker & Mueller, 2002; Katila et al., 2017). Given their strong attentional focus on the present and the future (Nadkarni & Chen, 2014; Yadav et al., 2007), they are also more likely to detect links among technological developments over time (Brown & Eisenhardt, 1997). Research-oriented CEOs are therefore more capable to strategically steer for the detection and development of new technologies and achieve a higher frequency of innovation outcomes for each R&D dollar invested. As such, I hypothesize that CEO research orientation positively moderates the relation between R&D intensity and innovation outcomes.

Hypothesis 4: CEO research orientation positively moderates the positive relationship between a firm's R&D intensity and its innovation outcomes.

Method

Sample and data

I studied U.S. research-based pharmaceutical firms to test my hypotheses (Standard Industrial Classification (SIC) codes: 2833, 2834, 2835, and 2836) (Caner, Cohen, & Pil, 2017). Especially in R&D-intensive environments, CEO characteristics become reflected in organizational outcomes because these environments demand action of a more strategic kind, offer a wide range of strategic options, and provide CEOs with more discretion (Gerstner et al., 2013; Wu et al., 2005). I limited my scope to publicly listed U.S. firms that were among the hundred largest employers, as recorded by Compustat, at any time during the period between 2001 and 2013. I identified the CEOs for these firms and years in BoardEx and Execucomp and applied four selection criteria to increase my study's internal validity. First, a CEO's first year in office was the first year in which he or she served for more than half the

calendar year. Second, I included only CEOs who served at least two full years, to observe at least a minimally potential effect of their research orientation on corporate strategy and innovation (Chin et al., 2013). Third, I excluded CEOs who had previously served as CEO somewhere else, as my measure of CEO research orientation was based on each CEO's "pre-CEO" experiences (Chin et al., 2013). Fourth, I excluded firms that focused only on generics or reformulations and did not actively engage in pharmaceutical innovation to maintain my focus on research-intensive firms (Kapoor & Klueter, 2015). This procedure resulted in a sample consisting of 109 CEOs at 87 firms, and 716 firm-year observations.

Although the sample of firms is not large in an absolute sense, it represents the vast majority of the population of U.S. research-based pharmaceutical companies over a period not studied before. It is also larger than the samples used in related studies of this industry. For instance, Gerstner, Konig, Enders, and Hambrick (2013) observed seventy-eight CEOs at thirty-three companies. In addition to increasing the study's internal validity, the study design resulted in a handcrafted sample that enabled detailed measurement of heterogeneity among CEOs' research orientation and extensive data collection using a variety of data sources. Data on CEO characteristics and experiences were collected using the BoardEx and Execucomp databases. However, where information was missing, I consulted numerous other sources, such as SEC filings, corporate websites, press releases, Thomson Reuters Eikon, Lexis Nexis, and Marquis Who's Who, and several other online directories containing information on executive backgrounds (e.g., Bloomberg Executive Profile & Biography, The Wall Street Transcript, and Equilar) to make my database as complete as possible. The accounting data were obtained from Compustat and the patent data were collected from the U.S. Patent and Trademark Office (USPTO). I used USPTO data because they match with my sample of U.S. publicly listed firms. Since the USPTO assigns patents to both parent firms and their subsidiaries, I constructed detailed family trees that included historical company names of all firms using Securities and Exchange Commission (SEC) 10-K filings and company websites (Caner et al., 2017; Grigoriou & Rothaermel, 2014). I matched company names, legal forms, and country data to USPTO assignees on patent applications. Eventually, all 9,953 patents of subsidiaries were aggregated at the parent-company level, which resulted in a total of 37,086 patent applications for the 87 firms under observation.

Dependent variables

I measured each firm's yearly *innovation outcomes* by counting the number of patent applications per year (dated by patent application date). Especially in the pharmaceutical industry, where firms have a strong incentive to file for patents, patent activity is commonly

used for studies on innovation (Caner et al., 2017; Grigoriou & Rothaermel, 2014; Hagedoorn & Cloodt, 2003; Hall et al., 2005). I used USPTO patent data because the USPTO recently made datasets available on patents granted from 1976 onwards and on patent applications published from 2001 onwards (i.e., patent applications with a pending instead of granted status). This allows me to count all patent applications (i.e., granted and pending applications) the firms in my sample filed for during the study period. Patent applications are preferred to granted patents, as each application represents a valuable kind of technology that results from the innovation process (Balsmeier & Buchwald, 2014). Patent applications are better suited to studying a CEO's more immediate impact on a firm's innovation outcomes than granted patents are, as whether a patent is filed for a given invention is determined mainly by the firm's own decision making, whereas the grant of a patent is dependent on the outcome of the patent office's appraisal of the invention.

To test the mediation effect, I measured *R&D intensity* as a firm's R&D expenditure divided by the number of employees. Dollars spent by the firm on R&D were converted to year 2000 U.S. dollars using the Consumer Price Index published by the U.S. Bureau of Labor Statistics (Barker & Mueller, 2002). In upper echelons studies, the amount of R&D dollars invested per employee is the standard and most robust measure of a firm's investments in intellectual human capital for research and innovation (Barker & Mueller, 2002; Baysinger, Kosnik, & Turk, 1991). A firm's R&D investments relative to its number of employees are a strong indicator of the strategic importance of innovation for a firm because human capital is critical to firms' capacity to build the capabilities necessary to innovate in biotechnology, (Kor, 2006; Zucker et al., 1998). Besides, even though my sample exclusively comprises publicly listed pharmaceutical firms, some of them did not generate significant revenues and did not possess substantial tangible assets. This inhibits the use of measures of R&D intensity such as R&D-to-sales or R&D-to-assets.

Independent variable

I coded *CEO research orientation* using four indicators that are indicative of a CEO's ability and motivation in relation to science and technology. More specifically, based on a person's career experiences prior to becoming CEO, I coded whether: (1) the CEO holds a PhD degree in science or engineering; (2) the CEO has academic experience; (3) the CEO's dominant functional experience is in R&D; and (4) the CEO holds any patents. I specifically looked at those experiences because they effectively reflect abilities and motivations that are of particular relevance to strategic leadership in biotechnology innovation (Judge et al., 1995; Roach & Sauermann, 2010; Zucker et al., 1998). A reliability analysis and factor analysis showed that

the four indicators reflect a latent construct that I call *CEO research orientation* (see Appendix 2.1). Subsequently, I calculated the main independent variable *CEO research orientation*, per CEO, as the sum of the mentioned indicators because the indicators had similar means and variances, and all varied between 0 and 1. The resulting variable ranges between 0 = no research orientation to 4 = high research orientation. I analyzed a CEO's research orientation prior to his or her becoming CEO of the focal firm to make sure that my operationalization was consistent with the causal logic of my arguments (Chin et al., 2013).

Moderator variables

Three contextual factors that determine CEOs' managerial discretion served as moderator variables to test Hypotheses 2a–c. *CEO duality* was measured as a dummy variable indicating whether the CEO was also board chairperson for each year (Chin et al., 2013). I measured slack resources as each firm's *financial slack* by dividing its current assets by its current liabilities (Nohria & Gulati, 1996). *Firm age* was measured as the difference between the observation year and the year of firm incorporation (Wu et al., 2005). These variables were lagged by one year in all regressions compared to the dependent variable.

Control variables

To control for potentially confounding factors, I included multiple managerial and firm variables that have been widely used in research on upper echelons and innovation. Based on prior studies that relate firm differences in R&D investments and firm patenting to CEO characteristics (Carpenter et al., 2004; Cummings & Knott, 2018), I controlled for *CEO tenure* (the total number of years a CEO had held office), *founder* (dummy variable indicating whether a CEO was a founder of the focal firm), *CEO ownership* (the percentage of stock owned by the CEO), and *insider* (dummy variable indicating whether the current CEO had been hired from inside the company rather than from outside of it). I controlled for the *board independence* (the number of inside directors to the total number of directors on the board) because of inside directors' influence through their monitoring and advising roles (Kor, 2006). At the firm level, I controlled for *firm size* (the logarithm of the number of employees) and *financial performance* (return on assets; net income divided by total assets) because these may influence a firm's innovation potential (Ahuja & Lampert, 2001). As a firm's ownership influences CEO behavior and innovation (Baysinger et al., 1991), I included *institutional ownership* (the total percentage of shares owned by external nonmanagement shareholders who individually owned at least 5 percent of company shares). All independent variables were lagged by one year in all regressions compared to the dependent variable. I also included SIC- and year-dummy

variables in all models to account for industry heterogeneity, macroeconomic conditions, and unobserved time effects.

Analysis

I used the generalized estimating equations (GEE) regression method because my investigation focuses on CEOs who are clustered within firms by analyzing longitudinal data with non-normal response variables (Liang & Zeger, 1986). This method accounts for firm heterogeneity and autocorrelation by estimating the within-subject correlation of repeated responses on dependent variables. GEE regressions also offer the flexibility to cope with the differing distribution of the two dependent variables in my models. In the models predicting patent applications, I specified a negative binomial distribution and used a log link function to calculate the variance because the number of patents takes on nonnegative integer values and is zero for some firms in some years. The goodness-of-fit and likelihood-ratio tests confirm that the distribution of this patent count variable shows overdispersion. In the models predicting R&D intensity, I specified a Gaussian distribution and used an identity link function to calculate the variance because this variable is a ratio measure, and thus of a nondiscrete nature. I chose an exchangeable correlation structure as my study design resulted in unbalanced observations with unequal spacing. Finally, I used Huber-White-sandwich standard errors to correct for heteroskedasticity.

I did not use a fixed-effects model because: (1) the CEO research orientation measure has an invariant score that has a limited range of five levels, (2) I only observed one CEO for most firms, and (3) I am interested in firm heterogeneity in innovation. Instead, I explicitly modeled the unobserved firm-invariant constant effect by including a presample variable in all models. More specifically, I constructed a *presample patent stock* variable as the accumulated number of granted patents of each focal firm and its subsidiaries from the year 1975 until a firm's first observation year using a 15% annual depreciation rate of knowledge. I also included a dummy that indicates when a firm has zero presample patent applications. Contrary to the presample patent-stock variable, this *presample dummy* variable controls for the fact that some firms do not have a history of filing patents[2]. This approach enables me to use the full variation in the sample (Balsmeier & Buchwald, 2014) and to control for the possibility that firms may enter the sample with inherently different innovation-generating capabilities (Ahuja & Lampert,

[2] Results are insensitive to constructing a presample patent stock variable assuming no knowledge depreciation or a higher depreciation rate of 30%. They are also insensitive to the inclusion or exclusion of the presample dummy.

2001). This ensures that my estimates are consistent despite the hierarchical panel-data structure (i.e., repeated observations of CEOs nested in firms).

This presample variable approach also limits the threat of endogeneity. Furthermore, I tried to control for endogeneity by closely following the approach of recent upper echelons studies (e.g., Chin et al., 2013; Gerstner et al., 2013). As the results of these efforts were unsatisfactory (see Appendix 2.2), I decided to include a rich and fine-grained set of controls to limit the threat of endogeneity. Further concerns for endogeneity were addressed by constructing the CEO research-orientation variable based on pre-CEO appointment experiences only, by accounting for a possible dynamic process of the innovation activity by including the lagged values of patent applications as a control, and by lagging all explanatory variables by a one-year period (*t*-1) to reduce possible simultaneity biases as well as to allow for the influence of the explanatory variables to become observable in a firm's innovation outcomes.

Results

Table 2.1 and Table 2.2 report the means, standard deviations and correlations among all variables. The mean variance inflation factor (VIF) of 1.69 is well below 3, and the VIF of each variable is far below 10, indicating very limited multicollinearity. The observed firms have a median size of 525 employees and are 15 years old. Regarding the distribution of CEO research orientation, 12 CEOs score 4, 17 CEOs score 3, 4 CEOs score 2, 11 CEOs score 1, and 65 CEOs score 0. For illustration, and providing face validity for this construct, Genentech's Arthur Levinson has a research orientation of 4 and Celgene's Robert Hugin received a score of 0. These descriptive statistics indicate that CEOs exhibit considerable heterogeneity in their research orientation.

Models 1 to 6 in Table 2.3 provide the results for H1 (i.e., the what question) and H2a–c (i.e., the when questions), while models 7 to 12 in Table 2.4 provide the results related to H3 and H4 (i.e., the how questions). I report Wald chi-square statistics to test the overall model significance and further include the quasi likelihood under the independence model (QIC) criterion to compare models (Cui & Qian, 2007). Models 1 and 7 only include the control variables and the lagged dependent variable. Model 1 shows that firm size is positively related to firm patent applications and firm age is negatively related to them. Model 7 illustrates that R&D intensity is significantly and positively influenced by financial slack and board independence, while firm size has a significant negative effect.

Model 2 shows that CEO research orientation is significantly and positively associated with a firm's number of patent applications ($\beta = 0.159$, $p = .002$). This translates into an average change in firms' patent applications is 17 percent when CEO research orientation increases by

one unit. This supports Hypothesis 1's postulation that increasing CEO research orientation increases firms' innovation outcomes. Models 3 to 5 indicate that CEO influence depends on the organizational context. In these models, the coefficient of the main effect (H1) becomes insignificant (except in Model 5), suggesting moderation is present. More specifically, the effect of CEO research orientation increases, as anticipated, in case of CEO duality (Model 3), when more financial slack is present (Model 4), or when the firm is younger (Model 5). However, when I simultaneously include all moderation effects in Model 6, the interaction effect of firm age becomes insignificant. Similar findings are obtained for Models 10 and 12, which also include R&D intensity as a mediator. Thus, I find strong support for H2a and H2b, and moderate support for H2c.

Given their strong significance, I further investigated Hypothesis 2a and Hypothesis 2b by plotting their marginal effects and calculating the predictive margins. Figure 2.1 shows that when a CEO with a research orientation of 4 is also board chairperson, the number of patent applications increases by 39 percent. Figure 2.2 illustrates that an increase of financial slack by one standard deviation (5.69) from the mean (5.24) for firms with a research-oriented CEO (score 4) results in 15 percent more patent applications.

Hypothesis 3 predicts that firm R&D intensity partially mediates the relationship between CEO research orientation and firms' innovation outcomes. To test for mediation, I first followed Baron and Kenny (1986). Their procedure indicates that there might indeed be mediation of R&D intensity because: (1) Model 8 reveals that CEO research orientation is significantly related to R&D intensity, (2) Model 9 shows that R&D intensity, in turn, is significantly related to firms' patents, and (3) the relationship between CEO research orientation and innovation drops in strength (from $\beta = 0.157$ in Model 2 to $\beta = 0.153$ in Model 9). Yet such a relatively small drop in the effect size indicates that R&D intensity only partially mediates the CEO-innovation relation. To further assess the significance of this mediation effect I applied the Sobel test to the focal coefficients and their standard errors, which shows a marginally significant mediation effect (z-value = 1.72, $p = 0.085$). These findings offer moderate support for Hypothesis 3.

In contrast to Hypothesis 4, models 11 and 12 reveal a significantly negative coefficient of the interaction term of R&D intensity and CEO research orientation. Figure 2.3 illustrates the marginal effects of this moderation. It can be observed that the R&D intensity-innovation relationship becomes less strong and even changes sign when a CEO has a research orientation of 3 or 4. For firms with a CEO with a research orientation of 1, increasing R&D intensity by one standard deviation (163.17) from the mean (151.28) increases patent applications by 46

percent. For firms with a CEO with research orientation of 4, increasing R&D intensity from low to high decreases patent applications by 17%. However, it is important to note that the patent output of firms led by more research-oriented CEOs is always higher for equal levels of R&D intensity.

Table 2.1: Descriptive statistics

		Mean	SD	Min	Median	Max
1	Innovation outcomes	36.67	89.18	0.00	8.00	715.00
2	R&D intensity	149.76	160.67	1.28	108.74	1967.55
3	CEO research orientation	1.14	1.51	0.00	0.00	4.00
4	Firm size[i]	8,911.56	22,798.33	11.00	525.00	122,200.00
5	Firm age	19.58	15.45	2.00	15.00	62.00
6	Financial slack	5.22	5.71	0.49	3.57	64.14
7	Financial performance	-0.10	0.29	-3.17	-0.02	0.76
8	Institutional ownership	29.31	18.61	0.00	28.93	92.38
9	Board independence	0.22	0.12	0.00	0.20	0.88
10	CEO tenure	8.05	7.10	0.00	5.81	36.02
11	Founder	0.31	0.46	0.00	0.00	1.00
12	CEO duality	0.58	0.49	0.00	1.00	1.00
13	CEO ownership	0.85	2.34	0.00	0.11	27.39
14	Insider	0.52	0.50	0.00	1.00	1.00
15	Presample patent stock	194.18	487.20	0.00	20.79	3178.40
16	Presample dummy	0.03	0.17	0.00	0.00	1.00

Note: 716 observations. [i]Log transformed variable but original values reported here.

Table 2.2: Correlation matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Innovation outcomes															
2	R&D intensity	-0.16														
3	CEO research orientation	-0.11	0.23													
4	Firm size	0.62	-0.43	-0.23												
5	Firm age	0.56	-0.25	-0.24	0.72											
6	Financial slack	-0.14	0.22	0.22	-0.33	-0.28										
7	Financial performance	0.21	-0.39	-0.18	0.46	0.37	-0.08									
8	Institutional ownership	-0.38	0.23	0.27	-0.46	-0.46	0.13	-0.25								
9	Board independence	-0.04	-0.09	0.05	-0.10	-0.14	0.10	-0.02	0.11							
10	CEO tenure	-0.10	0.00	0.16	-0.07	-0.04	0.10	0.01	0.05	0.03						
11	Founder	-0.17	0.04	0.38	-0.24	-0.33	0.24	-0.17	0.15	0.07	0.45					
12	CEO duality	0.25	-0.21	0.00	0.39	0.27	-0.10	0.17	-0.26	0.07	0.19	0.11				
13	CEO ownership	-0.11	-0.10	0.02	-0.16	-0.13	0.05	-0.03	-0.06	0.13	0.31	0.33	0.02			
14	Insider	0.22	-0.14	-0.02	0.26	0.27	-0.12	0.22	-0.14	-0.03	-0.36	-0.33	0.17	-0.22		
15	Presample patent stock	0.83	-0.15	-0.13	0.64	0.68	-0.17	0.22	-0.37	-0.04	-0.16	-0.20	0.21	-0.12	0.25	
16	Presample dummy	-0.07	-0.04	0.01	-0.09	-0.13	-0.06	-0.05	0.18	-0.09	-0.07	-0.11	-0.06	-0.04	0.10	-0.07

Note: Correlations greater than 0.07 are significant at $p < 0.05$ and those greater than 0.10 are significant at $p < 0.01$.

Table 2.3: Results of when CEO research orientation affects innovation

Dependent variable:	Innovation outcomes					
	1	2	3	4	5	6
CEO research orientation		0.16***	0.04	0.09	0.26***	0.02
		(0.05)	(0.07)	(0.06)	(0.07)	(0.08)
CEO RO*CEO duality			0.16**			0.19***
			(0.07)			(0.07)
CEO RO*Financial slack				0.01***		0.01***
				(0.00)		(0.00)
CEO RO*Firm age					-0.00**	-0.00
					(0.00)	(0.00)
Firm size	0.48***	0.51***	0.52***	0.52***	0.51***	0.52***
	(0.07)	(0.07)	(0.06)	(0.06)	(0.07)	(0.05)
Firm age	-0.02**	-0.02*	-0.02*	-0.02**	-0.01	-0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Financial slack	0.01*	0.01	0.01	-0.02*	0.01	-0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Financial performance	-0.10	-0.15	-0.16	-0.11	-0.14	-0.12
	(0.12)	(0.13)	(0.14)	(0.13)	(0.14)	(0.13)
Institutional ownership	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CEO tenure	0.00	0.00	0.01	-0.00	0.00	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Founder	0.13	-0.15	-0.18	-0.19	-0.22	-0.27
	(0.14)	(0.16)	(0.16)	(0.17)	(0.17)	(0.17)
CEO duality	-0.02	-0.14	-0.32**	-0.23**	-0.15	-0.46***
	(0.10)	(0.10)	(0.13)	(0.10)	(0.11)	(0.12)
CEO ownership	0.01	0.01	0.00	-0.00	0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Insider	-0.07	-0.12	-0.10	-0.21*	-0.16	-0.20*
	(0.11)	(0.11)	(0.11)	(0.12)	(0.11)	(0.12)
Board independence	-0.12	-0.15	-0.18	-0.30	-0.21	-0.35
	(0.39)	(0.38)	(0.36)	(0.39)	(0.36)	(0.37)
Presample patent stock	0.00**	0.00*	0.00	0.00*	0.00*	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Presample dummy	-1.97***	-2.04***	-2.17***	-2.15***	-2.10***	-2.32***
	(0.38)	(0.35)	(0.34)	(0.38)	(0.36)	(0.37)
Lagged dependent variable (patents)	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-1.23**	-1.42***	-1.42***	-1.05**	-1.41***	-1.05**
	(0.52)	(0.51)	(0.51)	(0.50)	(0.50)	(0.49)
Observations	716	716	716	716	716	716
QIC	5221	5161	5147	5159	5162	5144
Wald chi-square	547***	580***	595***	787***	614***	793***

Note: Robust standard errors in parentheses. All models include SIC and time dummies. Significance levels of two-tailed tests: * p <.10; ** p<.05; *** p<.01.

Table 2.4: Results of how CEO research orientation affects innovation

Dependent variable:	R&D intensity		Innovation outcomes			
	7	8	9	10	11	12
CEO research orientation		8.62**	0.16***	0.03	0.25***	0.11
		(4.27)	(0.05)	(0.08)	(0.05)	(0.08)
R&D intensity			0.00***	0.00***	0.00***	0.00***
			(0.00)	(0.00)	(0.00)	(0.00)
CEO RO*CEO duality				0.18**		0.18***
				(0.07)		(0.07)
CEO RO*Financial slack				0.01***		0.01***
				(0.00)		(0.00)
CEO RO*Firm age				-0.00*		-0.00
				(0.00)		(0.00)
R&D intensity*CEO RO					-0.00***	-0.00***
					(0.00)	(0.00)
Firm size	-23.53***	-22.07***	0.56***	0.56***	0.56***	0.56***
	(5.64)	(5.42)	(0.07)	(0.06)	(0.07)	(0.06)
Firm age	0.83	0.83	-0.02**	-0.02*	-0.01*	-0.01*
	(0.54)	(0.53)	(0.01)	(0.01)	(0.01)	(0.01)
Financial slack	1.64**	1.45**	0.01	-0.02**	0.01	-0.02**
	(0.68)	(0.71)	(0.01)	(0.01)	(0.01)	(0.01)
Financial performance	29.72*	30.56*	-0.08	-0.05	-0.06	-0.03
	(16.85)	(16.86)	(0.13)	(0.14)	(0.12)	(0.13)
Institutional ownership	0.44**	0.38**	0.00	0.00	0.00	0.00
	(0.19)	(0.19)	(0.00)	(0.00)	(0.00)	(0.00)
CEO tenure	-0.52	-0.58	0.00	0.01	0.01	0.01
	(0.86)	(0.81)	(0.01)	(0.01)	(0.01)	(0.01)
CEO founder	7.51	-3.55	-0.13	-0.26	-0.07	-0.19
	(11.03)	(10.25)	(0.16)	(0.17)	(0.14)	(0.15)
CEO duality	-9.02	-10.29	-0.15	-0.47***	-0.16	-0.45***
	(9.66)	(9.53)	(0.10)	(0.12)	(0.09)	(0.11)
CEO ownership	-1.54	-1.55	0.01	-0.01	0.00	-0.01
	(0.94)	(0.97)	(0.01)	(0.01)	(0.01)	(0.01)
Insider	6.88	2.05	-0.14	-0.22*	-0.08	-0.16
	(12.96)	(12.33)	(0.11)	(0.13)	(0.10)	(0.11)
Board independence	-30.43	-29.32	-0.17	-0.37	-0.23	-0.40
	(30.69)	(31.26)	(0.38)	(0.36)	(0.37)	(0.36)
Presample patent stock	0.02*	0.02	0.00	0.00	0.00	0.00
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Presample dummy	-41.55*	-43.61**	-1.93***	-2.21***	-1.80***	-2.09***
	(23.50)	(19.04)	(0.38)	(0.39)	(0.37)	(0.37)
Lagged dependent variable (R&D)	0.43***	0.43***				
	(0.05)	(0.05)				
Lagged dependent variable (patents)			0.01***	0.01***	0.01***	0.01***
			(0.00)	(0.00)	(0.00)	(0.00)
Constant	133.59***	126.83***	-1.68***	-1.31**	-1.88***	-1.48***
	(39.10)	(36.57)	(0.54)	(0.52)	(0.54)	(0.51)
Observations	716	716	716	716	716	
QIC	6164243	5975059	5127	5114	5114	5102
Wald chi-square	1163***	1383***	581***	808***	693***	959***

Note: Robust standard errors in parentheses. All models include SIC and time dummies. Significance levels of two-tailed tests: * p <.10; ** p<.05; *** p<.01.

Figure 2.1: Moderation impact of CEO duality on the marginal effect of CEO research orientation on innovation

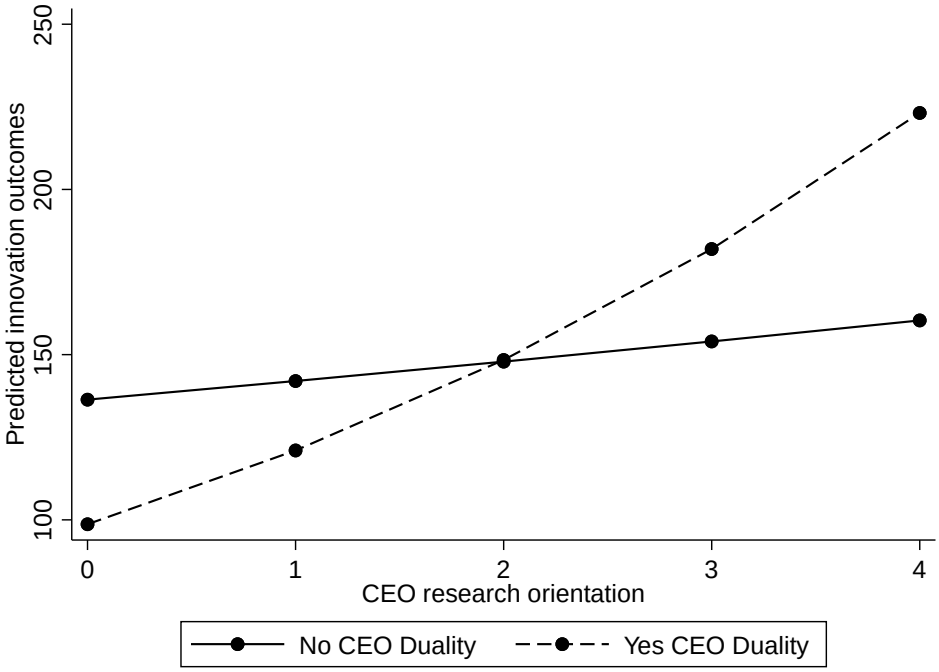


Figure 2.2: Moderation impact of financial slack on the marginal effect of CEO research orientation on innovation

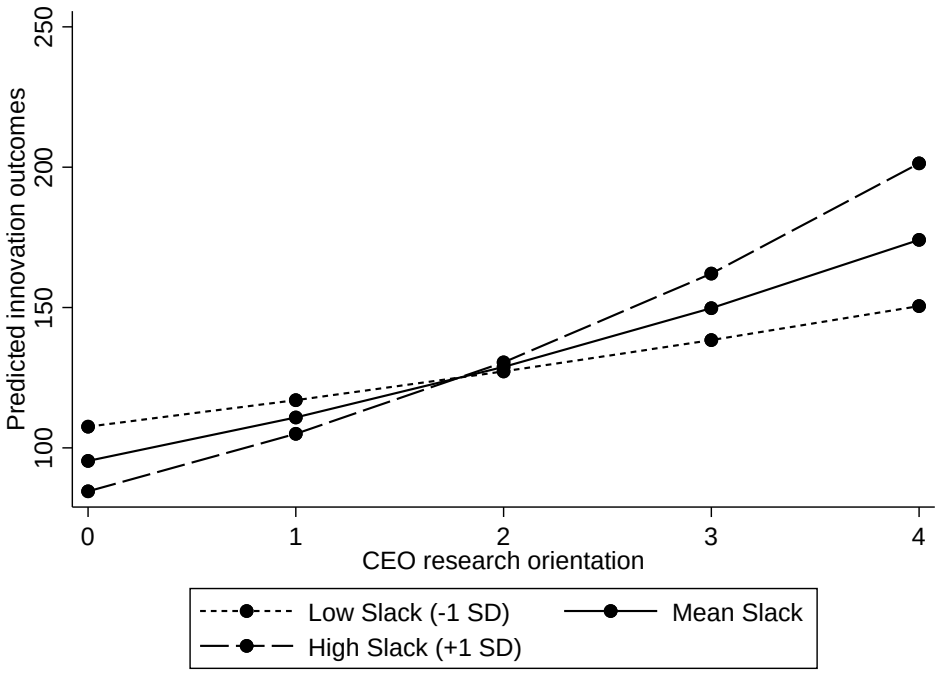
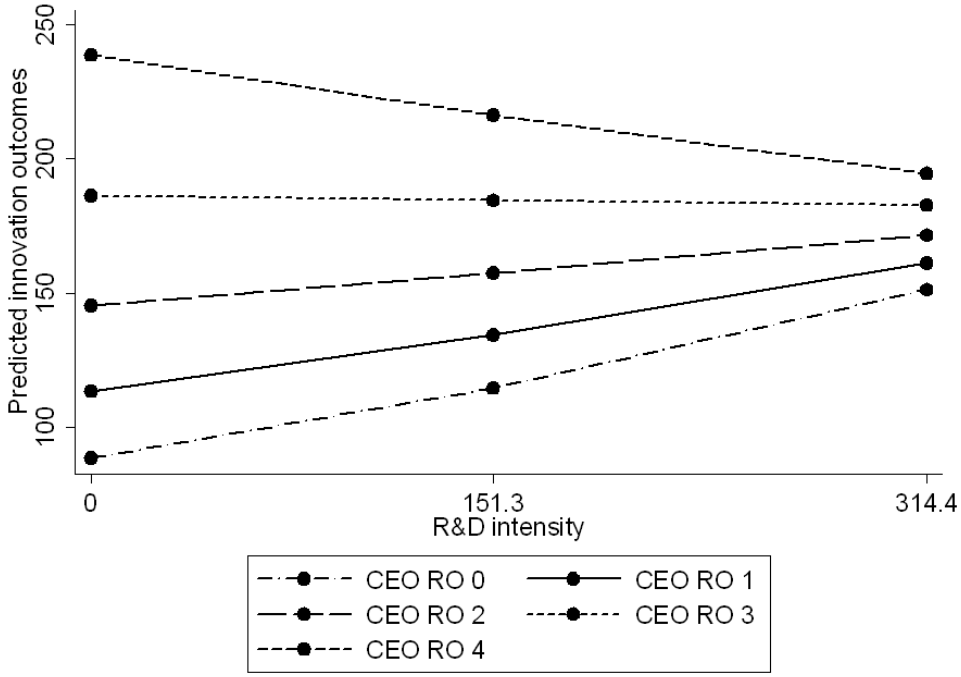


Figure 2.3: Moderation impact of CEO research orientation on the marginal effect of R&D intensity on innovation



Additional analyses

It might be the case that CEOs with a higher research orientation steer their organization toward developing patents of a higher quality, emphasizing less the actual quantity of patents. To investigate this, I conducted additional analyses using alternative dependent variables that account for such quality: (1) the granted patent count and (2) a forward citation-weighted patent count (using a 2001 to 2010 sample[3]). With these dependent variables, the moderation effect of CEO research orientation on the R&D-innovation relationship turns insignificant. CEOs with a low research orientation achieve higher R&D productivity (i.e., number of patents for each invested R&D dollar) as far as quantity of patents is concerned, but this productivity advantage disappears when accounting for the quality of the patents. The other results of these additional analyses are highly similar to the ones reported in the paper, which lends confidence to my main conclusions. I also ran robustness test with respect to the operationalization of CEO

[3] Given that I collected my patent data at the beginning of 2016, I used a sample that covers the years 2001 to 2010 to correct for the two years that elapse on average between the patent application date and the grant date and to allow for a five-year lag period between patent activity and other observations in order to reduce truncation bias in relation to patent citations (Fleming, 2001; Hall et al., 2005). In this sample, the correlation between patent application count and granted count is .97 and between number of patent applications and the citation-weighted patent variable is .76. These correlations are similar to Hagedoorn and Cloodt's (2003) findings.

research orientation and lag structure in my models. The results of these analyses are consistent with the reported findings in my main analyses.

Discussion

For a long time, scholars have been interested in understanding why firms differ in their innovation performance (Ahuja et al., 2008). Whereas prior research has predominantly emphasized a firm's capability to develop successful innovations, this study's focus is on the role of a firm's CEO as a key antecedent of variation in a firm's innovation strategy and its innovation outcomes. I introduce the concept of CEO research orientation, which reflects CEOs' aptitude and motivation for science and technology, to examine what CEO characteristics relate to firm heterogeneity in firms' innovation outcomes. Using a longitudinal sample of U.S. pharmaceutical firms, I found that CEO research orientation is positively associated with firms' innovation outcomes. Moreover, the extent to which CEO research orientation influences innovation increases when (1) the CEO is also the chair of the board and (2) slack resources are available to the firm. I also found that R&D intensity partially explains how research-oriented CEOs achieve higher levels of innovation: they invest more in R&D compared to CEOs with a low research orientation. It is not the case that they are more effective at implementing an R&D-intensive investment strategy. In fact, the marginal productivity of R&D investments in generating patent applications decreases with R&D intensity for CEOs with a high research orientation. Additional analyses, however, qualify this finding as these differences in productivity of R&D investment intensity disappear when accounted for the quality of the patent applications. This might indicate that CEOs with a low research orientation achieve higher R&D productivity based on the quantity of patents per R&D dollar but not when accounting for the quality of those patents.

These findings have several important implications on the upper echelons and innovation literatures. First, I show that research-oriented CEOs are associated with higher innovation outcomes for firms. This insight contributes to the long-standing debate on whether and how much CEOs impact their firms' outcomes (DiMaggio & Powell, 1983; Hambrick & Mason, 1984; Hannan & Freeman, 1984; Quigley & Hambrick, 2015). There is growing evidence that CEOs are important to their firms' adaptation to technological discontinuities (Eggers & Kaplan, 2009; Gerstner et al., 2013). I extend this line of research by highlighting that CEO human capital not only underlies the dynamic capabilities for organizational adaptation and strategic change (Helfat & Martin, 2015) but also initiates the "evolution of technology" by directing the firm's innovation development toward promising new research areas (Kaplan & Tripsas, 2008). Thus, some CEOs are more inclined to lead organizational members toward the

development of new technologies and the introduction of new products (Nadkarni & Chen, 2014; Yadav et al., 2007), while others have a stronger orientation toward the commercialization of existing technologies and products, which could impede an organization's engagement in technological innovation (Leonard-Barton, 1992).

Second, when CEOs influence innovation strongly depends on the organizational context. In this study, I found that a CEO's structural power and a firm's slack resources determine to what extent the CEO's research orientation becomes reflected in innovation outcomes. By integrating aspects of CEO characteristics and organizational context, I contribute to a more comprehensive understanding of CEO effects on firm performance (Busenbark et al., 2016; Liu et al., 2018). I show that CEOs' unique characteristics, notably their research orientation, might not be enough on their own to stimulate innovation; CEOs may also need power and resources to influence firm strategy and outcomes. Given sufficient managerial discretion (Hambrick & Finkelstein, 1987), research-oriented CEOs may shape R&D resource-allocation processes and support organizational processes that steer their firms towards frontier-pushing scientific research and technology development.

Third, this study also contributes to the literature by shedding more light on a hitherto key source of unobserved heterogeneity that affects a firm's innovation capabilities. I show that a CEO constitutes, through his or her research orientation, a key antecedent of variation in a firm's innovation-strategy choices and its attendant performance consequences. Whereas the dominant emphasis in the literature has been on the ability to innovate (Ahuja & Lampert, 2001), this study focuses on the role of a CEO's research orientation is also indicative of the firm's motivation to innovate (Ahuja et al., 2008). In this way, the findings suggest that firms also differ in their motivation to pursue innovation because some CEOs are more research oriented and allocate more resources to R&D in comparison to their counterparts at other firms.

However, there are also potential downsides to highly research-oriented CEOs. This insight comes from the surprising finding of a negative moderation effect of CEO research orientation on the R&D-innovation relationship. This finding may suggest two things: First, a research-oriented CEO may be less effective in the implementation of substantial R&D investments. This could be the result of micromanagement by the CEO, which stifles innovation, or of inexperience due to a CEO's substantial technical training and experience having come at the cost of that CEO having less developed managerial skills. This is in line with recent studies that found that experts in managerial or evaluator roles are less accurate in forecasting others' novel ideas or assessing proposals that are closer to their expertise domains (Berg, 2016; Boudreau, Guinan, Lakhani, & Riedl, 2016; Katila et al., 2017). Second, research-

oriented CEOs might perceive themselves, and their tendency for innovation, as highly central to the organization (Busenbark et al., 2016; Narayanan et al., 2011). Such organizational "overidentification" is associated with behaviors that exploit the organization's existence and resources for personal benefit (Galvin, Lange, & Ashforth, 2015). As a result, a research-oriented CEO might overinvest in R&D, despite increases in innovation outcomes, only to position himself or herself as the inventor of a new technology or because of personal interests. However, the productivity differences in R&D investments related to a CEO's research orientation seem to disappear when accounting for the quality of patent applications. Gaining more insight into this pattern of findings constitutes an interesting avenue for further research.

Managerial implications

This study also has important managerial implications. First, R&D investments form an important—though not the only—instrument for executives to influence their firms' innovation outcomes. Second, this study's insights help to identify the characteristics of CEOs who are most likely to be associated with innovation. Executives with technical background are important to spur innovation of firms. Especially when the organizational context increases managerial discretion of executives and the slack resources available to them. These insights might help corporate boards, executive search services, and firm owners to influence a firm's strategy and future trajectory by hiring (or firing) a (non)research-oriented CEO. However, board directors should remain cautious about the possibility of CEOs aiming for technological success at the expense of commercial success.

Limitations and future research

This study has a number of limitations, which provide directions for future research. Although this study's findings may be generalizable to other R&D-intensive industries such as semiconductors and chemicals, future research should examine whether my proposed theory is transferable to other industries. The strategic process of increasing firms' innovation outcomes through R&D investments might even be stronger in other industries, compared to the weak mediation effect I found, because R&D investment intensity is "the norm" for research-based firms in the pharmaceutical industry. Second, although this is one of the first studies that explicitly tests for a potential mediating mechanism that links CEO characteristics to firms' innovation outcomes, I only focused on one underlying mechanism and, therefore, could only partially open the "black box" of this relationship. The finding of a weak partial mediation effect suggests the plausibility of additional mechanisms that could be examined and tested empirically. Such a mechanism could be the external R&D activities of firms, which was not

tested and controlled for in this study due to data availability. Further, while I controlled for potential endogeneity in all ways available to us, it remains a central issue to upper echelons studies in general. I avoided problems with the causality of the studied relationship by incorporating different lag structures that ensure that my antecedent variables temporally precede the dependent variable, by constructing the CEO research orientation variable based on pre-CEO appointment experiences only, by including rich and fine-grained control variables, and by adding a presample patent-stock control variable. Moreover, the theoretical mechanisms introduced and tested by the complex interaction effect are difficult to explain by reverse causality logic. Thus, the statistical techniques employed here confirm the hypothesis that the degree of CEO research orientation is positively associated with innovation. Finally, strategic leadership in large, publicly traded firms may go beyond the CEO to other top managers and board directors, and even to middle managers. As strategic decision making is a shared activity, future research might consider the research orientation of the entire executive team and configurations of research and commercialization orientations among executives. It could perhaps even include the composition of the board directors.

Conclusion

This study sets out to show what CEO characteristics positively impact firms' innovation outcomes, and when and how do they do so. The central argument is that such research-intensive industries require CEOs with context-specific skills to strategically lead the firm's innovation. The results show that CEO research orientation is positively associated with firms' innovation outcomes. This relation is moderated by CEO duality, financial slack, and firm age, and it is partially mediated by R&D intensity. These insights contribute to a more comprehensive understanding of CEO characteristics, strategic choices and processes that result in firms' innovation outcome.

CHAPTER 3:
Managerial Human Capital, Diversification, and Exploratory Search

This study examines how available managerial human capital affects exploratory search behavior by firms. The main argument is that the positive association between managerial human capital and firms' propensity to engage in exploratory search is moderated by the degree of managerial complexity faced by senior management, as indicated by the degree of diversification. My analysis of 133 pharmaceutical firms over the 2000–2013 period provides support for my predictions of firms' propensity for emerging technologies but not for my predictions of firms' propensity for unfamiliar technologies. The results contribute to the understanding of the origins of innovation capabilities through exploratory search and the strategic importance of human capital.

Introduction

Search behavior by firms is a key driver of their innovation performance, growth, and long-term success. Search, defined as the problem-solving activities that involve exploration and refinement of technologies, knowledge elements, or other sources of innovation (Kim, Arthurs, Sahaym, & Cullen, 2013), facilitates changes in organizational routines, capabilities, and technological trajectories (Greve & Taylor, 2000; Nelson & Winter, 1982). Research has repeatedly shown that the exploration of diverse technologies by a firm enhances the likelihood that it will create breakthrough inventions (Ahuja & Lampert, 2001; Jung & Lee, 2016; Kaplan & Vakili, 2015) and increase its level of product and process innovation (Katila, 2002; Katila & Ahuja, 2002; Terjesen & Patel, 2017). Improvements in these areas in turn enable the firm to enter and create new markets (Silverman, 1999), obtain a greater market share and market value (Miller, 2006; Mitchell & Singh, 1993), and demonstrate superior capacities to adapt and survive (Ahuja, Lampert, & Tandon, 2014; Levinthal & March, 1993).

The above research has considerably advanced our understanding of the performance implications of firms' search behavior, but less attention has been paid to the strategic decisions that underpin firms' search behavior and the reasons why firms differ in their decisions about where to search. Research has documented that firms have a propensity to search locally—that is, they solve problems by searching for knowledge that is closely related to their prior experience and existing knowledge base (Dosi, 1982; Helfat, 1994; Teece & Dosi, 1988). Much less is known about why some firms overcome this predisposition and decide to engage in exploratory search—that is, solving problems by searching for knowledge in emerging and

unfamiliar technological domains (Ahuja & Lampert, 2001). Since the decision as to where to search is an important part of a firm's innovation strategy (Katila, 2002; Kim et al., 2013; Nelson & Winter, 1982), at present the literature is clearly overlooking an important factor that explains why firms differ in their search behavior.

The purpose of this study is to shed light on the antecedents of firms' search behavior. It does so by examining the pivotal yet understudied premise that firms' managerial human capital "shape[s] the scope and direction of the search for knowledge" (Penrose, 1959, p. 69). Given that firms expand to utilize their excess resource capacity (Penrose, 1959), I argue that the managerial human capital that is available to the firm is a major factor affecting the firm's propensity to engage in exploratory search. I theorize not only that managerial human capital, which encompasses generic, industry-specific, and firm-specific skills, influences where firms search, but also that this influence may depend on the managerial complexity faced by senior management. Such complexity determines the managerial human capital that is available for exploratory search. Specifically, I hypothesize that a firm's managerial human capital, depending on its level of diversification, significantly influences whether it deviates from its path-dependent quest for innovation and explores new technologies. An analysis of a longitudinal dataset comprising 133 U.S. publicly listed pharmaceutical firms over the 2000–2013 period shows that managerial human capital that is available to the firm positively affects a firm's propensity to explore emerging technologies but does not affect a firm's propensity to explore unfamiliar technologies.

This study provides several novel insights into why firms show persistent differences in innovation through exploratory search. Previous studies have focused on the performance implications of firms' search behavior (Ahuja & Lampert, 2001; Katila & Ahuja, 2002) as well as on how firms search (e.g., Phelps, 2010; Vermeulen and Barkema, 2001) and when they do so (e.g., Greve, 2003; Lungeanu, Stern, and Zajac, 2016). This study provides a more profound understanding of why firms differ in their search behavior by focusing on managers' strategic choices and activities that underpin where firms choose to search. In doing so, it considers senior management as one of the still unobserved originators of firms' search behavior. Ultimately, this can help to explain the differences between firms in terms of innovation performance. This study also contributes to and extends research on the behavioral determinants of search and innovation (Gavetti, Greve, Levinthal, & Ocasio, 2012). While previous research has mainly focused on financial and social aspirations as triggers of search, in particular search intensity (Chen, 2008; Chen & Miller, 2007; Greve, 2003), this study focuses on how managerial human capital explains the direction of firms' search behavior. Its

findings show that managerial human capital is an important factor in determining a firm's expansion of its search behavior into new technological directions. This underscores the point that the managerial resources available to the firm "are, for the enterprising firm, at the same time a challenge to innovate, an incentive to expand, and a source of competitive advantage" (Penrose, 1959, p. 76).

Theory and hypotheses

Managerial influence on firms' search behavior

Previous studies have theorized and broadly documented firms' search for knowledge and technologies that can be used for innovation (Ahuja et al., 2008; Gavetti et al., 2012). Two fundamentally different learning and search behaviors are exploitation and exploration (Levinthal & March, 1993; March, 1991). In line with prior research on search (e.g., Katila and Ahuja, 2002), this study views exploration and exploitation as two distinct search behaviors (Lavie, Stettner, & Tushman, 2010). This implies that resources allocated to exploration decrease resources available for exploitation, and vice versa. Exploitation involves local search that builds on existing knowledge and results in the refinement of technology. In contrast, exploration involves distant search for new knowledge and creates new technology (Benner & Tushman, 2002; Phelps, 2010). Although it is more uncertain, riskier, and costlier (March, 1991), exploratory search helps firms to escape from success traps (Ahuja & Lampert, 2001; Levinthal & March, 1993), change organizational routines (Nelson & Winter, 1982), and shift to new technological trajectories (Ahuja et al., 2014; Greve & Taylor, 2000). A firm's capacity to engage in exploratory search is therefore critical for sustained innovation success, and as a result it is among a firm's most important capabilities (Brown & Eisenhardt, 1997; Teece, 2007).

Firms' exploratory search behavior can vary over two dimensions. On the one hand, firms can search over time. Exploratory search behaviors that fall within this dimension are those which focus on experimentation with relatively recent emerging technologies (Ahuja & Lampert, 2001; Katila, 2002). On the other hand, firms can search over technological domains. Exploratory search activities that belong in this dimension focus on experimentation with technologies that come from a domain that is unfamiliar to the focal firm (Ahuja & Lampert, 2001; Fleming, 2001). A firm's propensity for exploratory search can therefore be examined based on that firm's experimentation with both emerging and unfamiliar technologies.

It is important to study firms' exploration in terms of both emerging and unfamiliar technologies because doing so sheds light on their strategic intent concerning different types of innovation (Ahuja & Katila, 2001; Kim et al., 2013). A firm's propensity to experiment with

emerging technologies that have only recently been developed can be regarded as that firm's pursuit of innovation that is "new to the industry" and potentially "new to the world" (Ahuja et al., 2014). Search at the technological frontier by experimenting with emerging cutting-edge technologies can offer solutions to fundamental problems at an early stage of a paradigm, because these technologies likely differ from older, more mature technologies in terms of both the nature of the technical problems that they pose and the possibilities for technical solutions that they present (Ahuja & Lampert, 2001). Emerging technologies therefore spur innovation by generating perspectives that are paradigm changing—that is, they change the "pattern" of solutions (Dosi, 1982)—"for a broad set of players outside the firm" (Ahuja et al., 2014, p. 666; Katila, 2002). A firm's propensity to experiment with what is unfamiliar technology in the firm's eyes is particularly important to that firm's pursuit of "new to the firm" innovation (Ahuja et al., 2014; Gilsing, Nooteboom, Vanhaverbeke, Duysters, & van den Oord, 2008). Search in technological domains that are unrelated to a firm's existing knowledge and capabilities enhances innovation by generating perspectives that are new and path-changing to the focal firm but not necessarily to others (Benner & Tushman, 2002; Fleming, 2001; Jung & Lee, 2016; Rosenkopf & Nerkar, 2001). Missing from the literature on search and innovation, however, is a specific understanding of why firms differ in their search behavior and thus of their strategic intentions in relation to innovation.

It has long been recognized that senior management is responsible for the firm's key strategic decisions (Child, 1972; Thompson, 1967). Although the contributions of people at all hierarchical levels are important, senior management is especially critical when it comes to establishing successful innovation in firms (Morris, Kuratko, & Covin, 2010). Top executives reside at the strategic apex of firms (Simsek et al., 2015). This makes them responsible for the managerial task of balancing the inherent trade-off between local and exploratory search (Gavetti & Levinthal, 2000). It also makes them deeply involved in the strategic decision-making process that defines their firm's strategic direction in line with this balancing act (O'Reilly & Tushman, 2013). Recent research shows how executives influence the innovation process through strategic choices and actions—for example, identifying new technological opportunities and bringing those opportunities to the attention of organizational members (Gerstner et al., 2013; Li et al., 2013; Talke et al., 2010). Moreover, senior management can influence where the firm and its employees search by modifying the context within which others generate and promote the proposals that management responds to (Burgelman, 1983b; Elenkov & Manev, 2005). Thus, a firm's senior management influences the organization's

strategic behavior in relation to innovation in multiple ways that go well beyond its direct decisions.

Given the significance of the literatures on search, innovation, and the impact of managers on organizations, it is surprising that comparably little is known about managerial influence on the firm's search behavior. This study contributes to a more profound understanding of the antecedents of firms' search behavior by examining the influence of senior management. My main contention is that available managerial human capital is a key factor that affects a given firm's propensity for exploratory search. To gauge the managerial human capital available to the firm, I examine how the relationship between managerial human capital and firms' exploratory search behavior is moderated by the managerial complexity faced by management. Acknowledging the seminal works on technological search (Ahuja & Lampert, 2001; Katila, 2002; Katila & Ahuja, 2002), I follow their conceptualization of a firm's propensity to explore either emerging technology or unfamiliar technology as two distinct types of exploratory search that are influenced by managerial human capital in different ways.

Managerial human capital and the exploration of new technologies

The term "human capital" originally referred to learned skills and knowledge that individuals develop through their prior experience, education, and training (Becker, 1964). Recent work has conceptualized human capital as a firm-level resource that is created from the emergence of individuals' knowledge, skills, and abilities (Ployhart, Nyberg, Reilly, & Maltarich, 2014). Human capital, and particularly that of managers at the top of the firm, can be considered a valuable and finite resource over which firms compete because it is scarce and difficult to copy or substitute, and also because it generates rents (Castanias & Helfat, 1991; Coff & Kryscynski, 2011). This makes human capital a resource that firms could utilize to achieve innovation and competitive advantage (Barney, 1991; Penrose, 1959). Managerial human capital, defined as "the skills and knowledge repertoire of managers, which are shaped by their education and personal and professional experiences" (Kor & Mesko, 2013, p. 234), is therefore an important factor that creates firm-level capacities (Ployhart et al., 2014). This suggests that managerial human capital is an important antecedent of firm strategic behavior, including firms' search for new technologies.

Managerial human capital is composed of managers' generic, industry-specific, and firm-specific skills and knowledge (hereafter referred to as "skills") (Castanias & Helfat, 1991, 2001; Kor, 2003). Generic skills comprise managers' general levels of intelligence and cognitive abilities; these determine their receptiveness to new ideas, their ability to understand large volumes of complex information, and their ability to span knowledge boundaries (Barker

& Mueller, 2002; Hambrick & Mason, 1984; Wiersema & Bantel, 1992). In particular, the cognitive abilities associated with a PhD and technological work experience provide managers with a higher awareness of new technologies, a greater capacity to process technological information, and an ability to assess the potential value of new technologies (Brown & Eisenhardt, 1997; Kaplan, Murray, & Henderson, 2003; Wiersema & Bantel, 1992). Industry-specific skills involve knowledge about the industry setting such as the competitive conditions and specific technologies in the industry (Kor, 2003). These skills allow managers to identify new opportunities, absorb external knowledge, apply new research techniques, and position new inventions and products (Castanias & Helfat, 2001; Cohen & Levinthal, 1990). Firm-specific skills are those that are unique to the firm such as tacit knowledge about the firm's strategies, resources, and capabilities (Kor, 2003). They allow managers to identify internal innovation opportunities and to make more informed and effective resource-allocation decisions (Kor & Mahoney, 2005). To the extent that managers differ in terms of their human capital, they will have different skills and knowledge repertoires that lead them to make different strategic decisions and to engage in different strategic activities.

One useful way to explain how managerial human capital results in organizational search processes through strategic choice and action is offered by the dynamic capability literature (Adner & Helfat, 2003; Helfat & Martin, 2015). Managers can draw on "their bundle of generic and specialized managerial capabilities" to sense and shape technological innovation opportunities, seize innovation opportunities, and reconfigure the firm's search processes in line with these opportunities (Kor & Mesko, 2013, p. 237; Teece, 2007). Prior research suggests that the human capital embodied in the manager produces a capacity to absorb different types of information and technologies (Cohen & Levinthal, 1990; Kor & Mesko, 2013). Senior management's noticing and interpreting the nature of technological change is a crucial first step in translating those perspectives into strategic choices and actions that facilitate exploration of new directions of technological innovation (Kaplan et al., 2003). Managers are also likely to differ in terms of their investments in and other commitments to those technologies as a result of differences in their human capital (Castanias & Helfat, 2001; Custódio et al., 2017). Compared to managers who are relatively new to the firm and industry, experienced managers are more likely to identify and execute a superior "subjective opportunity set for the firm" (Penrose, 1959) because these managers have experience-based and often tacit knowledge of existing strategies, resources, and capabilities within the firm and industry (Kor, 2003; Williams, Chen, & Agarwal, 2017). Furthermore, differences in managerial skills likely cause managers to differ when they reconfigure resources, capabilities,

and structures so that these are in line with technological opportunities (Castanias & Helfat, 1991; Teece, 2007). This is so because managers with tacit knowledge of employee skills and firm resources can do a superior job of matching these skills to R&D projects. They can also more accurately dedicate or reconfigure resources to promising R&D projects and other exploratory search initiatives (Kor & Mahoney, 2005). As a whole, these considerations show that managerial human capital affects firms' exploratory search behavior through managers' strategic choices and actions, as well as through shaping organizational search processes that facilitate the implementation of their strategic choices for exploration.

Managerial human capital likely relates differently to each distinct dimension of exploratory search because such capital plays a key role in shaping management's dominant logic. This logic refers to "the way in which managers conceptualize the business and make critical resource allocation decisions—be it in technologies, product development, distribution, advertising, or in human resource management" (Prahalad & Bettis, 1986, p. 490). Based on their dominant logic, managers evaluate opportunities and alternatives, make critical resource-allocation decisions, and act to modify their firm's resource and capability configuration (Kor & Mesko, 2013). This implies that managerial human capital may increase a firm's propensity to explore emerging technologies because such capital and the related dominant logic may enable forward-looking behavior (Gavetti & Levinthal, 2000). Skilled and experienced managers have a higher awareness of recent or newly developed technologies in their environment, and they are able to detect links between technological developments that have come about at different times (Brown & Eisenhardt, 1997; Nadkarni & Chen, 2014). Managerial human capital increases not only the absorptive capacity of a company's senior management but also the managerial capacity to seize emerging technological opportunities in line with the firm's resources and capabilities (Adner & Helfat, 2003; Kor & Mesko, 2013). Research indeed suggests that foresight in areas such as technology opportunity and competitive situation can lead to forward-looking search behavior (Chen, 2008; Chen & Miller, 2007). Managerial human capital may therefore lead to forward-looking strategic choices and actions by senior management that increase firms' propensity for emerging technology.

Hypothesis 1a: Managerial human capital is positively associated with a firm's propensity for emerging technology.

By contrast, managerial human capital may negatively influence a firm's propensity for unfamiliar technology. Managerial human capital can result in a managerial dominant logic that impedes strategic behavior that takes the firm away from its core technological domain. When top managers are immersed in managing the firm's existing business, previously used

cognitive maps and decision routines may, due to existing commitments, managerial myopia, and cognitive rigidities, constrain their ability to identify and seize technological opportunities that are not in the neighborhood of prior experience (Leonard-Barton, 1992; Levinthal & March, 1993; Tripsas & Gavetti, 2000). It has been argued that incumbent managers who have prior work experience rooted in the firm's original environment are detrimental to strategic change and innovation because they become nearsighted and therefore remain attached for too long to their established paradigms for success (Hambrick & Fukutomi, 1991; Miller, 1991). These physical and cognitive limitations constrain firms to search in the neighborhood of their existing activities rather than at some distance from them (Gavetti & Levinthal, 2000; Helfat, 1994). This suggests that managerial human capital decreases a firm's propensity for unfamiliar technology.

Hypothesis 1b: Managerial human capital is negatively associated with a firm's propensity for unfamiliar technology.

The moderating role of managerial complexity

The managerial human capital that is available for the firm's exploratory search behavior depends on the managerial complexity faced by senior management because such complexity may divert managerial resources away from the firm's exploratory search behavior. An important source that intensifies managerial complexity is a firm's diversification across product and geographical markets (Carpenter, 2002; Sanders & Carpenter, 1998). Such diversification poses information-processing demands because it increases the need for strategic action, the number and complexity of strategic decisions to be made, and the amount of information that must be evaluated for decision-making purposes (Carpenter & Fredrickson, 2001; Henderson & Fredrickson, 1996; Michel & Hambrick, 1992). A firm's diversification also increases coordination demands because senior management experiences a greater need for and difficulties in coordinating, integrating, and monitoring when divisions, operations, and R&D projects become more dispersed across product markets and geographical areas (Michel & Hambrick, 1992; Sanders & Carpenter, 1998).

Increases in managerial complexity lower the managerial human capital that is available for exploratory search because more managerial resources need to be allocated to strategic leadership activities related to the management of diversified businesses. In the context of the notions of bounded rationality, limited information-processing capacity, and limited attentional capacity (Cyert & March, 1963; Ocasio, 1997; Thompson, 1967), managerial resources (e.g., senior management's time, effort, and attention) may be perceived as scarce resources with limited availability. This implies that the information-processing and coordination demands

emerging from diversification therefore compete for managerial resources that otherwise could be allocated to the firm's exploratory search activities (Hitt, 1990; O'Reilly & Tushman, 2013). These latter activities also require senior management to expend intense cognitive attention and engage in extensive experimental search (Gavetti & Levinthal, 2000). Indeed, a recent study shows that senior management's effort-intensive search for new information and knowledge is negatively related to the firm's number of new products releases, possibly because senior management's exploratory search efforts compete for managerial resources with other activities (Li et al., 2013). Thus, the greater the proportion of managerial resources that need to be allocated to the strategic choices and activities required to cope with the managerial complexity of the diversified firm, the lower the proportion of managerial resources that can be devoted to the strategic choices and activities required for the firm's engagement in exploratory search. A highly diversified firm will therefore have a lower level of managerial human capital that is available for exploratory search behavior.

Managerial complexity decreases a firm's propensity for both emerging and unfamiliar technologies because the resulting job demands that it places on executives may result in their holding cognitive biases and preferences that increase the localness of both exploratory search behaviors (Hambrick et al., 2005). Research shows that managers' limited cognitive capacities make their strategic choices and actions subject to various cognitive biases that enforce experiential learning, routinized action, and the binding effects of path dependency and technological trajectories (Gavetti et al., 2012; Powell, Lovallo, & Fox, 2011). These cognitive biases and other perceptual filters have a great impact on executives' environmental assessment, resource-allocation decisions, and other dynamic managerial capabilities (Amit & Schoemaker, 1993; Teece, 2007). Similar issues may arise when senior management sets the strategic direction for the firm's search activities and thus decides on where to search. When executive job demands are high, as they are in the global and complex context of the diversified firm, managers may dedicate more priority, effort, and time to current business issues. They may fall back on heuristics and mental shortcuts that are rooted in their past knowledge, skills, and experiences (Tversky & Kahneman, 1974). This may lead managers to engage less in forward-looking, cognitive search and more in backward-looking, experiential search (i.e., they may search more among older, mature technologies that have emerged further back in time) (Gavetti & Levinthal, 2000). They may even only search within domains related to their prior experience and existing knowledge and capabilities (i.e., their search may be more localized to familiar technological domains).

This line of argument suggests that there is a limit to the utilization of managerial human capital in either type of exploratory search behaviors. When a firm's levels of product and geographic diversification is high, firms may overutilize its managerial human capital, and thus have less managerial human capital that is available to allocate to exploratory search. As a result, managerial human capital may provide a weaker impetus for a firm to engage in exploratory search behavior, and it may induce local search behavior. I therefore expect that the relationship between managerial human capital and both types of exploratory search behavior are negatively influenced by a firm's level of diversification.

Hypothesis 2a: A firm's level of diversification negatively moderates the positive association between managerial human capital and a firm's propensity for emerging technology.

Hypothesis 2b: A firm's level of diversification negatively moderates the positive association between managerial human capital and a firm's propensity for unfamiliar technology.

Method

Sample and data

I tested the hypotheses on a sample that consisted of publicly listed U.S. pharmaceutical firms and that covered the 2000–2013 period. The focus on a single industry is important for handling the challenge of testing the resource-based view of the firm, which requires identifying and measuring firms' resources and strategy, elements that vary by industry (Hitt, Bierman, Shimizu, & Kochhar, 2001; Hitt, Bierman, Uhlenbruck, & Shimizu, 2006). The pharmaceutical industry offers an excellent research setting because it is characterized by its strategic prioritization of technological innovation, its high degree of managerial discretion, the critical role that human capital plays within it, and the availability of detailed data on changes in pharmaceutical firms' strategies and exploration activities over time (Gerstner et al., 2013; Zucker et al., 1998).

The sample was drawn from an initial list of 195 pharmaceutical firms (SICs 2833–2836) that were among the sector's hundred largest employers at any time during the period under study according to the Compustat database and for which data were available in the BoardEx database. This approach ensured that I could observe substantial innovation activity, employment, and assets in the pharmaceutical industry. At the same time, it facilitated the data-collection process across multiple databases. After I deleted ten firms that had no patents during the study period, seven firms that had only one observation during the study period, and forty-

five firms due to listwise deletion to handle missing data, the sample consisted of 133 firms and 1,108 firm-year observations.

I constructed a unique firm-level panel dataset that included information on firms' senior management and search activity. I first identified subsidiaries, joint ventures, and historical company names using Securities and Exchange Commission (SEC) 10-K filings and company websites to construct detailed family trees of all firms (Phelps, 2010). I subsequently collected data on all firms' patenting, joint venture, and acquisition activities through extensive name matching of the entities in the family trees. I used patent records held by the U.S. Patent and Trademark Office (USPTO) for the 1975–2016 period and joint venture and acquisition records from the Thomson Reuters SDC Platinum database for the 1962–2016 period. I matched firms to USPTO patent filings based on company names (i.e., USPTO assignees and applicants), and legal form and country data to company information contained in SEC filings. I matched SDC records in the same way but also used CUSIP numbers as firm identifiers to link records where possible. I used these data sources because they match with the sample of U.S. publicly listed firms. Eventually, I aggregated all data for my 133 focal firms and their wholly owned subsidiaries at the ultimate parent level to capture each focal firm's full patenting and external R&D activity (Arora, Belenzon, & Rios, 2014). To identify each firm's executives and collect data on their backgrounds, I used the BoardEx, Execucomp, and Thomson Reuters Eikon databases. I supplemented the data from these sources with hand-collected data from company reports, SEC filings, and other online databases (e.g., Marquis Who's Who; Bloomberg Executive Profile and Biography, and Equilar). All financial data are from Compustat, and data on firms' ownership structures are from the Thomson Reuters Institutional Holdings (13F) database.

Dependent variables

I used patent citations to proxy each firm's exploratory search behavior. Prior research has extensively used patent citations to observe firms' search behavior (e.g., Benner and Tushman, 2002; Phelps, 2010; Rosenkopf and Nerkar, 2001). Firms that apply for a patent are legally required to cite to prior art, or technological knowledge, upon which a patent is based (Katila, 2002). The use of patent data is particularly appropriate in this study's research setting because my sampled firms have a strong incentive to file patents at the USPTO, and therefore patent data represent a substantial part of firms' search activities (Cohen et al., 2000). I used patents that were ultimately granted. I dated the observation year as a patent's application year because this allows for the most precise identification of the actual moment of a firm's search activities.

There is a growing recognition among innovation scholars that innovation is a broad and complex process that requires consideration of knowledge and discoveries from different technology domains and time frames (Ahuja & Lampert, 2001; Fleming, 2001; Jung & Lee, 2016; Katila, 2002). I therefore developed measures that comprehensively capture the multidimensional conceptualization of firms' search behavior. I measured each firm's propensity for *emerging technology* based on the dates associated with patents. I classified the backward citations from each firm's patent applications in year *t* as emerging when the cited patent was applied for less than three years before the filing date of the patent that cites it (Ahuja & Lampert, 2001). Results are robust to using a two-year cut off to signify an emerging technology. Prior research suggests that firms that cite such new patents experiment with emerging technologies and search for state-of-the-art knowledge (Ahuja & Lampert, 2001; Katila, 2002). I computed each firm's propensity for *emerging technology* score by dividing emerging citations by total citations.

I measured each firm's propensity for *unfamiliar technology* based on its prior patenting history. I classified the backward citations from its patent applications in year *t* as unfamiliar when a cited patent listed a three-digit main technology class that was not listed by any other patent that the same firm had cited in the previous five years. The use of the technological classes of the cited patents and the choice of a five-year period to incorporate knowledge depreciation over time are consistent with previous studies (Ahuja & Lampert, 2001; Gilsing et al., 2008). I computed each firm's propensity for *unfamiliar technology* score by dividing unfamiliar citations by total citations.

My measures have strong similarities to several prior measures in the literature. First, my measures are similar to Ahuja & Lampert's (2001) measures of "emerging technologies" and "novel technologies," though my measures allow me to measure firms' search activities independently from firm size[4] (Phelps, 2010). Second, my measures are similar to prior measures of exploratory search and innovation (e.g., Katila, 2002; Katila & Ahuja, 2002; Phelps, 2010), though these measures captured the repeated use of a specific patented technology (i.e., repeated citations of a specific patent), whereas my measures capture the extent to which firms search among technological dimensions (i.e., the extent to which they explore different types of technologies). This also allows for better comparison between firms of search activities over domains. Third, the range of my propensity measures is consistent

[4] This is important because the sample consists of large firms and their smaller counterparts, and firm size has been shown to play an important role in firms' patenting, exploration, and expansion behavior (e.g., Audia and Greve, 2006; Eggers and Kaul, 2017; Zucker and Darby, 1997).

with research that has conceptualized and measured exploitation and exploration as the ends of a continuum (Lavie et al., 2010). Fourth, in a similar vein to Trajtenberg, Henderson, and Jaffe's (1997) measure of "originality," I look at the three-digit main technology class of cited patents. However, their measure focuses on the diversity of a patent's citations, while my unfamiliar technology measure focuses on the listing of an unfamiliar technology class in a patent's citations. Lastly, the unfamiliar technologies measure is also similar to Eggers and Kaul's (2017) measure that is based on technology class level comparisons, which makes the measure both more sensitive to search patterns and less prone to bias from examiner-added citations (Alcácer & Gittelman, 2006).

Independent variable

I measured each firm's *managerial human capital* using a composite construct consisting of its top management team (TMT) members' generic, industry-specific, and firm-specific skills (Castanias & Helfat, 1991, 2001). I operationalized each firm's top management team as consisting of executives who had an executive directorship or held the position of senior vice president or higher. Thus, I included the chief executive officer, chief financial officer, chief operating officer, other chief officers, executive vice presidents, and senior vice presidents. Following Hambrick, Humphrey, and Gupta (2014), I included executives with a vice president title when a team consisted of only five or fewer executives. This procedure maintains consistency across large firms and their smaller counterparts to identify senior management as the CEO and the executives with whom he or she regularly interacts to make and implement important strategic decisions (Williams et al., 2017). This empirical definition matches the study's focus of senior management's influence on firm search behavior and results in a TMT size within common bounds for upper echelons research (Carpenter et al., 2004).

In line with prior studies on managerial human capital (e.g., Hitt et al., 2001, 2006), I created a composite construct for each firm's *managerial human capital* by standardizing and averaging three indicators for each TMT and each year. First, TMT educational level was measured as the team average of each executive's highest formal educational qualification prior to his or her appointment to the TMT. I only considered tertiary-level qualifications that were awarded to managers based on formal studies (e.g., excluding honorary degrees) (Crossland et al., 2014). I coded each manager's highest degree as follows: 1= Bachelor of Arts, 2 = Bachelor of Science, 3 = Master of Arts, 4 = Master of Science, 5 = Master of Business Administration, and 6 = doctorate (Talke et al., 2010). Second, TMT industry experience was measured as the team average of the number of years during which each executive had worked in the pharmaceutical industry before joining the focal firm. I matched entries for firms in BoardEx

to those in Thomson Reuters Eikon, Datastream, and Compustat and complemented those data with manual data collection to obtain the SIC codes of both U.S. and international firms where executives worked (Custódio et al., 2017). The third indicator was TMT company tenure, measured as the team average of each executive's company tenure prior to appointment to the TMT. As a result, a higher number indicates a higher level of managerial human capital for a firm.

Although upper echelons researchers have used education and professional experience as indicators of psychological constructs such as executives' beliefs and values (Hambrick & Mason, 1984), the resource-based view and strategic human capital literature use TMT members' education and work experience as indicators of human capital (Crook, Todd, Combs, Woehr, & Ketchen, 2011; Helfat & Martin, 2015). Moreover, upper echelons studies tend to treat diverse background characteristics as independent of one another. However, studies on managerial human capital suggest that the configuration of diverse characteristics instead of individual variables in isolation better reflects the "bundle" of competences that managers contribute to the firm (Carpenter et al., 2004).

Moderator variable

I measured *diversification* as each firm's level of product and geographic diversification of its sales. Specifically, I used Palepu's (1985) entropy measure to separately calculate the proportional distribution of a firm's sales over business segments and the proportional distribution of a firm's sales over geographical segments. This measure reflects the number, importance, and relatedness of a firm's diversification (Crossland et al., 2014; Lungeanu et al., 2016). I summed the indicators of each dimension (i.e., business diversity and geographic diversity) to form a composite measure of each firm's level of diversification. Therefore, the higher the number, the higher a firm's level of diversification. Summing was not a problem in this case because each indicator had the same metric—it was gauged as a proportional distribution—and the two indicators were highly correlated. This approach is consistent with previous studies that construct a measure of firms' levels of diversification (e.g., Carpenter and Fredrickson, 2001).

Control variables

Based on prior empirical research on the role of senior management in innovation (e.g., Hambrick et al., 2014; Kaplan et al., 2003), I controlled for *TMT size* (the number TMT members), *TMT age* (the average age of TMT members), *tenure diversity* (the standard deviation of each executive's number of years in TMT), *gender composition* (the proportion of

females in the TMT), and *functional heterogeneity* (the Herfindahl-Hirschman index to calculate the concentration of TMT members' primary functional backgrounds). Functions were categorized based on the eight-track scheme (e.g., Cannella, Park, and Lee, 2008; Wiersema and Bantel, 1992): production/operations, R&D/engineering, accounting/finance, management/administration, marketing/sales, personnel/labor relations, law, and other. Since founders and CEOs can shape managerial attention to and beliefs about new technologies (Eggers & Kaplan, 2009; Gerstner et al., 2013), I controlled for *founders* (the number of founders in the TMT) and *CEO research orientation* (a score that ranges from 0 = no research orientation to 4 = high research orientation depending on whether the CEO holds a PhD degree in science or engineering, has academic experience, has dominant functional experience in R&D, and holds any patents prior to appointment as CEO). I controlled for *firm size* (the logarithm of the number of employees) and *firm age* (the number of years since IPO or first recording in Compustat) because incumbent firms differ in their ability and motivation to engage in technological innovation (Eggers & Kaul, 2017; Zucker & Darby, 1997). Previous literature suggests that important predictors of firm search activities and innovation are *performance* (return on assets, as net income divided by total assets), *financial slack* (current ratio, as current assets divided by current liabilities), *R&D intensity* (R&D expenditure, deflated by the consumer price index, divided by the number of employees), the number of *acquisitions*, *institutional ownership* (the proportion of outstanding shares held by institutional blockholders), and *board independence* (the number of independent directors divided by board size) (Aghion, Van Reenen, & Zingales, 2013; Barker & Mueller, 2002; Kor, 2006; Lungeanu et al., 2016). To control for R&D organization structure, I measured each firm's degree of *R&D centralization* (a Herfindahl-Hirschman index that calculates the concentration of patent applications among the parent firm and its subsidiaries), and *knowledge diversity* (a Palepu entropy measure that calculates the extent to which knowledge held by a firm's inventors is dispersed across many different technological domains) (Carnabuci & Operti, 2013). I assigned unique inventors to the firms in the sample by matching my fine-grained patent dataset with the disambiguated inventor names provided by the FUNG database (Li et al., 2014). In the case of multiple patent assignees, I assigned unique inventors using inventors' historical or future patent activity.

To control for other unobserved heterogeneity in firms' innovation capabilities, I introduced fixed effects by including the presample "mean scaling" estimator[5] (Blundell, Griffith, & Van Reenen, 1995).This approach exploits the availability of a long presample history on patenting behavior (of up to twenty-five years per firm) to construct the presample average of patent applications. I accounted for the variation across pharmaceutical industry segments and the unobserved time-changing macroeconomic conditions that may affect firms by including SIC and year dummies. All explanatory variables and controls were lagged by a one-year period (*t*-1) to reduce possible simultaneity biases and to better reflect the logic that the firm's strategic choices and actions precede the observable outcomes of search activities.

Analysis

I estimated fractional response models to test the hypotheses because the exploratory search measures are proportions between 0 and 1. Specifically, I estimated models using a generalized estimating equation (GEE) approach in which I specified a probit link function, a binomial distribution, an exchangeable within-group correlation structure, and robust standard errors clustered by firm (Phelps, 2010). These models account for the fact that proportions are naturally bounded and have values at the boundaries, which raises issues in terms of inference and functional form (Papke & Wooldridge, 2008). I first entered the control variables to assess the baseline model and then added the managerial human capital variable followed by the interaction term of managerial human capital and firms' diversification.

Results

Table 3.1 presents the descriptive statistics and Table 3.2 shows the correlation matrix for all variables. The variance inflation factor (VIF) for all variables are below the recommended threshold of 10 and the mean VIF is 2.25. This prompts no concerns about multicollinearity. The descriptive statistics show that the average sampled firm has a propensity for local search. The sampled firms have a low propensity for unfamiliar technology (mean = 0.01) and a slightly higher propensity for emerging technology (mean = 0.12). The low, nonsignificant correlation (r = 0.02) between the propensity for emerging technology and propensity for

[5] This approach relaxes the strict exogeneity assumption that x_{it} is strictly exogenous (i.e., uncorrelated with past, present, and future shocks to y_{it}) underlying conditional fixed-effects models, such as the fixed-effects Poisson estimator of Hausman et al. (1984), which isolates the within-firm variation. Although there will be some finite sample bias in using presample mean-scaling estimator, Monte Carlo evidence shows that this estimator performs well compared to alternative econometric estimators for dynamic panel data models with weakly endogenous variables (Blundell, Griffith, & Windmeijer, 2002).

unfamiliar technology confirms that these two variables represent two distinct dimensions of search behavior (Ahuja & Lampert, 2001; Katila, 2002; Katila & Ahuja, 2002). The weak correlations of firm size with emerging technology (r = -0.02) and with unfamiliar technology (r = -0.01) also confirm that these new measures of search behavior are unrelated to firm size. Furthermore, the high mean of R&D intensity and the fact that all firms were awarded at least on patent a year indicates that R&D and patenting are key strategic priorities among the sampled firms.

Table 3.3 reports the empirical results used for hypotheses testing. Hypothesis 1 argued that managerial human capital would result in (in the case of Hypothesis 1a) a higher propensity for emerging technology among firms; and (in the case of Hypothesis 1b) a lower propensity for unfamiliar technology. Model 2 shows that the coefficient of managerial human capital is positively and significantly related to firms' propensity for emerging technology (β = 0.103; p = .047). The average marginal effect of managerial human capital on firms' propensity for emerging technology is 0.023 (p = .020). This means that a firm's propensity for emerging technology on average changes by 2.3% when managerial human capital increases or decreases by one standard deviation (SD) from the mean while all other variables are kept at their original values. Since the average firm has a rather low propensity for emerging technology (0.12; see Table 3.1), this translates into an increase of nearly 20%. These findings offer support for Hypothesis 1a. Model 5 shows that managerial human capital did negatively influence a firm's propensity for unfamiliar technology, but no statistical significance was achieved here (β = -0.121; p = .466). This does not provide support for Hypothesis 1b.

Hypotheses 2a and 2b predicted that firms' diversification negatively moderates the association between managerial human capital and firms' propensity for emerging and unfamiliar technology. Model 3 in Table 3.3 shows a significant and negative coefficient for the interaction term between managerial human capital and firms' propensity for emerging technology (β = -0.131; p = .024). To aid interpretation in view of the nonlinearity of the models, Figure 3.1 displays a graph of the average marginal effect of managerial human capital on a firm's propensity for emerging technology conditional on firms' diversification, with 95% confidence intervals. Using values between high (+1 SD) and low (−1 SD) levels of firms' diversification reveals that increasing diversification negatively moderates managerial human capital's association with firms' propensity for emerging technology. The figure illustrates that the positive relationship between managerial human capital and firms' propensity for emerging technology is weakened by 53% as firms' level of diversification increases from low to mean. There is no relationship between managerial human capital and firms' propensity for emerging

technology when firms' level of product and geographic diversification is high. This provides support for Hypothesis 2a. Model 6 shows a negative coefficient for the interaction term between managerial human capital and firms' propensity for unfamiliar technology that is not statistically significant (β = -0.015; p = .913). This does not provide support for Hypothesis 2b.

Table 3.1: Descriptive statistics

		Mean	SD	Min	Median	Max
1	Emerging technology	0.12	0.11	0.00	0.09	1.00
2	Unfamiliar technology	0.01	0.06	0.00	0.00	1.00
3	Managerial human capital	0.00	0.50	-1.65	0.03	1.71
4	Diversification	0.67	0.87	0.00	0.28	4.15
5	Firm size[i]	8,220.44	21,532.91	9.00	525.00	127,600.00
6	Firm age	25.30	34.36	0.00	14.00	163.00
7	Performance	-0.12	0.30	-1.32	-0.04	0.76
8	Financial slack	5.56	6.10	0.23	3.75	64.14
9	R&D intensity	170.57	503.96	0.51	117.35	1,6131.76
10	Acquisitions	0.45	1.00	0.00	0.00	8.00
11	Institutional ownership	0.65	0.25	0.00	0.68	1.00
12	Board independence	0.83	0.10	0.40	0.86	1.00
13	Presample patent stock	17.22	35.61	0.00	3.57	218.92
14	R&D centralization	0.80	0.30	0.00	1.00	1.00
15	Knowledge diversity	2.01	0.74	0.00	2.05	4.08
16	TMT size	8.38	2.95	3.00	8.00	23.00
17	TMT age	50.27	3.61	38.60	50.38	69.67
18	Gender composition	0.12	0.12	0.00	0.11	0.63
19	Functional heterogeneity	0.81	0.07	0.48	0.82	0.95
20	Tenure heterogeneity	3.81	2.00	0.00	3.65	17.04
21	Founders	0.38	0.68	0.00	0.00	4.00
22	CEO research orientation	1.32	1.44	0.00	1.00	4.00

Note: 1108 Observations. [i]Log transformed variable but original values reported here.

Table 3.2: Correlation matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	Emerging technology																					
2	Unfamiliar technology	0.02																				
3	Managerial human capital	0.12	-0.02																			
4	Diversification	-0.10	-0.01	0.09																		
5	Firm size	-0.02	-0.01	0.27	0.59																	
6	Firm age	-0.03	-0.02	0.30	0.56	0.87																
7	Performance	-0.08	-0.02	-0.04	0.41	0.27	0.29															
8	Financial slack	0.10	0.08	0.05	-0.31	-0.22	-0.23	-0.04														
9	R&D intensity	0.02	-0.01	0.04	-0.15	-0.09	-0.08	-0.08	0.04													
10	Acquisitions	-0.01	0.04	0.17	0.45	0.61	0.49	0.21	-0.16	-0.06												
11	Institutional ownership	-0.08	-0.04	0.12	0.09	-0.01	0.02	0.27	0.03	0.05	0.01											
12	Board independence	-0.12	0.04	0.11	0.10	0.10	0.09	-0.04	-0.04	0.03	0.01	0.02										
13	Presample patent stock	0.02	0.00	0.32	0.47	0.83	0.77	0.22	-0.18	-0.06	0.46	-0.02	0.15									
14	R&D centralization	0.06	-0.06	0.07	-0.24	-0.33	-0.26	-0.16	0.19	-0.03	-0.30	0.04	0.03	-0.19								
15	Knowledge diversity	-0.06	0.01	0.27	0.47	0.52	0.44	0.18	-0.12	-0.07	0.35	0.16	0.18	0.52	0.04							
16	TMT size	-0.04	-0.01	0.24	0.42	0.52	0.50	0.24	-0.17	-0.04	0.40	0.23	0.12	0.49	-0.14	0.45						
17	TMT age	-0.08	-0.08	0.16	0.14	0.22	0.28	0.01	-0.24	-0.04	0.11	0.03	0.04	0.19	-0.11	0.06	0.12					
18	Gender composition	0.11	-0.02	0.12	0.02	0.16	0.14	-0.03	-0.08	0.13	0.05	0.05	0.12	0.19	0.00	0.01	0.15	0.04				
19	Functional heterogeneity	-0.06	0.00	0.11	0.34	0.39	0.40	0.25	-0.17	-0.01	0.30	0.28	0.09	0.38	-0.10	0.34	0.84	0.10	0.13			
20	Tenure heterogeneity	-0.05	-0.04	-0.11	0.02	0.01	0.11	0.13	0.01	-0.08	0.03	0.06	-0.15	-0.01	-0.05	0.02	0.01	0.29	-0.11	0.02		
21	Founders	0.06	-0.03	-0.09	-0.25	-0.19	-0.25	-0.26	0.15	0.02	-0.15	-0.02	-0.15	-0.19	0.11	-0.11	-0.20	-0.19	-0.05	-0.20	0.06	
22	CEO research orientation	0.10	0.04	0.20	-0.23	-0.21	-0.21	-0.21	0.22	0.04	-0.12	-0.17	0.02	-0.13	0.13	-0.09	-0.16	-0.07	0.09	-0.25	0.04	0.17

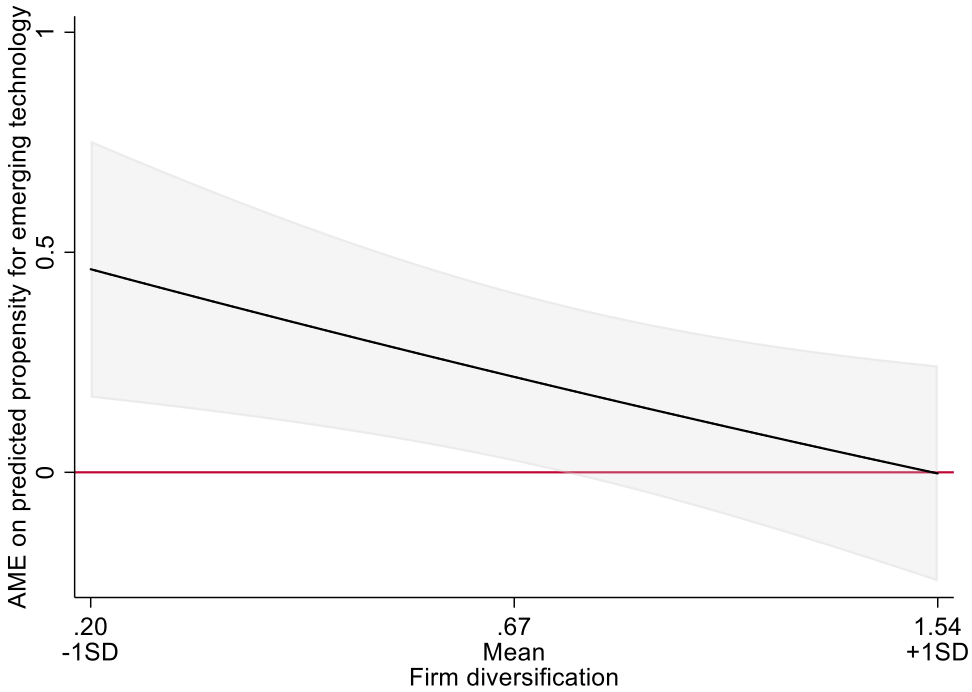
Note: Correlations greater than 0.06 are significant at $p < 0.05$ and those greater than 0.09 are significant at $p < 0.01$.

Table 3.3: Results predicting exploratory search

	Emerging technology			Unfamiliar technology		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Managerial human capital		0.103**	0.199***		-0.121	-0.109
		(0.052)	(0.066)		(0.166)	(0.207)
Managerial human capital*Firm diversification			-0.131**			-0.015
			(0.058)			(0.135)
Firm diversification	-0.057	-0.046	-0.056	0.001	-0.008	-0.010
	(0.042)	(0.042)	(0.034)	(0.109)	(0.115)	(0.106)
Firm size	-0.001	-0.004	-0.005	-0.071	-0.065	-0.065
	(0.029)	(0.029)	(0.028)	(0.074)	(0.076)	(0.077)
Firm age	-0.000	-0.000	0.000	-0.002	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Performance	0.032	0.042	0.061	-0.370	-0.357	-0.355
	(0.089)	(0.090)	(0.088)	(0.244)	(0.240)	(0.251)
Financial slack	0.003	0.003	0.003	0.008	0.008	0.008
	(0.003)	(0.003)	(0.003)	(0.015)	(0.015)	(0.015)
R&D intensity	-0.000	-0.000	-0.000	-0.001*	-0.001*	-0.001*
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Acquisitions	0.036**	0.035**	0.042**	0.114*	0.115*	0.116*
	(0.016)	(0.017)	(0.018)	(0.062)	(0.062)	(0.067)
Institutional ownership	-0.047	-0.090	-0.102	0.352	0.364	0.363
	(0.102)	(0.098)	(0.097)	(0.346)	(0.346)	(0.346)
Board independence	-0.603***	-0.601***	-0.597***	1.054	1.078	1.075
	(0.210)	(0.205)	(0.200)	(0.855)	(0.861)	(0.866)
Presample patent stock	0.001	0.001	0.001	0.003*	0.003*	0.003*
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
R&D centralization	0.109	0.100	0.096	-0.302	-0.284	-0.284
	(0.082)	(0.084)	(0.083)	(0.215)	(0.215)	(0.215)
Knowledge diversity	-0.031	-0.039	-0.039	-0.060	-0.055	-0.055
	(0.041)	(0.041)	(0.039)	(0.180)	(0.184)	(0.182)
Senior team size	0.013	0.009	0.008	-0.010	-0.006	-0.006
	(0.011)	(0.011)	(0.011)	(0.033)	(0.032)	(0.032)
Senior management age	0.007	0.005	0.004	-0.008	-0.004	-0.004
	(0.006)	(0.006)	(0.007)	(0.020)	(0.021)	(0.021)
Gender composition	0.562***	0.565***	0.530***	-0.256	-0.225	-0.230
	(0.190)	(0.194)	(0.198)	(0.572)	(0.555)	(0.552)
Functional heterogeneity	-0.880*	-0.713	-0.649	3.437**	3.229**	3.227**
	(0.502)	(0.496)	(0.498)	(1.717)	(1.628)	(1.619)
Tenure heterogeneity	-0.028***	-0.023**	-0.022**	-0.058	-0.064	-0.064
	(0.009)	(0.010)	(0.010)	(0.047)	(0.048)	(0.049)
Founders	0.002	0.009	0.015	-0.134	-0.138	-0.138
	(0.039)	(0.038)	(0.037)	(0.135)	(0.134)	(0.135)
CEO research orientation	0.017	0.009	0.008	0.101	0.109	0.109
	(0.017)	(0.017)	(0.017)	(0.071)	(0.077)	(0.077)
Constant	-0.500	-0.384	-0.403	-4.152***	-4.336***	-4.324***
	(0.487)	(0.494)	(0.506)	(1.413)	(1.485)	(1.453)
Observations	1108	1108	1108	1108	1108	1108
QIC	831.53	830.86	829.4	111.9	112.07	112.24
Wald chi-square	242.91***	242.04***	261.38***	206.55***	217.79***	221.68***

Note: Table shows coefficients and robust standard errors (in parentheses) clustered by firms. All models include SIC and time dummies. Significance levels of two-tailed tests: * p <.10; ** p<.05; *** p<.01.

Figure 3.1: Marginal effect of managerial human capital given diversification



Additional analyses

In addition to considering a firm's degree of diversification, I examined how each firm's degree of strategic portfolio diversification operates as an indicator of managerial complexity faced by senior management that determines the managerial resources available for exploration. Specifically, I used the entropy measure (Palepu, 1985) to separately calculate the proportional distribution of firms' divestitures, joint ventures and alliances, and acquisitions over industry segments (using SIC codes) as well as the proportional distribution of these strategic activities over geographical segments (using country codes).[6] While such a diverse range of strategic activities is associated with innovation and firm performance (e.g., Stettner and Lavie, 2014), it may also increase the information-processing and coordination demands that divert managerial resources away from exploratory search (Hitt, 1990). The analyses using this indicator of managerial complexity resulted in a similar pattern of findings (see Appendix 3.1). Notably, strategic portfolio diversification negatively moderates managerial human capital's association with firms' propensity for emerging technology (β = -.082; p = .078). The concern

[6] To correctly identify these activities for each firm and its subsidiaries using the SDC database, I followed Villalonga and Mcgahan (2005), who provide a detailed explanation of how to measure a broad range of strategic activities, including: acquisitions (including mergers, full or majority acquisitions, and minority acquisitions), alliances (including joint ventures and other equity alliances as well as nonequity alliances), and divestitures (including spinoffs and sell-offs).

that strategic portfolio diversification operated as a mediator of the association between managerial human capital and exploratory search was reduced by nonsupportive findings in post hoc analyses.

I further investigated the nonfinding regarding firms' propensity for unfamiliar technology through estimating models in which I included the three indicators of managerial human capital separately instead of as a composite measure. This analysis (see Appendix 3.2) shows that TMT educational level is positively and significant related to firms' propensity for unfamiliar technology (β = 0.272; p = .005), whereas firms' propensity for unfamiliar technology is negatively and significant affected by TMT industry experience (β = -0.069; p = .018) and TMT company tenure (β = -0.063; p = .036). These findings suggest that managers' context-specific skills and knowledge are less applicable to searching for technologies in unfamiliar domains.

I conducted two additional analyses to check the robustness of the results in the main analyses. First, I estimated the models using panel linear regression and robust standard errors. The results from this analysis (in Appendix 3.3) were consistent with those reported in Table 3.3. Second, the Wooldridge test for autocorrelation in panel data showed first-order autocorrelation was present in the models predicting firms' propensity for unfamiliar technology. This is in line with the literature on path dependency and technology development trajectories that highlights the persistence in firm search activities (Dosi, 1982; Nelson & Winter, 1982). To account for the firm-specific factors reflected in any remaining correlation or heteroscedasticity between the residuals within the firm (which the presample "mean scaling" estimator does not account for), I estimated GEE models using a probit link function, a binomial distribution, a first-order autoregressive within-group correlation structure, and robust standard errors clustered by firm. After the removal of gaps in firm panels, the analysis on a resulting set of 132 firms and 992 observations reported results that were identical to those reported in Table 3.3 (see Appendix 3.4).

Discussion

The management literature provides ample evidence that firms' exploratory search behavior is essential to their innovation performance, growth, and long-run success. However, questions remain as to why firms show persistent differences in their search behavior in general and in their propensity for exploratory search in particular. This study explores to what extent senior management, through its strategic decisions and actions, serves as an antecedent of a firm's search behavior. It develops the argument that managerial human capital that is available to the firm is an important factor affecting the type of exploratory search by firms. Empirical evidence

from the pharmaceutical industry supports the hypothesis that managerial human capital is positively associated with firms' propensity for emerging technologies. This association is weakened by the managerial complexity faced by senior management, as indicated by a firm's level of diversification. No supporting evidence was found for the existence of these effects in predicting firms' propensity to explore unfamiliar technologies.

The findings suggest that the managerial human capital that is available to firms increases their search for emerging recently developed technologies. The knowledge and skills of experienced and well-trained managers lead them to make forward-looking strategic choices and engage in strategic actions that increase their firms' exploration of cutting-edge technologies. However, even a firm with the most experienced and talented managers can divert its managerial resources from exploratory search by confronting management with too much managerial complexity. This insight helps to explain why some firms stay ahead of their competitors by adapting to technological change and introducing new technologies, while others lose their technological leadership. It offers a behavioral explanation of why formerly leading firms are replaced by other firms that introduce a new technology (Eggers & Kaul, 2017). The leading firm may lose its technological leadership because the focus on the commercialization of its technology results in dispersed business over multiple product and geographical markets. This diversification increases managerial complexity, which, in turn, decreases the managerial human capital available for exploration of new technologies. My results, which support the executive job demands argument (Hambrick et al., 2005), also add to the literature that indicates that managerial rigidities are not only the result of managers' knowledge, skills, and limited cognitive abilities (Kaplan, 2008; Leonard-Barton, 1992). Those rigidities can also be the result of an organizational context that forces executives to shift their focus away from long-term strategic priorities such as exploratory search and innovation.

The findings are consistent with the predictions of the theoretical framework, but the negative association between managerial human capital and firms' propensity to explore unfamiliar technologies is statistically insignificance. Additional analyses show that the individual indicators of managerial human capital have conflicting effects on a firm's propensity to search beyond the core knowledge domain in which it currently operates. In line with my theoretical predictions, a firm's propensity for unfamiliar technology is significantly and negatively influenced by TMT industry-specific experience and TMT firms-specific experience. By contrast, TMT educational level, as an indicator of managers' generic skills, has a significant and positive association with a firm's propensity for unfamiliar technology. This is consistent with prior research that suggests that a high level of education makes

managers receptive to new ideas and provides them with an aptitude for boundary spanning behavior and "integrative complexity", which results in a complete understanding of technology and innovation (Bantel & Jackson, 1989; Barker & Mueller, 2002; Wiersema & Bantel, 1992, p. 99).

These findings highlight the contextual specificity of managers' skills and knowledge. The experience gained by managers while working in a specific industry and for a specific firm results in knowledge and skills that are particularly useful in this specific context and have limited transferability and applicability to other contexts. This inhibits these specific types of managerial human capital from being utilized for expansions of a firm's technological search into unfamiliar domains. In fact, since managers accumulate industry- and firm-specific knowledge and skills in a path-dependent pattern, it shapes the managerial dominant logic in such a way that it results in managerial rigidities serving as a liability to firms' propensity to explore unfamiliar technology. Whereas cognitive ability enables managers to overcome their cognitive limitations and thus enable searching in unfamiliar domains, accumulated knowledge and skills gained by managers through path-dependent firm- and industry-specific experiences increase a firm's propensity to explore familiar technologies. These insights suggest that physical and cognitive limitations such as limited resources and cognitive frames (Gavetti & Levinthal, 2000; Helfat, 1994), which restrict firms to search in the neighborhood of their existing technologies, therefore originate in both the amount as well as the type of firms' managerial human capital.

These findings also highlight that the choice of where to search is largely determined by the relation between the firm's resource base and the resource requirements of the domain that is new to the firm (Miller, 2006; Mitchell & Singh, 1993; Silverman, 1999). When firms search in directions that are consistent with their resources and capabilities, they can utilize them and capture synergy-based value. However, firms may not be able to utilize managerial human capital in unfamiliar (i.e., unrelated) domains because such capital can be context specific. The results of this study imply that managerial human capital is to some extent context specific. Managerial human capital can be utilized by firms to search for emerging technologies, as this resource results in a managerial capacity for forward-looking cognitive search. However, managerial human capital cannot be utilized by firms to search in unfamiliar (i.e., unrelated) technological domains because this resource does not result in a managerial capacity for firms to engage in cognitively distant search (Gavetti, 2012; Schumpeter, 1934).

An explanation for why managerial human capital does increase a firm's propensity for emerging technologies but does not affect its propensity for unfamiliar technologies might be

that top managers may be unable to break their firms' tendency for local search. The continuity of firm-specific R&D activities over time carries the implication that firms' innovation capabilities are tied closely to their past technological search behaviors (Helfat, 1994; Rosenkopf & Nerkar, 2001). This path dependency places firms on distinct technological trajectories (Dosi, 1982). While following this trajectory, firms develop R&D processes, competences, routines, and norms that are hard to change (Henderson & Cockburn, 1994; Nelson & Winter, 1982). Even though managers at a given firm perceive the need to change and might know where to search, their strategic choices and actions to set the firm on a path toward unfamiliar technologies ultimately are not reflected in organizational outcomes because management's efforts are counteracted by the inertial forces originating from the firm's technological trajectory (Hannan & Freeman, 1984). Hence, managerial influence does not result in deviation from the firm's path-dependent pursuit of innovation unrelated to its core technology. But it does play a role in actively leading the technological search where firms and possibly their management do have prior experience.

This study makes an important contribution to the strategy literature by exploring the origins of firms' search behaviors that underpin their innovation capabilities. Strategy scholars have long argued that firms can sustain heterogeneous innovation capabilities over time and have shown that the possession of these unique capabilities explains the emergence and persistence of interfirm performance differences (Amit & Schoemaker, 1993; Cockburn, Henderson, & Stern, 2000; Henderson & Cockburn, 1994; Teece & Dosi, 1988). While this research has considerably advanced our understanding of strategy and innovation dynamics, prior research argues that advancing our knowledge of firms' capabilities requires studies that "not only identify those factors that are correlated with superior performance but also attempt to explore the[ir] origins" (Cockburn et al., 2000, p. 1124). The insights of this study help to explain why firms' innovation capabilities tend to persist over time by emphasizing the role of senior management, its human capital, and its strategic choices and actions.

This study also contributes to the innovation and search literature. Much of this literature stresses firms' proclivity for a pursuit of local search, but few studies explore why some firms overcome learning traps and inertial tendencies of local search (e.g., Ahuja and Lampert, 2001; Rosenkopf and Nerkar, 2001). The results of this study suggest that the managerial human capital available to the firm is important. This finding reinforces and complements the results of recent research, which shows that senior management plays an important role in organizational responses to external technological change (Eggers & Kaplan, 2009; Kaplan et al., 2003). While studies have found that managerial cognition influences firms' investments

and strategic initiatives in new technology domains (Kaplan, 2008; Tripsas & Gavetti, 2000), my results show that managerial human capital influences firms' propensity for exploratory search. Interestingly, managerial human capital increases firms' propensity to explore emerging technology (i.e., experimentation with technologies that were developed within a recent time frame) but does not affect firms' propensity for unfamiliar technology. This latter lack of effect suggests a propensity for familiar technology, which requires searching to be undertaken in domains that are more local to the firm's existing technological core. This reveals a general pattern of managerial human capital leading firms to search for technologies to enforce "localness of search" over space and time (i.e., local search in terms of temporal proximity to the present as well as in terms of spatial proximity to familiar technological domains).

Lastly, this study may add to the behavioral factors that influence firms' innovative performance. Penrose (1959, p. 2) emphasized that "human motivation and conscious human decisions"—as opposed to the equilibrium models found in neoclassical economics—explain the growth of firms. Accordingly, researchers in the tradition of the behavioral theory of the firm show that firm performance and the amount of slack resources available to the firm are important predictors of innovation in firms (Greve, 2003; Nohria & Gulati, 1996). This may be the case because managers become risk seeking when slack resources are abundant and risk averse when resources are scarce (Audia & Greve, 2006; Lungeanu et al., 2016). However, research on organizational slack appears to have stagnated. Notwithstanding occasional exceptions (Chen & Miller, 2007; Greve, 2003), there has been relatively little new activity in this area (Ahuja et al., 2008). Moving beyond the literature's traditional focus on financial slack, I highlight that the managerial human capital (or "managerial slack") available to the firm is a form of nonfinancial slack that shapes search behavior that underpin firms' innovation performance. This underscores Penrose's (1959, p. 4) early insight that the managerial human capital available to the firm creates the possibilities for, provides the inducements to, and limits the rate of growth and innovation by firms.

Managerial implications

My theorizing and findings have some important managerial implications. While today's executives are well aware of the importance of innovation, what is not so well understood is what they can do to augment their firms' innovation capabilities and success. This study's insights stress that how firms use their managerial resources is at least as important as the nature of such resources because serious cognitive and organizational constraints limit a firm's capacity to attend to all paths to value creation simultaneously. When an entire management

team is overutilized, executives become caught up in day-to-day management, and biases creep into their decision making. These preoccupations lead them to devote too little time and effort to exploratory innovation. By contrast, underutilized or unevenly utilized teams are more receptive to technological change and more inclined to initiate strategic renewal, and they therefore induce exploratory innovation within the firm. Consequently, firms should free up managerial resources when they want to take new directions by asking: What will we stop doing to create the time, money, and resources required for our expansion plans? Freeing up resources in this fashion is an alternative to executive hiring aimed at bringing about alignment between the skills and knowledge of the management team and the firm's strategic agenda. This insight shows managers the strategic importance of managing and allocating human capital as a critical driver of firms' innovativeness.

Limitations and future research

This study is not without limitations. Many of these result from my choice to focus on patents as a measure of search behavior. The pharmaceutical industry presents a context where patenting is a particularly salient indicator of search and innovation, and the use of patent-based measures allowed me to test my theory in a systematic way across a range of search activities and firms. However, the choice limited the study's scope to consideration of technological outcomes that are the result of successful search processes because I could not observe innovation efforts that did not result in a patent. For a similar reason, I could not explain differences between firms in their search for pioneering technologies (i.e., technologies that do not build on any existing technologies) because the patents related to these technologies do not contain citations (Ahuja & Lampert, 2001). Besides, although research has extensively used "prior art" citations as indicators of search behavior and knowledge flows (Benner & Tushman, 2002; Eggers & Kaul, 2017; Phelps, 2010; Rosenkopf & Nerkar, 2001), they are admittedly noisy indicators due to the inclusion of examiner-added citations (Alcácer & Gittelman, 2006). If anything, however, examiners introduce common citations to the vast majority of patents in seeking to link new technologies to established technologies in the same class (Roach & Cohen, 2013). This implies that the found effects are biased downward and thus represent the lower bound of the real effects. I therefore remain confident that the patent-application process reveals substantial and valid information about search behavior.

Furthermore, I could not observe the different mandates that managers at diversified firms may have been working to fulfill and that may have led them to focus more on other strategic activities such as the commercialization of existing technologies instead of the exploration of new ones. Yet it seems reasonable to assume that my sampled firms have a strategic priority to

innovate and patent because they all patented at least once a year and they all compete in the highly dynamic pharmaceutical industry (Cohen et al., 2000). Moreover, in supplementary analyses where sales diversification as a managerial complexity is replaced by strategic portfolio diversification, which is less related to commercialization, the pattern of the findings remains consistent.

Another possible limitation is that the research setting is restricted to a single, research-intensive industry. This may limit the generalizability of this study's findings to other empirical settings such as low-technology firms or stable industries. Furthermore, because this study sampled publicly listed firms, its findings may not be generalizable to privately owned firms, unlisted technology startups, or family firms. However, human capital has been shown to spur strategic renewal and firm performance in a variety of empirical settings (Crook et al., 2011; Helfat & Martin, 2015).

Finally, there might be other indicators of human capital that may be of relevance to the managerial human capital of the firm, such as the type of education received by managers and their work experience in related industries. However, it is empirically challenging to capture all of the dimensions because human capital is a multidimensional construct (Kor & Leblebici, 2005). Instead, different indicators of human capital used over various studies may complement each other theoretically and enrich our empirical knowledge of how different dimensions of human capital can be measured (Crook et al., 2011). Moreover, I combined the dimensions of human capital into one measure of firms' managerial human capital, as previous studies in the resource-based tradition have done to measure human capital (e.g., Hitt *et al.*, 2001, 2006). This allowed me to examine how the overall managerial resources available to firms provide a firm-level capacity for exploration. However, the impact of each separate dimension on exploratory search may be interesting in isolation, as might be the theoretical mechanisms linking each dimension to the sensing, seizing, and reconfiguring tasks described in the dynamic capability literature. In fact, the preliminary findings in my additional analyses strongly encourage future inquiry in this direction.

Future research could further detail the cognitive and behavioral processes that underpin strategic decision making focused on the firm's search behavior, dynamic capabilities, and pursuit of innovation. It has long been recognized that managers' cognitive biases have a great impact on how firms approach their external environments and internal resource decisions (Amit & Schoemaker, 1993; Teece, 2007). Yet the microfoundations and related cognitive and behavioral processes underpinning the capabilities that promote firms' search behavior, strategic renewal, and innovation remain largely unexamined. Until this research area is

explored, scholarly understanding of what drives firms' innovation performance, why some firms succeed while others fail, and what, if anything, managers can do to increase the likelihood of success, will remain incomplete. Future research could also examine other forms of managerial experiences, skills, and knowledge. For instance, it may be the case that a diverse management team may lead to innovative decision making and exploratory innovation, as having such a team may increase the diversity of information sources and perspectives at the top of the firm. Alternatively, managers' experiences in related industries may induce firms to explore unfamiliar but related technologies.

Conclusion

This study suggests that firms' exploratory search behavior originates from the managerial human capital that is available to a given firm. The findings show that managerial human capital, which encompasses generic, industry-specific, and firm-specific skills, increases the firm's propensity for emerging technology. This positive association between managerial human capital and propensity for emerging technology is negatively moderated by a firm's degree of diversification. A firm's propensity for unfamiliar technology, which represents a fundamentally different search behavior, is not significantly influenced by managerial human capital or firm diversification. These results provide greater empirical support for and a better theoretical understanding of the origins of firms' innovation capabilities, highlighting the role that senior management plays in shaping firms' search behavior while also showing that cognitive biases may limit firms' exploratory search behavior.

CHAPTER 4:
Knowledge Diversity, Innovation, and the Moderating Role of Formal Structure

While the existing literature suggests that knowledge diversity spurs innovation performance, there is still only a limited understanding of how firms achieve coordination to enable knowledge exchange and combination for innovation. To address this, this study examines the role of three formal structural attributes of the firm that influence senior management's ability to resolve coordination issues across its firm's inventors. I develop rival hypotheses that the positive relation between knowledge diversity and innovation performance is either positively or negatively moderated by the administrative intensity, hierarchical structure, and functional structure of a firm's top management team. Empirical evidence from the pharmaceutical industry suggests that the positive relation between knowledge diversity and innovation performance weakens with higher administrative intensity and strengthens with higher functional structure. This study contributes to the management literature by illustrating the importance of the firm's formal structure that underpins its senior management's ability to coordinate the firm's knowledge diversity for the purposes of innovation performance.

Introduction

Understanding the determinants of technological innovation has been a central question in the management literature (Ahuja et al., 2008; Teece, 1996; Tushman & Nadler, 1986). Researchers have placed knowledge diversity at the core of firms' innovation performance (Ahuja & Lampert, 2001; Caner et al., 2017; Gruber, Harhoff, & Hoisl, 2013; Hoisl et al., 2017). More specifically, it has been argued that a higher degree of knowledge diversity within the firm creates more possibilities for knowledge recombination, which increases opportunities for technological innovation (Carnabuci & Operti, 2013; Fleming, 2001; Henderson & Clark, 1990). At the same time, however, coordination problems may arise that limit a firm's ability to seize such recombination opportunities (Ahuja & Lampert, 2001; Kaplan & Vakili, 2015).

Coordination problems in the innovation process are especially likely to arise when inventors possess diverging knowledge (Barney et al., 2018; Grant, 1996; Kogut & Zander, 1996). When knowledge among inventors becomes more dispersed over technological domains, insufficient mutual understanding and shared interpretations of goals and activities may obstruct knowledge sharing and recombination (Ahuja & Lampert, 2001; Carnabuci & Operti, 2013). The coordination of such knowledge diversity therefore constitutes a distinct

managerial challenge that requires senior management's involvement in the innovation process (Barney et al., 2018). Indeed, earlier work stresses the key role of senior management in establishing the coordination necessary to facilitate knowledge exchange and combination for innovation (Grant, 1996; Lawrence & Lorsch, 1967a).

However, we still lack a deep and empirically grounded understanding regarding what structural attributes of firms enable senior management to coordinate and facilitate knowledge exchange and combination for innovation. To offset this paucity of research and advance scholarly understanding, I focus on three structural attributes that are particularly relevant in allowing coordination by senior management: administrative intensity, hierarchical structure in top management teams (TMTs), and functional structure in TMTs. Given the dearth of empirical research on the matter, I offer a positive and negative hypothesis for each structural attribute's influence on senior management's ability to enable knowledge exchange and combination. An analysis of a fine-grained dataset of 119 pharmaceutical firms for the period between 2000 and 2011 sheds light on the matter and highlights how a firm's key structural attributes affect its senior management's ability to manage the firm's knowledge diversity and, subsequently, innovation performance. I find, for instance, that the anticipated positive relation between knowledge diversity and innovation performance weakens with increasing administrative intensity.

This study contributes to the neo-Schumpeterian recombination literature by adding to our understanding of the double-edged sword of knowledge diversity. While the literature has predominantly focused on firms' activities that increase knowledge diversity (Jung & Lee, 2016; Kaplan & Vakili, 2015), I argue that it is of equal importance to pay attention to the coordination of such knowledge diversity. More specifically, the results suggest that the positive relationship between knowledge diversity and technological innovation is significantly influenced by a firm's formal structure, which influences senior management's ability to resolve coordination issues. This insight offers a more nuanced perspective on the popular notion encountered in practice and theory that innovation is all about creativity and diversity, a position that implicitly suggests that structure and coordination imposed by senior management are harmful to innovation.

This study also complements prior research on organizing for innovation. It demonstrates that the extent to which firms reap the benefits from knowledge diversity is contingent on the organizational structure as it determines the coordination of such diversity. Indeed, formal structure has long been suggested to be part of firms' ability to innovate through technological recombination (Burns & Stalker, 1961; Lawrence & Lorsch, 1967a; Mintzberg, 1979). Yet past

research indicates that firms' innovation performance depends on their design choices regarding R&D organization structure (Argyres & Silverman, 2004; Arora et al., 2014), incentive systems (Manso, 2011), and intraorganizational networks (Grigoriou & Rothaermel, 2017; Paruchuri, 2010). I argue and show that firms' structural attributes related to their senior management explain differences in knowledge exchange, combination capabilities, and subsequent innovation performance among firms.

Theory and hypotheses

Knowledge diversity among inventors and innovation

From a Schumpeterian perspective, innovation can emerge from either a new combination of technologies or a new relationship between previously combined technologies (Fleming, 2001; Henderson & Clark, 1990). The innovation process within firms can therefore be characterized as the process by which firms' inventors create new technologies through knowledge recombination (Gruber et al., 2013; Maggitti, Smith, & Katila, 2013). Previous research has emphasized the importance of firms' combinative capability, defined as the ability to exchange and combine knowledge (Kogut & Zander, 1992; Nahapiet & Ghoshal, 1998), as it frequently underpins innovation (Fleming, 2001; Henderson & Clark, 1990). Since capabilities originate from the activities undertaken by people within firms (Leonard-Barton, 1992; Verona, 1999), a firm's combinative capability for technological innovation is particularly enabled by its ability to exchange and combine knowledge (Grant, 1996; Kogut & Zander, 1992; Smith, Collins, & Clark, 2005).

As knowledge resides within the minds of individuals, they need to contribute and recombine their knowledge for innovation (Fleming, Mingo, & Chen, 2007; Maggitti et al., 2013). This makes the pursuit of innovation a socially intensive process (Hargadon & Sutton, 1997). In this respect, research in the pharmaceutical industry shows that the knowledge that inventors hold and can access explains substantial differences between firms in innovation activities and outcomes (Grigoriou & Rothaermel, 2017, 2014). Knowledge diversity among a firm's inventors is conducive to innovation because it increases the set of possible knowledge combinations available to the firm (Carnabuci & Operti, 2013; Hargadon & Sutton, 1997). More specifically, inventors specialized in different technological areas develop distinct expertise, and combining such specialized knowledge facilitates the innovative process by enabling the firm to make novel associations and linkages between the different bodies of knowledge held by its inventors (Cohen & Levinthal, 1990). This may lead to novel interpretations of existing and newly acquired knowledge, as well as varied viewpoints regarding the solution to a given problem (Hoisl et al., 2017; Taylor & Greve, 2006). Multiple

understandings of a given problem prevent intellectual lock-in, and they prompt new ways of framing the problem that "lead to additional insights and profundity" (Ahuja & Lampert, 2001, p. 526). Studies have repeatedly shown that a diverse pool of knowledge helps firms and their inventors to identify and solve problems that could otherwise not have been addressed (Ahuja & Lampert, 2001; Cardinal, 2001; Gruber et al., 2013; Maggitti et al., 2013). The baseline hypothesis therefore states that knowledge diversity amongst a firm's inventors positively relates to the firm's innovation performance.

Hypothesis 1 (baseline): There is a positive relationship between the degree of knowledge diversity among a firm's inventors and the firm's innovation performance.

The need for coordination and the role of senior management

Given that inventors are cognitively bounded, they can only focus on a limited number of technological domains and, therefore, the technological knowledge that they possess tends to be highly specialized (Gruber et al., 2013; Maggitti et al., 2013). This also implies that the firm's overall knowledge base is dispersed over many different inventors (Carnabuci & Operti, 2013; Lawrence & Lorsch, 1967b). This results in a need for coordination in the management of knowledge diversity for innovation (Grant, 1996; Kogut & Zander, 1996). Acknowledging the existence of such a need, the literature on organizing for innovation argues that formal and informal organizational attributes serve to achieve coordination among distinct inventors and their activities and units (Conti, Gambardella, & Mariani, 2014; Lawrence & Lorsch, 1967b; Mintzberg, 1979; Teece, 1996). I argue that the need for coordination limits inventor knowledge diversity's positive returns on firms' innovation performance. This argument implies that coordination by senior management might strengthen the positive relationship between knowledge diversity and innovation performance.

Internal organization offers potential advantages for knowledge recombination and innovation because firms can have superior abilities in both exchanging and combining knowledge (Kogut & Zander, 1996). Knowledge exchange and combination across the boundaries between technological domains within firms is enabled by shared organizational codes, languages, narratives (Grant, 1996), managerial systems (Conti et al., 2014; Leonard-Barton, 1992), and other firm-specific attributes and routines (Henderson & Cockburn, 1994; Teece, 1996). Indeed, previous research shows that the organizational structure of R&D explains differences in firms' innovation activities and outcomes owing to differences in R&D decision-making authorities and information-processing structures (Argyres & Silverman, 2004; Arora et al., 2014). For instance, Cardinal (2001) shows that managerial control structures are critical to innovation in drug development because they facilitate the extent to

which firms benefit from knowledge diversity, and in particular from scientific diversity, via cross-fertilization of ideas and knowledge recombination. Other studies demonstrate how collaboration structures relate to knowledge recombination and innovation because they resemble firms' internal knowledge-exchange patterns and information-processing structures (Carnabuci & Operti, 2013; Grigoriou & Rothaermel, 2017, 2014; Hargadon & Sutton, 1997; Paruchuri, 2010).

Knowledge diversity, as such, poses distinct managerial challenges that are rooted in problems of coordination. Coordination is the alignment of actions (Barney et al., 2018; Grant, 1996). In the specific context of this study, coordination issues (such as confusion about goals, roles, and responsibilities, or lack of coordination among inventors' diverse activities and interpretations) may emerge as a firm spreads its inventors and R&D activities too thinly over technological domains. This course of action diverts resources away from the firm's primary technological context and increases fragmentation of knowledge within the firm's boundaries (Ahuja & Lampert, 2001; Caner et al., 2017; Kogut & Zander, 1996). As a result, recombination opportunities are less likely to be identified and seized because inventors fail to understand each other or to combine each other's knowledge.

Such issues of coordination call for senior management involvement in the innovation process (Barney et al., 2018). In the case of drug discovery, for example, Pisano (2006) emphasizes the powerful role of senior managers in shaping technological capabilities through decisions and actions that take place during the innovation process. Indeed, a firm's senior management is in a unique position to engage in boundary-spanning activities, acquire and process information, and develop an overview of strategic and organizational (e.g., coordination) demands across the wider firm (Jansen, Tempelaar, van den Bosch, & Volberda, 2009; Wiersema & Bantel, 1992). Moreover, TMTs often serves as the locus of control and decision making. This provides them with the authority to address coordination issues that cut across the firm and to steer innovation initiatives to ensure fit with the firm's strategic agenda (Elenkov et al., 2005). Hence, a key responsibility of senior management is to resolve the coordination issues arising from knowledge diversity to enable knowledge exchange and recombination for innovation (Grant, 1996; Lawrence & Lorsch, 1967a).

Although this is a responsibility of great importance, some management teams may differ in the extent to which they are empowered to manage their own firm's knowledge diversity. I will argue that such differences are explained by the structures that exist within the organization. The structure of an organization is typically defined as "the sum total of the ways in which it divides its labor into distinct tasks and then achieves coordination among them"

(Mintzberg, 1979, p. 2). I focus on formal structure in this paper—that is, "the documented, official relationships among members of the organization" (Mintzberg, 1979, pp. 9–10). Specifically, I focus on three fundamental structural attributes of the firm: (1) administrative intensity; (2) hierarchical structure in TMTs; and (3) functional structure in TMTs. I have chosen these attributes because they capture important aspects of both horizontal and vertical organizational structures that shape a firm's innovative behavior and capabilities, such as managerial control, authority, and specialization (Burns & Stalker, 1961; Teece, 1996; Verona, 1999). They therefore likely affect the senior management of a firm's ability to coordinate knowledge diversity during the pursuit of innovation. Research suggests that a firm's capability to exchange and combine knowledge derives from the organizational structures by which individuals (e.g., managers and inventors) and functional expertise are organized, coordinated, and communicated (Cardinal, 2001; Kogut & Zander, 1992; Nahapiet & Ghoshal, 1998).

These structural attributes relate to firms' information-processing activities—for example, decision making and communication for the purposes of task allocation and execution—within TMTs and among senior management and inventors (Grant, 1996; Hambrick et al., 2014). Processing information is central to coordination through organizational design (Galbraith, 1974; Tushman & Nadler, 1978), and it entails the need to ensure alignment in the specialist knowledge and actions of interdependent managers and inventors (Grant, 1996). Hence, these structural attributes determine the extent to which senior management can effectively intervene in the firm's innovation process by coordinating knowledge exchange and combination.

The moderating role of administrative intensity

Senior management's ability to respond to the increasing need for coordination that results from knowledge diversity is influenced by the firm's administrative intensity. Such administrative intensity is reflected in the ratio of executives to inventors. A greater number of executives per employee indicates a narrower span of control and results in a context that allows more managerial coordination and control (Andrews & Boyne, 2014; Blau & Schoenherr, 1971). Higher levels of administrative intensity can help to match the increasing need for coordination and facilitation that emerges when knowledge is dispersed across inventors and their various technological domains (Grant, 1996). Technological innovation activities are complex and often involve interdisciplinary research (Maggitti et al., 2013). This increases the extent of interdependence among inventors and their innovation activities, and it poses challenges in terms of coordination and monitoring difficulties for senior management (Cardinal, 2001; Thompson, 1967). Indeed, a narrower span of control is effective when activities have higher degrees of complexity, interdependence, and variability (Andrews &

Boyne, 2014; Blau & Schoenherr, 1971). This scenario implies a more top-down involvement of senior management, which has been shown to help in resolving coordination problems and seizing recombination opportunities (Barney et al., 2018).

Administrative intensity may also increase the connectedness and the shared social experiences (e.g., common routines, collective skills, and shared norms and language) between executives and inventors (Grant, 1996; Kogut & Zander, 1992; Nahapiet & Ghoshal, 1998). The resulting denser networks and "high bandwidth" communication channels facilitate knowledge exchange and information processing between senior management and inventors (Caner et al., 2017). Moreover, dense networks serve as a governance mechanism and encourage a greater sense of ownership of the technologies developed in the firm (Fleming et al., 2007). This improves the decision making and alignment of actions among inventors, and it increases knowledge exchange, knowledge recombination, and ultimately innovation (Carnabuci & Operti, 2013). Overall, I expect that the coordination problems that relate to increasing knowledge diversity are mitigated through higher levels of administrative intensity.

Hypothesis 2a: Administrative intensity positively moderates the relationship between knowledge diversity and innovation performance.

While a higher level of administrative intensity allows senior management to expand its span of control, it could also result in excessive management control and bureaucracy. It has been suggested that this hampers decision making, information processing, and innovation because it reduces the amount of rich information used in decision making (Cardinal, 2001; Sine, Mitsuhashi, & Kirsch, 2006). A higher ratio of executives to inventors also leads to more managerial resources for coordinating and facilitating the firm's R&D and recombination activities, which encourages micromanagement by senior management. Instead of resolving coordination issues, such micromanagement might increase them because it can increase confusion about goals, roles, and responsibilities among executives and inventors (Elenkov et al., 2005; Sine et al., 2006). Senior management is often constrained by a firm's current business and operating procedures, and so its adoption of obstructive cognitive frames and its lack of detailed knowledge may prevent it from intervening effectively in the innovation process (Leonard-Barton, 1992). As a result, managerial control and selection of ideas may actually limit the exchange and combination of knowledge and thereby inhibit innovation success (Conti et al., 2014; Katila et al., 2017). Furthermore, increased managerial control and bureaucracy limit inventors' autonomy (Burgelman, 1983b; Tushman & Nadler, 1986). Such a loss of autonomy can hamper decision making, which increases coordination problems that lower innovation brought about through knowledge recombination (Gambardella, Panico, &

Valentini, 2015; Grant, 1996). This suggests that higher levels of administrative intensity might prevent firms from benefiting from knowledge diversity among inventors and therefore lower innovation performance.

Hypothesis 2b: TMT administrative intensity negatively moderates the relationship between knowledge diversity and innovation performance.

The moderating role of top management teams' hierarchical structure

The hierarchical structure of TMTs constitutes another structural attribute that determines senior management's ability to manage knowledge diversity. Hierarchical structures become more complex when the number of hierarchical distinctions within the team increases (Hambrick et al., 2014). The hierarchical structure determines the location and concentration of authority and the reporting structure within the team, one example of which is centralized decision making and activity planning (Hambrick et al., 2014; Menz, 2012). Centralization of decision-making authority in relation to innovation offers senior management the authority to resolve coordination problems related to knowledge diversity among inventors (Barney et al., 2018). A hierarchical structure may result in a clear line of authority, which facilitates information processing and increases problem-solving efficiency and decision-making speed in firms' pursuit of innovation (Eisenhardt, 1989). For instance, the structural choice to have a chief operating officer (COO), which results in an extra hierarchical layer in TMTs, is driven by heavy organizational and executive task demands and has been found to increase senior management's ability to process information and coordinate internal operations (Hambrick & Cannella, 2004; Hambrick et al., 2014). In the context of drug development, research has also suggested that clear lines of authority reduce confusion and interpersonal competition and facilitate communication and mutual adjustment (Caner et al., 2017; Cardinal, 2001). This may help senior management to integrate managers' contradictory agendas and thereby achieve strategic congruence. I therefore expect that more hierarchically structured top management teams are better able to obtain an overarching perspective on the firm's innovation agenda, more responsive to recombination initiatives, and more effective in initiating or steering initiatives focused on knowledge sharing and combination. For these reasons, I predict that firms with higher levels of TMT hierarchical structure will benefit more from knowledge diversity in their pursuit of innovation.

Hypothesis 3a: TMT hierarchical structure positively moderates the relationship between knowledge diversity and innovation performance.

A hierarchical structure results in more hierarchical layers within management teams and may also be a reflection of the overall structure of the firm (Menz, 2012). Such additional layers not only slow down decision making, narrow communication channels, and decrease responsiveness to change but also prevent recombination opportunities and ideas from flowing from the bottom to the top of the firm (Burns & Stalker, 1961; Teece, 1996). Research shows that hierarchical structures can hamper innovation as they impose hurdles that inventors must overcome if they wish to present their new ideas and autonomous R&D initiatives within the firm (Burgelman, 1983b). I therefore hypothesize that a multilayered hierarchical structure for management teams may increase coordination problems that arise from knowledge diversity. This negatively affects senior management's ability to manage knowledge diversity and consequently decreases the firm's innovation performance.

Hypothesis 3b: TMT hierarchical structure negatively moderates the relationship between knowledge diversity and innovation performance.

The moderating role of top management teams' functional structure

The last structural attribute of firms that relates to coordination by senior management is the functional structure of the management team. In functionally structured TMTs, the roles and positions of all members are clearly defined and separated in specialized functions (Menz, 2012). Each executive is functionally specialized and responsible for only part of the firm's value-creation process, in a way that depends on the behavior and effectiveness of all other TMT members (Hambrick et al., 2014). The complexity resulting from diverse knowledge among inventors especially necessitates managerial task division and specialization (Grant, 1996; Hambrick & Cannella, 2004). Having formal and specialized functions enables senior management to increase decision-making speed and quality because "everyone knows exactly what to do" and whose role it is to do which task, and everyone has rich information available for decision making (Mintzberg, 1979, p. 83). Functional specialization allows managers to concentrate on the execution of specified and narrowly defined tasks and to accumulate task-related knowledge, and thus it enhances information-processing capabilities (Hambrick et al., 2014; Thompson, 1967). Besides, the clear role division within a strong functional structure makes it possible for managers from distinct units to reach a common frame of reference and to build understanding and agreement (Jansen et al., 2009).

Having formal and specialized functions also makes coordination of resources with other functional managers more effective because TMTs can operate as a cross-functional interface at the firm's highest management level (Jansen et al., 2009; Menz, 2012). Such an interface reflects the firm's managerial capacity for effective integration of inventors and business units

(Grant, 1996). It brings together managers from various units and results in higher levels of expertise within TMTs and facilitates interdependent decision making across organizational units (Hambrick et al., 2014; Teece, 1996). Research on the functional structure of management teams examines its relation to the structure of firms in explaining how firms achieve alignment between their strategy and organization (Menz, 2012). Some of these studies show that the presence of functional positions in TMTs positively relate to firms' innovation levels because they help to bridge organizational silos by creating synergy through strategic coherence and a shared planning process. Others argue that TMT functional structure operates as an "organizational integration mechanism" because it results in a compressive strategic perspective and establishes communication and resource-sharing channels between R&D units (Jansen et al., 2009). Following from these arguments, I expect that functional structure enables senior management to handle coordination issues of knowledge diversity and thereby facilitates the exchange and recombination of knowledge within firms. Hence, I hypothesize that TMT functional structure positively moderates knowledge diversity's relationship with innovation performance.

Hypothesis 4a: TMT functional structure positively moderates the relationship between knowledge diversity and innovation performance.

By contrast, and by extension of the previous reasoning, increasing TMT functional structure can also result in functional silos and an "us versus them" mentality within the management team and the wider firm (Menz, 2012). Functional silos increase coordination costs and decrease firms' responsiveness in dynamic environments, as such silos hamper organization-wide information-processing and decision-making processes (Burns & Stalker, 1961; Mintzberg, 1979). The "us versus them" mentality, meanwhile, prevents the firm from achieving the common understanding and mental frame required for knowledge exchange and combination (Grant, 1996; Nahapiet & Ghoshal, 1998). This might reduce cross-functional collaboration and therefore decrease the extent to which a firm is able to reap the benefits from knowledge diversity for the purposes of innovation. For these reasons, Lawrence and Lorsch (1967b, 1967a) argue that effective coordination requires a management team with less formalized and less specialized functional structures. These insights suggest that TMT functional structure increases coordination issues by limiting senior management's ability to enable knowledge exchange and combination for innovation.

Hypothesis 4b: TMT functional structure negatively moderates the relationship between knowledge diversity and innovation performance.

Method

Sample and data

I drew my sample from the pharmaceutical industry, as this sector provides an almost ideal setting for this study for three main reasons. First, the industry's relentless focus on innovation has lent critical importance to the pursuit of new technologies and to the role of senior management and inventors within it (Grigoriou & Rothaermel, 2017; Pisano, 2006). Second, the interdisciplinary nature of drug discovery makes the ability to exchange and combine knowledge effectively across the boundaries of scientific disciplines and therapeutic areas within a firm key to its innovation capacity, yet firms differ in this ability (Henderson & Cockburn, 1994; Kogut & Zander, 1992). Third, pharmaceutical firms have a strong incentive to file for patents, which makes patent data a rich data source for studies on a firm's knowledge base at the inventor level, and the success of a firm's innovation activities (Caner et al., 2017; Hall et al., 2005).

I compiled an initial list of 195 public U.S. pharmaceutical firms (SICs 2833–2836) that were among the industry's hundred largest employers at any time during the period between 2000 and 2014 according to the Compustat database and for which data were available in the BoardEx database. This sample ensured that I observed the vast majority of the innovation activity, employment, and assets in the pharmaceutical industry that originated from both large firms and their smaller counterparts. At the same time, it facilitated the data-collection process across multiple databases. I shortened the study's time panel to the 2000–2011 period to allow for a three-to-five-year lag period between patent activity (up to early 2016) and other observations to reduce truncation bias in patent citations (Fleming, 2001; Hall et al., 2005). By doing so, two firms were removed from the sample. Owing to the study's focus on firms that are actively engaged in pharmaceutical innovation, twenty-nine firms were omitted because they had fewer than five active inventors over at least one five-year time window or because they were awarded no patents during the study period (Carnabuci & Operti, 2013). Twelve firms were deleted because of gaps in their time panel or because they had fewer than two observations. After conducting listwise deletion to handle missing data, my sample consisted of 119 firms and 862 firm-year observations.

I constructed a unique firm-level panel dataset that included information on firms' senior management, inventors, R&D activities, and innovation outcomes. I first identified subsidiaries, joint ventures, and historical names using Securities and Exchange Commission (SEC) 10-K filings and company websites in order to construct detailed family trees of all firms (Caner et al., 2017). I subsequently collected data on all firms' patenting, joint venture, and

acquisition activities through extensive name matching of the entities in the family trees. More specifically, I used patent records held by the U.S. Patent and Trademark Office (USPTO) for the 1975–2016 period and joint venture and acquisition records from the Thomson Reuters SDC Platinum for the 1962–2016 period. I used data extracted from SEC filings pertaining to firm names, corporate legal forms, and the country in which the firm operates to match firms to USPTO and SDC records. I used these data sources because they match my sample of U.S. publicly listed firms. Eventually, I aggregated all data for my 117 focal firms and their wholly owned subsidiaries at the ultimate parent level to capture each focal firm's full patenting and external R&D activity (Arora et al., 2014). I identified firms' executives and gathered data on their backgrounds using the BoardEx, Execucomp, and Thomson Reuters Eikon databases; these data were complemented with hand-collected data from a rich variety of databases, such as company reports, SEC filings, Lexis Nexis, and Bloomberg Executive Profile and Biography. All financial data are from Compustat, and data on firms' ownership structures are from the Thomson Reuters Institutional Holdings (13F) database.

Dependent variable

I examined patent data to assess each firm's *innovation performance*, measured as a citation-weighted patent count (Aghion et al., 2013; Kaplan & Vakili, 2015). Technological innovations can be viewed as successful when they serve as the basis for many subsequent technical developments (Ahuja & Lampert, 2001). Specifically, I counted patents that are ultimately granted and weighted these by future citations received in each patent's grant year and the following five years. The observation year is dated by patent application year because this is the closest to the actual inventive activity. The use of a five-year citation window for all patents helps to deal with censoring. Drug patents tend to receive the highest number of citations within three to four years after application, and the bulk of citations are received within five years from grant date (Hall et al., 2005). I also included a full set of time dummies to control for the fact that patents published later in the panel had less time to be cited than did patents published earlier in the panel (Aghion et al., 2013). In addition, I corrected for patent families as they might seriously affect patent counts—for instance, by leading to a double count of new technologies.[7]

[7] Even after these extensive efforts and manual checks of patent counts, some citation-weighted patent counts of a few big pharma firm observations are still clear outliers in my dataset. The 99th percentile of the citation count variable consists of nine outliers that all relate to Johnson & Johnson. The 95th percentile of this variable is mainly observations of other big pharma firms. Winsorizing my dependent variable at the 99th or 95th percentiles or removing these outliers from the sample does not substantially alter my results.

Independent variable

I measured *knowledge diversity* as the extent to which the knowledge held by a firm's inventors is dispersed across different technological domains(Carnabuci & Operti, 2013; Gruber et al., 2013). I first matched my fine-grained patent dataset with the disambiguated inventor names provided by the FUNG database (Li et al., 2014). In the case of multiple patent assignees, I correctly assigned unique inventors to my sampled firms using inventors' historical or future patent activity. I subsequently measured knowledge diversity using Teachman's entropy index (1980). Knowledge diversity$_{t\text{-}1}$ = $\sum_{j=1}^{N} P_j \times \ln(\frac{1}{P_j})$, where P$j$ is the share of the firm's inventors who filed a patent in technology class j during the previous five years, summed over the total number of patent classes (N) in a firm's patent stock in this period (Carnabuci & Operti, 2013). Here, I considered both primary and secondary patent classifications at a three-digit class level. The index approaches ln(N) when the inventors are fully dispersed over distinct technological domains. This is a direct measure of diversity that takes into account the total number of technology classes and the distribution of inventors over these classes within the firm.

Moderator variables

I measured the three structural attributes of firms related to senior management based on data on each firm's top management team and inventors. I operationalized each firm's TMT as consisting of executives who had an executive directorship or worked at the level of senior vice president or higher (e.g., chairman, vice chairman, CEO, CFO, CxOs, executive vice presidents, and senior vice presidents). When a team consisted of only five executives or fewer, I included executives with a vice president title (Hambrick et al., 2014). This procedure maintains consistency across firms to identify senior management as the CEO and the executives with whom he or she regularly interacts to make and implement important strategic decisions (Williams et al., 2017). This empirical definition matches the study's focus on senior management's influence on the coordination of knowledge diversity in the innovation process.

Administrative intensity was measured as the number of executives in a management team divided by the total number of inventors. A higher administrative intensity score means a narrower span of control by senior management and thus greater managerial resources and control per inventor. This measure treats TMT as one of the factors of total labor capital for innovation. This measure was adapted from Blau and Schoenherr's (1971) administrative ratio measure—the ratio of administrators to employees. Classical sociological studies originally introduced the concept of administrative intensity as a reflection of the intensity of coordination issues that firms have to manage (Sine et al., 2006).

Hierarchical structure was created by standardizing and averaging the following two indicators: (1) number of distinct hierarchical levels as the number of title gradations in the management team each year (always including a CEO and possibly COO, EVPs, SVPs, and VPs); and (2) the presence of a COO; a value of 1 was given if a COO was present and 0 if one was not (Hambrick et al., 2014). The presence of COOs represents an important aspect of the hierarchical structure of TMTs, as it indicates a structural distinction between strategy formulation and implementation, adds an organizational layer to management teams, and splits the reporting structure in and to the team (Hambrick & Cannella, 2004; Hambrick et al., 2014).

Functional structure was measured as the proportion of functional titles per management team—that is, the number of executives with titles indicating they were primarily functional managers divided by the total number of executives. Each team's functional roles were coded based on Menz (2012). As an alternative measure, I also adopted Hambrick et al.'s (2014) index that measures TMT horizontal interdependence structure, which was created by standardizing and averaging two indicators: (1) functional structure, which was coded 1 if the team was based entirely on functional roles or 0 if the team consisted of multiple general managers; and (2) functional titles, which was the proportion of functional titles within the senior management team. Although this index measure resulted in a skewed distribution and troubled the interpretation of its coefficient, it resulted in very similar findings (see Appendix 4.1). Contrary to Hambrick et al.'s (2014) study that explicitly looks at interdependence among executives, this study focuses on the extent to which a TMT has a functional structure. The proportion of functional titles therefore serves as a better measurement for this study's purpose.

Control variables

I controlled for multiple variables that are widely used in research on senior management and innovation (e.g., Aghion et al., 2013; Barney et al., 2018; Williams et al., 2017). At the firm level, I controlled for *firm size* (the logarithm of the number of employees), *firm age* (the number of years since the IPO or first recording in Compustat), *financial performance* (return on assets, as net income divided by total assets), *financial slack* (current ratio, as current assets divided by current liabilities), *R&D intensity* (R&D expenditure, deflated by the consumer price index, divided by the number of employees), *R&D centralization* (the Herfindahl-Hirschman index to calculate the concentration of patent applications among the parent firm and its subsidiaries), the number of *acquisitions*, *diversification* (a Teachman's entropy index to calculate the proportional distribution of firm sales over business and geographical segments), *institutional ownership* (the proportion of outstanding shares held by institutional blockholders), *board independence* (the number of independent directors divided by board

size), and *CEO research orientation* (a score ranging from 0, indicating no research orientation, to 4, reflecting a high research orientation; the measure depends on whether the CEO holds a PhD degree in science or engineering, has academic experience, has dominant functional experience in R&D, and holds any patents prior to his or her appointment as CEO). I controlled for *founders* (the number of founders in the TMT), *TMT size* (the number of TMT members), *TMT age* (average TMT members' age), *gender composition* (the proportion of females in the TMT), *tenure heterogeneity* (the standard deviation of each executive's number of years in the TMT), *proportion PhDs* (the proportion of executives holding a PhD or MD prior to TMT appointment), *company tenure* (the team average of each executive's company tenure), and *functional heterogeneity* (the Herfindahl-Hirschman index to calculate the concentration of TMT members' primary functional backgrounds). I manually coded each manager's background and professional experience prior to appointment to the TMT using the comprehensive information that I collected on executives. Functions were categorized based on the eight-track scheme: production/operations, R&D/engineering, accounting/finance, management/administration, marketing/sales, personnel/labor relations, law, and other (Wiersema & Bantel, 1992).

I included the number of *inventors* and the number of patent *classes* to control for size-related factors in each firm's knowledge diversity and patenting activity (Carnabuci & Operti, 2013). I also controlled for the number of ultimately *granted patents* in year *t*, dated by application year and corrected by patent families (Caner et al., 2017). This means that the coefficient estimates for other independent variables capture marginal contributions to the mean impact of a firm's innovation performance. I account for variation across industry segments and time by including a full set of four-digit SIC and year dummies. All explanatory variables and controls were lagged by a one-year period (*t*-1) to reduce possible simultaneity biases and to allow for the influence of the explanatory variables to become observable in firms' innovation outcomes.

Analysis

I used generalized estimating equations (GEE) models to analyze my longitudinal data based on a count-based measure of innovation because I had multiple observations for each firm that may be correlated over repeated measures. I specified a negative binomial distribution with a log-link function because both innovation performance's mean and standard deviation (SD) (see Table 4.1) and the likelihood-ratio test indicate overdispersion of the dependent variable. To control for unobserved heterogeneity between firms, I introduced fixed effects by including the presample "mean-scaling" estimator (Blundell et al., 1995). This approach exploits the fact

that I had a long presample history on patenting behavior (of up to twenty-five years per firm) to construct the presample average of citation-weighted patents. GEE allowed me to account for firm-specific factors reflected in any remaining correlation or heteroscedasticity between the residuals within the firm (which the fixed-effects estimator does not take into account). I clustered robust standard errors by firm and modeled first-order serial autocorrelation because the Wooldridge test for serial correlation in panel-data models reported a significant test statistic.

For the tests of hypotheses 2a, 2b, 3a, 3b, 4a, and 4b, I constructed interaction terms between knowledge diversity and the three moderator variables, (i.e., administrative intensity, hierarchical structure, and functional structure).[8] I estimated the interaction effects by hierarchically entering their terms into my statistical models. Specifically, Model 1 contains only control variables. Model 2 includes the main predictor, knowledge diversity, to assess the baseline model. Models 3, 4, and 5 each introduce one of the three interaction terms. Model 6 includes all variables and interaction terms. Finally, Model 7 serves as a robustness check of Model 6 and excludes "big pharma" firms[9] from the sample. I report Wald chi-square statistics to test the overall model significance and further include the quasi-likelihood under the independence model (QIC) criterion to compare models.

Results

Table 4.1 provides descriptive statistics of all variables, and Table 4.2 shows the correlation matrix. The mean variance inflation factor (VIF) indicated concerns of multicollinearity between the size-related variables of firm size, inventors, classes, and presample patent stock. I kept these variables in my models because of the importance of controlling for size-related factors among my sampled firms. Instead, I reduced multicollinearity concerns in two ways. First, I estimated models with orthogonalized variables (see Appendix 4.2). Specifically, I orthogonalized firm size, inventors, classes, and presample patent stock using a modified Gram-Smidt procedure (Sine et al., 2006). This technique "partials out" the common variance between collinear variables. The resulting mean variance inflation factor (VIF) in the models was 3.07, which is only slightly above the commonly maintained threshold of 3. Second, I

[8] It did not make a difference whether the variables that were part of the interaction terms were mean-centered prior to constructing the interaction term or not.

[9] The big pharma firms in my sample are clearly identified by those firms that belong to the 90th percentile of firm size, or in other words, those with more than 40,450 employees. They include: Abbott Laboratories, Bristol-Myers Squibb Co., Eli Lilly and Co., Hospira, Johnson & Johnson, Merck & Co., Pfizer, Schering-Plough, and Wyeth.

examined the impact of the collinear variables following Kalnins's (2018) procedure. Specifically, I specified models that include each collinear variable (i.e., firm size, inventors, classes, and presample patent stock) alone as a control followed by a model without these variables. The signs, significance, and magnitudes of estimates were highly consistent among all models and with the models that included the orthogonalized variables. This shows that multicollinearity did not affect my results. I therefore estimated models using the original variables and report those results as the main analysis here.

Table 4.3 reports the results of the GEE negative binomial regression analyses. Model 1 shows that administrative intensity is negatively and significantly related to innovation performance (β = -1.162; p = .004). In support of baseline Hypothesis 1, Model 2 shows a strongly positive and significant relationship between knowledge diversity and innovation performance (β = 0.490; p = .002). This is an economically meaningful relationship, as increasing knowledge diversity by one standard deviation from the mean is associated with a 35.7% increase in innovation performance, on average.

In line with Hypothesis 2b, I find a negative and significant moderation effect of administrative intensity on the relationship between knowledge diversity and innovation performance (β = -1.599; p = .000) in Model 3. Model 4 reports that the interaction term between knowledge diversity and hierarchical structure positively but insignificantly relates to innovation performance (β = 0.084; p = .452). This provides no support for hypotheses 3a and 3b. The coefficient of the interaction term between knowledge diversity and functional structure in Model 5 (β = 1.716; p = .003) suggests there is a positive and significant moderation effect of functional structure on the relationship between knowledge diversity and innovation performance. This provides support for Hypothesis 4a. When all three interaction terms are included in Model 6, the signs and magnitude of the observed coefficients remain consistent. In support of Hypothesis 2b, the negative interaction term between knowledge diversity and administrative intensity remains significant (β = -1.534; p = .000). In support of Hypothesis 4a, the positive interaction term between knowledge diversity and functional structure remains statistically significant (β = 1.508; p = .010).

Since I estimated nonlinear models, I further tested the significance of the interaction terms by plotting marginal effects at the means (MEM) with 95% confidence intervals using the estimates of Model 6. The predicted values of innovation performance are calculated over the entire range of values for knowledge diversity when the moderating variable is low and high (one SD below and above its mean), while all other variables were held constant at their means. Figure 4.1 shows that the positive relationship between knowledge diversity and innovation

performance decreases as administrative intensity increases. The MEM effect of knowledge diversity on innovation performance decreases by 60.5% when administrative intensity increases from low to mean, and innovation performance decreases by 75.4% when administrative intensity increases from mean to high. This empirical evidence provides further support to Hypothesis 2b, which states that administrative intensity negatively moderates the relationship between knowledge diversity and innovation performance. Lastly, the positive moderation effect of hierarchical structure in TMTs on the relationship between knowledge diversity and innovation performance is charted in Figure 4.2. When functional structure increases from low to mean, the MEM effect of knowledge diversity on innovation performance increases by 63.8%. When functional structure increases from mean to high, the MEM effect of knowledge diversity on innovation performance increases by 37.7%. This finding provides further support for Hypothesis 4a.

Table 4.1: Descriptive statistics

		Mean	SD	Min	Median	Max
1	Innovation performance	325.97	1,466.65	0.00	34.00	17,961.00
2	Knowledge diversity	2.13	0.62	0.00	2.12	4.08
3	Administrative intensity	0.22	0.24	0.00	0.15	1.60
4	Hierarchical structure	0.00	0.69	-1.45	0.29	1.29
5	Functional structure	0.87	0.16	0.14	0.89	1.00
6	Firm size[i]	8,969.18	22,251.38	15.00	575.00	122,200.00
7	Firm age	26.23	36.19	0.00	14.00	161.00
8	Financial performance	-0.12	0.29	-1.33	-0.04	0.76
9	Financial slack	5.84	6.61	0.37	3.78	64.14
10	R&D intensity	155.12	151.03	0.65	119.71	1,285.52
11	R&D centralization	0.84	0.24	0.00	1.00	1.00
12	Acquisitions	0.47	1.04	0.00	0.00	8.00
13	Diversification	0.70	0.87	0.00	0.39	3.66
14	Institutional ownership	0.66	0.24	0.01	0.68	1.00
15	Board independence	0.82	0.09	0.50	0.85	1.00
16	CEO research orientation	1.49	1.47	0.00	1.00	4.00
17	Founders	0.39	0.68	0.00	0.00	4.00
18	TMT size	8.43	2.95	3.00	8.00	23.00
19	TMT age	50.01	3.52	38.60	50.00	60.50
20	Gender composition	0.11	0.12	0.00	0.11	0.63
21	Functional heterogeneity	0.81	0.07	0.48	0.82	0.95
22	Tenure heterogeneity	3.79	1.83	0.00	3.68	11.36
23	Proportion PhDs	0.41	0.20	0.00	0.40	1.00
24	Company tenure	7.70	3.75	1.00	7.13	31.00
25	Inventors	245.93	551.24	5.00	50.00	3,801.00
26	Classes	21.50	28.58	1.00	12.00	186.00
27	Granted patents	26.68	69.07	0.00	5.00	557.00
28	Presample patent stock	137.83	266.90	0.48	34.36	1,582.67

Note: 862 Observations. [i] Log transformed variable but original values reported here.

Table 4.2: Correlation matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Innovation performance															
2	Knowledge diversity	0.43														
3	Administrative intensity	-0.18	-0.61													
4	Hierarchical structure	-0.26	-0.16	0.15												
5	Functional structure	-0.55	-0.45	0.12	0.13											
6	Firm size	0.41	0.63	-0.41	-0.21	-0.52										
7	Firm age	0.43	0.50	-0.31	-0.19	-0.42	0.75									
8	Financial performance	0.16	0.25	-0.04	0.02	-0.26	0.51	0.32								
9	Financial slack	-0.11	-0.19	0.15	0.13	0.14	-0.36	-0.24	-0.06							
10	R&D intensity	-0.13	-0.22	0.02	0.07	0.26	-0.47	-0.26	-0.51	0.21						
11	R&D centralization	-0.41	-0.30	0.13	0.11	0.40	-0.44	-0.37	-0.24	0.19	0.19					
12	Acquisitions	0.45	0.41	-0.20	-0.12	-0.41	0.52	0.47	0.23	-0.17	-0.14	-0.44				
13	Diversification	0.31	0.54	-0.24	-0.10	-0.51	0.73	0.55	0.47	-0.32	-0.45	-0.35	0.45			
14	Institutional ownership	-0.05	0.07	-0.10	0.05	0.08	0.17	-0.01	0.27	0.01	0.01	-0.05	0.00	0.11		
15	Board independence	0.01	0.20	-0.17	-0.10	0.06	0.05	0.09	-0.03	-0.06	0.04	0.03	0.01	0.10	0.00	
16	CEO research orientation	-0.15	-0.15	-0.08	-0.01	0.17	-0.30	-0.27	-0.26	0.23	0.24	0.16	-0.14	-0.29	-0.26	0.05
17	Founders	-0.10	-0.17	0.11	0.01	0.06	-0.26	-0.26	-0.33	0.16	0.11	0.13	-0.16	-0.28	-0.05	-0.15
18	TMT size	0.34	0.52	-0.30	0.00	-0.38	0.62	0.50	0.23	-0.19	-0.08	-0.27	0.40	0.44	0.18	0.12
19	TMT age	0.11	0.12	-0.15	0.00	-0.07	0.28	0.32	0.04	-0.26	-0.08	-0.17	0.14	0.19	0.03	0.04
20	Gender composition	0.09	0.04	-0.07	-0.19	-0.01	0.07	0.13	-0.02	-0.08	0.12	-0.01	0.04	0.02	0.03	0.14
21	Functional heterogeneity	0.22	0.40	-0.16	0.05	-0.29	0.56	0.40	0.25	-0.17	-0.09	-0.24	0.30	0.35	0.25	0.09
22	Tenure heterogeneity	0.01	0.06	-0.06	0.02	-0.08	0.13	0.12	0.11	0.02	-0.13	-0.08	0.02	0.01	0.07	-0.15
23	Proportion PhDs	-0.21	-0.23	-0.06	0.08	0.26	-0.43	-0.33	-0.29	0.27	0.39	0.23	-0.19	-0.40	-0.12	-0.11
24	Company tenure	0.19	0.30	-0.21	-0.11	-0.26	0.49	0.55	0.27	-0.15	-0.26	-0.20	0.28	0.36	0.02	-0.07
25	Inventors	0.71	0.61	-0.36	-0.30	-0.53	0.71	0.78	0.27	-0.21	-0.21	-0.46	0.61	0.51	-0.04	0.13
26	Classes	0.75	0.77	-0.41	-0.28	-0.61	0.74	0.72	0.30	-0.23	-0.26	-0.44	0.58	0.60	-0.01	0.15
27	Granted patents	0.83	0.58	-0.30	-0.28	-0.55	0.62	0.65	0.24	-0.18	-0.19	-0.44	0.52	0.45	-0.06	0.09
28	Presample patent stock	0.73	0.64	-0.37	-0.29	-0.54	0.70	0.74	0.25	-0.21	-0.22	-0.41	0.55	0.50	-0.05	0.12

Table 4.2: Correlation matrix (continued)

		16	17	18	19	20	21	22	23	24	25	26	27
17	Founders	0.14											
18	TMT size	-0.21	-0.20										
19	TMT age	-0.13	-0.24	0.13									
20	Gender composition	0.12	-0.08	0.15	0.01								
21	Functional heterogeneity	-0.28	-0.20	0.83	0.12	0.14							
22	Tenure heterogeneity	-0.02	0.00	-0.02	0.26	-0.14	0.01						
23	Proportion PhDs	0.53	0.11	-0.25	-0.09	0.07	-0.39	0.06					
24	Company tenure	-0.13	-0.10	0.23	0.37	-0.04	0.17	0.54	-0.12				
25	Inventors	-0.22	-0.19	0.54	0.24	0.18	0.39	0.02	-0.26	0.39			
26	Classes	-0.24	-0.20	0.55	0.20	0.14	0.41	0.03	-0.32	0.38	0.93		
27	Granted patents	-0.19	-0.16	0.47	0.19	0.15	0.33	0.01	-0.23	0.35	0.91	0.90	
28	Presample patent stock	-0.19	-0.20	0.53	0.19	0.21	0.39	-0.01	-0.28	0.40	0.94	0.92	0.89

Note: Correlations greater than 0.07 are significant at $p < 0.05$ and those greater than 0.09 are significant at $p < 0.01$.

Table 4.3: Results predicting innovation performance

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7[i]
Knowledge diversity		0.490***	1.096***	0.504***	-1.188**	-0.383	0.636
		(0.160)	(0.246)	(0.159)	(0.557)	(0.671)	(0.587)
Knowledge diversity* Administrative intensity			-1.599***			-1.534***	-0.528
			(0.337)			(0.397)	(0.374)
Knowledge diversity* Hierarchical structure				0.084		0.179	0.254**
				(0.111)		(0.115)	(0.115)
Knowledge diversity* Functional structure					1.716***	1.508***	-0.051
					(0.577)	(0.582)	(0.489)
Administrative intensity	-1.162***	-0.795*	1.382**	-0.757*	-0.821*	1.358**	0.207
	(0.399)	(0.423)	(0.584)	(0.430)	(0.431)	(0.692)	(0.643)
Hierarchical structure	-0.038	-0.042	-0.070	-0.221	-0.058	-0.464*	-0.560**
	(0.074)	(0.073)	(0.075)	(0.255)	(0.075)	(0.269)	(0.252)
Functional structure	0.299	0.308	0.146	0.294	-3.583***	-3.307**	-0.840
	(0.443)	(0.448)	(0.412)	(0.444)	(1.380)	(1.386)	(1.153)
Firm size	0.285***	0.279***	0.216***	0.278***	0.244***	0.188***	0.001
	(0.077)	(0.077)	(0.071)	(0.077)	(0.075)	(0.070)	(0.064)
Firm age	-0.002	-0.002	-0.002	-0.002	-0.002	-0.003	-0.024***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)
Financial performance	-0.123	-0.137	-0.142	-0.140	-0.098	-0.116	-0.034
	(0.235)	(0.243)	(0.246)	(0.241)	(0.234)	(0.232)	(0.205)
Financial slack	0.003	0.003	0.003	0.003	0.001	0.002	0.000
	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.005)
R&D intensity	0.001*	0.001*	0.001	0.001*	0.001*	0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D centralization	0.304	0.299	0.285	0.306	0.314	0.303	0.194
	(0.232)	(0.240)	(0.231)	(0.243)	(0.229)	(0.224)	(0.184)
Acquisitions	-0.020	-0.016	-0.012	-0.016	-0.019	-0.015	-0.028
	(0.030)	(0.031)	(0.031)	(0.030)	(0.030)	(0.030)	(0.041)
Diversification	-0.029	-0.031	0.004	-0.034	-0.034	-0.009	-0.051
	(0.090)	(0.093)	(0.094)	(0.093)	(0.090)	(0.093)	(0.088)
Institutional ownership	0.114	0.154	0.018	0.167	0.248	0.121	0.445**
	(0.243)	(0.234)	(0.223)	(0.234)	(0.236)	(0.224)	(0.197)
Board independence	-0.868*	-0.839	-1.066*	-0.851*	-0.921*	-1.167**	-1.604***
	(0.520)	(0.516)	(0.580)	(0.507)	(0.527)	(0.558)	(0.510)
CEO research	0.049	0.048	0.029	0.049	0.052	0.035	0.006
	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.043)	(0.037)
Founders	-0.025	-0.018	-0.005	-0.020	-0.017	-0.013	-0.086
	(0.074)	(0.074)	(0.071)	(0.074)	(0.073)	(0.071)	(0.067)
TMT size	0.091***	0.086***	0.080**	0.084**	0.092***	0.079**	0.018
	(0.035)	(0.033)	(0.032)	(0.034)	(0.033)	(0.032)	(0.031)
TMT age	-0.030	-0.030	-0.024	-0.030	-0.029	-0.023	-0.012
	(0.019)	(0.019)	(0.017)	(0.019)	(0.018)	(0.017)	(0.017)
Gender composition	0.592	0.624	0.736	0.612	0.640	0.722	1.000**
	(0.523)	(0.540)	(0.578)	(0.535)	(0.543)	(0.569)	(0.450)
Functional heterogeneity	-2.303	-2.256	-1.575	-2.190	-2.423	-1.614	-0.513
	(1.944)	(1.917)	(1.922)	(1.951)	(1.870)	(1.911)	(1.313)
Tenure heterogeneity	0.046	0.038	0.041	0.038	0.050	0.054	0.106***
	(0.037)	(0.037)	(0.039)	(0.037)	(0.035)	(0.038)	(0.036)

Proportion PhDs	-0.115	-0.104	-0.035	-0.098	-0.295	-0.183	-0.230
	(0.327)	(0.323)	(0.322)	(0.329)	(0.326)	(0.328)	(0.290)
Company tenure	-0.029	-0.026	-0.022	-0.027	-0.030*	-0.028	-0.058**
	(0.019)	(0.018)	(0.017)	(0.019)	(0.018)	(0.017)	(0.024)
Inventors	-0.000	-0.000	0.000	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Classes	0.014**	0.001	-0.013	0.001	0.010	-0.004	-0.005
	(0.007)	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)	(0.011)
Granted patents	0.011***	0.011***	0.012***	0.011***	0.012***	0.013***	0.071***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)
Presample patent stock	0.000	0.000	0.000	0.000	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	4.729***	3.761**	2.945*	3.697**	7.794***	6.447***	5.042***
	(1.694)	(1.654)	(1.624)	(1.666)	(2.278)	(2.338)	(1.897)
Observations	862	862	862	862	862	862	772
QIC	8900.11	8884.00	8842.47	8880.39	8879.38	8834.96	7171.61
Wald chi-square	1191.86***	1166.25***	1557.41***	1163.94***	1239.95***	1627.14***	1422.8***

Note: Table shows coefficients and robust standard errors (in parentheses) clustered by firms. All models include SIC and time dummies. Significance levels of two-tailed tests: * p <.10; ** p<.05; *** p<.01. [i]This model excludes observations of big pharma firms.

Figure 4.1: Marginal effect of knowledge diversity given administrative intensity

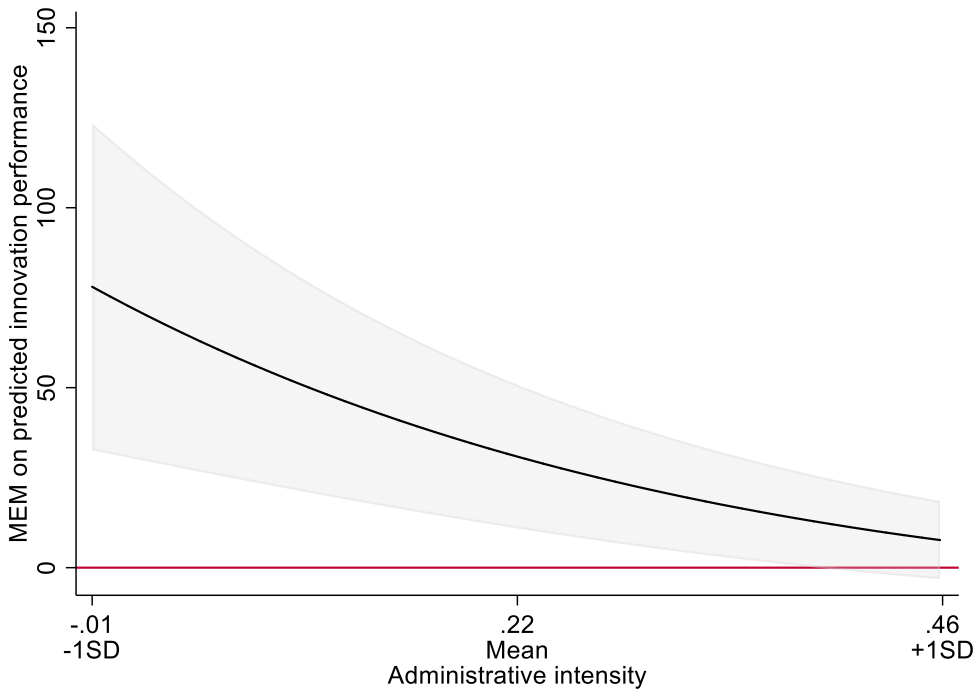
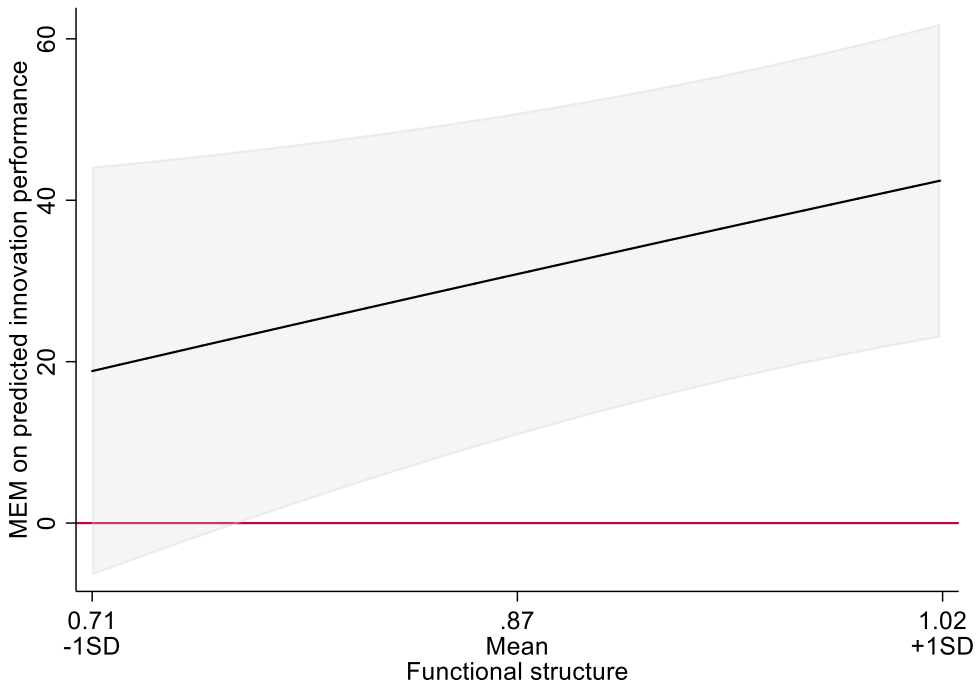


Figure 4.2: Marginal effect of knowledge diversity given functional structure



Additional analyses

I checked the robustness of these findings in three ways. First, as I have explained, I ran regression models that excluded "big pharma" companies to make sure that they did not skew my results. Big pharma companies were revealed to be significantly different, as was indicated by their scores above the 90th percentile of the distribution in any given year for the total number of employees (mean = 69,250.50; SD = 2,800.20; compared to mean = 2,288.51; SD = 190.56 for smaller firms), as well as for their age (mean = 116.29; SD = 2.87; compared to mean = 16.25; SD = .69 for smaller firms). Firms' knowledge diversity and patent activity strongly relate to their size, and how firms organize for innovation as well as the role of senior management likely differ between smaller and larger firms (Argyres & Silverman, 2004; Arora et al., 2014). The results of the analysis of the full model are presented in Model 7 in Table 4.3. Knowledge diversity is positively and significantly related to innovation performance (β = 0.336; p = .027) in the model without interaction terms. The coefficient of the interaction term between knowledge diversity and administrative intensity turns insignificant (β = -.528, p = .157), as does the coefficient of the interaction term between knowledge diversity and functional structure (β = -0.051; p = .916). The positive coefficient of the interaction term between knowledge diversity and hierarchical structure is statistically significant (β = 0.254; p = .027). This shows that the hierarchical structure of TMTs positively influences senior management's ability to coordinate its firm's knowledge diversity in a sample that excludes big pharma companies, whereas the main analyses based on the complete sample show that administrative intensity and functional structure play a significant role in determining such ability.

Second, I exploited my rich panel dataset to control for endogeneity because it enabled me to use a five-year lag of knowledge diversity as an instrument (Bettis & Gambardella, 2014). This instrument satisfies the exclusion criteria because it is unlikely that depreciated knowledge diversity affects firms' innovation performance directly (Caner et al., 2017). As expected, my instrument is positively and significantly correlated with the knowledge diversity variable (r = .77; p = .000). The Kleibergen-Paap rk Wald F statistic clearly exceeded the Stock and Yogo (2005) critical value for a maximal instrumental variable (IV) bias of 10% (i.e., 61.19 > 16.38). This confirms that my instrument is strong and that my IV estimates are not severely biased due to weak instruments. The Davidson and MacKinnon test of endogeneity is insignificant. This shows that endogeneity does not bias the parameter estimates of knowledge diversity. The results of the IV regressions are consistent with the reported findings in my main analyses (see Appendix 4.3).

Third, I tried alternative model specifications and variable constructions. Since the three structural attribute variables might be interrelated, I included each of them in the models separately. This did not alter the results reported in my main analyses. I employed models using three-year and seven-year windows for the knowledge diversity measure and by measuring knowledge diversity at the mainline subclass level (instead of at the three-digit class level). The results are highly comparable to those reported here. Furthermore, I explored whether an inverted U-shaped relationship existed between knowledge diversity and innovation. I did not find support for such a relationship. This finding is in line with previous work that uses the same fine-grained measurement of knowledge diversity (Carnabuci & Operti, 2013).

Discussion

A substantial body of work on technological innovation shows that firms' knowledge diversity increases their innovation performance (Ahuja et al., 2008). At the same time, it stresses the importance of the managerial task of establishing coordination within the firm to effectively enable knowledge exchange and combination for innovation (Grant, 1996; Nahapiet & Ghoshal, 1998; Smith et al., 2005). The extant literature fails, however, to offer specific insights or evidence on how senior management varies in its ability to manage its firm's knowledge diversity. The purpose of this study has been to examine how structural attributes of firms that underpin the managerial ability to resolve coordination issues affect the extent to which they benefit from knowledge diversity in their pursuit of innovation. I argued that a TMT's administrative intensity, hierarchical structure, and functional structure play a key role in determining senior management's ability to achieve coordination. This study's results show that the positive relation between knowledge diversity among a firm's inventors and its innovation performance weakens when administrative intensity increases and strengthens when management teams are functionally structured. However, analysis on a sample that excludes the big pharma firms shows that the positive relationship between knowledge diversity and innovation performance is strengthened when TMTs become more hierarchically structured.

These results provide insights into the competing perspectives on the role of senior management in establishing coordination for the purposes of knowledge exchange and recombination. They not only show how structural attributes of firms differ in their impact on firms' ability to innovate through knowledge diversity but also demonstrate the heterogeneity of effective structural attributes across firms of different sizes. Overall, the extent to which firms achieve coordination for knowledge exchange and recombination decreases with intense coordination and control by senior management, while it increases with functional

specialization and a clarity of roles and responsibilities within management teams. However, for smaller firms, the concentration of authority and decision-making responsibilities at senior management level is beneficial to achieving coordination for knowledge exchange and recombination. These findings are consistent with recent research that shows that the centralization of decision-making authority is beneficial for senior management's ability to manage knowledge diversity for innovation in smaller organizations (Barney et al., 2018; Sine et al., 2006). These structural attributes related to TMTs impact the amount of rich information processed and used in decision making, and they therefore shape organizational behavior and capabilities for innovation.

These findings have a number of important implications. One of their key contributions is a reinforcement of the idea that, next to diversity and creativity, coordination by senior management are important in explaining how successful firms execute innovation (e.g., Kahn et al., 2012). While the ability of senior management to establish the coordination of knowledge exchange and recombination has long been theorized and recognized to matter when it comes to innovation (Grant, 1996; Kogut & Zander, 1996), a deep and empirically grounded understanding of it is still missing. I argue and show that, to the extent there is knowledge diversity, there is a need for coordination. The extent to which senior management can effectively resolve coordination issues arising from knowledge diversity among firms' inventors significantly affects the relationship between such diversity and innovation performance. This study contributes to the innovation literature by showing that the senior management's ability to coordinate its firm's knowledge diversity is key for the firm's innovation performance.

This study adds to the organization design literature by highlighting the importance of formal structure in organizing for innovation. In the tradition of organization design, scholars have long proclaimed the necessity of alignment between a firm's strategy and its organization (Burns and Stalker 1961; Lawrence and Lorsch 1967; Mintzberg 1979). As a consequence, recent research highlights the importance of senior management's involvement in the innovation process to achieve such alignment (Barney et al., 2018; Elenkov et al., 2005). This study provides additional insights into how organizational structure can enable or constrain senior management in its task of achieving coordination for innovation brought about through knowledge diversity. My preliminary analyses also suggest that the role of managerial structures differs between larger and smaller firms. The results indicate that administrative intensity harms the ability of firms, particularly larger ones, to benefit from knowledge diversity for innovation, while the functional structure of the management team increases this

ability. For smaller firms, the concentration of authority and decision-making responsibilities at senior management level fosters such an ability. This provides a more in-depth understanding of how firms' structural attributes related to senior management affect decision making and information processing within firms and lead to differences between them in terms of innovation performance.

The findings in this study contribute to the discussion on the nature of the diversity-performance relationship in research-intensive environments. Scholars generally agree that knowledge diversity generates fundamental benefits for innovation and that greater levels of diversity imply increasing communication and coordination costs. However, some argue that these costs may at some point become so large that they could outweigh any gains from increased knowledge diversity and thus innovation performance may start to decrease. This logic suggests an inverse U-shaped relationship instead of a positive relationship. The studies that report on the existence of such a curvilinear relationship measure knowledge diversity as the extent to which patents in a firm's patent portfolio are dispersed across technology classes (Ahuja & Lampert, 2001; Caner et al., 2017). Since inventors hold and create knowledge, I instead adopt a more fine-grained conceptualization of knowledge diversity and measure to what extent the knowledge held by a firm's inventors is dispersed across different technological domains. In doing so, I respond to a recent call to examine the use of labor composition as a measure of a firm's knowledge base (Eggers & Park, 2018, p. 376), and I contribute to the growing empirical evidence that indicates a positive relationship between diversity within organizations and their performance (Cardinal, 2001; Carnabuci & Operti, 2013; Horwitz & Horwitz, 2007).

My theoretical arguments and empirical findings also relate to firms' innovation capabilities insofar as they refer to the exchange and recombination of knowledge (Kogut & Zander, 1992; Nahapiet & Ghoshal, 1998; Smith et al., 2005). The strategy literature has long been interested in the origins of capabilities, as it has been argued that they explain why firms perform differently (Carnabuci & Operti, 2013; Henderson & Cockburn, 1994). I show that differences in firms' combinative capabilities reside in the interplay between formal structure and knowledge diversity. My microanalytic approach has enabled me to more closely examine firms' structural attributes at the senior management level and firms' knowledge diversity at the inventor level. By doing so, I provide additional empirical insights into the structural microfoundations of innovation capabilities (Grigoriou & Rothaermel, 2014).

Managerial implications

The findings in this chapter have important implications for managerial practice. Attempts to create value in the modern organization through innovation and organizational restructuring have led to a recent surge in management concepts such as holacracy (Robertson, 2015), podularity (Wal & Gray, 2014), teal organizations (Laloux, 2014), delayering (Ostroff, 1999), and agile management (Rigby, Sutherland, & Takeuchi, 2016). These popular approaches view structure as a burden and management as a cost, and they choose instead to favor flatter organizational hierarchies in which individuals hold autonomy, authority, and decision-making responsibilities. Since these new organizational forms radically change the managerial structures of organizations and redefine the role of senior management, this study highlights how managerial structures relate to a firm's innovativeness. It shows managers that a firm's formal structure determines the effectiveness of its involvement in the process of innovating. Specifically, senior management's ability to manage knowledge diversity for innovation increases when the top management team is structured based on functional positions rather than on general management positions. However, this ability is limited by top-heavy administrative structures, which suggests that bureaucracy, micromanagement, and other forms of excessive managerial control by senior management decrease a firm's innovation performance. Managers should therefore be aware that their role varies with organizational structure, as it changes their playing field and how they should operate within it.

Limitations and future research

The findings of this study should be viewed in light of some limitations. First, this study's focus is on how the firm's structural attributes related to TMTs affect coordination (alignment of actions), but these attributes may also affect cooperation (alignment of interests). Cooperation issues impede knowledge sharing and communication between disparate inventors and R&D units as a result of low organizational commitment, citizenship behavior, mistrust, and other problems of moral hazard (Grant, 1996). Firms' incentive systems are another organizational design element that plays a critical role in motivating human capital in knowledge-intensive activities but that continues to puzzle managers and researchers (Gambardella et al., 2015; Manso, 2011). Henderson and Cockburn (1994), for instance, find that firms with systems that encourage inventors to work together and develop knowledge across disciplinary and therapeutic domains within the firm are significantly more productive in terms of drug discoveries. I am not able to tease out whether the structural attributes of the firms in this study are related to coordination or cooperation issues. Second, I took great effort in examining size-related differences among firms, but I cannot completely rule out the

capturing of size-related effects. Third, although this study's findings may be generalizable to other research-intensive industries, future research should examine whether my proposed theory is transferable to other industries.

Future research could explore how middle and lower management play a role in handling coordination issues, or it could identify the subgroups that are primarily responsible for certain types of decisions or specific domains of action and managerial tasks. Indeed, my interviews with pharmaceutical firms reveal that it is common, particularly among larger firms, to set up an R&D council or innovation committee composed mostly of middle managers and chief scientists and only one or a few top executives to ensure direct report and support channels to senior management. Another promising direction of future research is knowledge exchange and combination across the firm's boundaries. This study focuses on knowledge exchange and combination for innovation within firms, but external knowledge is another important source of innovation.

Conclusion

Existing research explains how increasing knowledge diversity within firms enhances their innovative performance, but it left unaddressed a related question of pivotal theoretical and practical relevance: How can the requirement for coordination arising from knowledge diversity be managed to improve innovation performance? This study suggests that a firm's formal structure influences senior management's ability to coordinate knowledge exchange and combination for technological innovation. The results show that TMT administrative intensity decreases firms' ability to innovate, whereas functional structure increases it. This provides new insights into the origins of innovation capabilities and the differences between firms in innovation performance.

CHAPTER 5:
Conclusion

The need for technological innovation can hardly be overemphasized in the context of the fast-paced change that characterizes numerous business sectors. New technologies increasingly provide key opportunities for organizational adaptation and corporate rejuvenation as they can destroy whole businesses and create new ones (Christensen, 1997; Eggers & Park, 2018). Despite the importance of innovation for firms' survival, they differ widely in terms of their innovative performance. Prior research explains these differences by focusing on how firms organize for innovation and on their resources and capabilities (Ahuja et al., 2008; Teece, 1996). Whereas the impact of top executives on organizations has dramatically increased in recent decades (Quigley & Hambrick, 2015), our understanding of the role of senior management in the directing of innovation and its firm's creation of new technologies remains in its infancy. This suggests that inquiry into the antecedents of technological innovation is more than a fundamental research issue; it is key to our understanding of how managers shape the fates and fortunes of firms. This dissertation has described to what extent, in what specific ways, and under what conditions senior management influences a firm's strategic behavior in relation to innovation, as well as how such behavior translates into technological innovation.

The first study in this dissertation examined what, when, and how CEO characteristics influence firms' innovation outcomes. This study argued and showed that research-oriented CEOs have a positive and economically significant impact on their firms' technological innovation. It also showed that CEO duality and slack resources positively moderate this positive association between CEO research orientation and firms' innovation outcomes. This finding implies that the influence of research-oriented CEOs on innovation depends on the organizational context in which they operate. This study also finds that the strategic choice for an intense R&D investment strategy partially mediates the relationship between CEO research orientation and innovation outcomes. The implementation of an R&D-intensive strategy by research-oriented CEOs decreases the extent to which firms' R&D investments translate into innovation outcomes. However, this negative strategy-implementation effect is not found in models predicting the quality of new technologies. This suggests that research-oriented CEOs aim for quality, instead of quantity, in terms of their firms' innovation outcomes.

The second study examined how the managerial human capital that is available to the firm affects its exploratory search behavior. The results suggest that the bundle of managerial human capital—which comprises the generic, industry-specific, and firm-specific skills and knowledge of all top executives in a management team—positively affects a firm's propensity

to explore emerging technologies. However, this positive relation weakens as a firm's level of diversification increases, suggesting that the increased levels of managerial complexity associated with diversification decrease the managerial resources available to the firm for exploratory search. Interestingly, managerial human capital does not significantly affect a firm's propensity for unfamiliar technology. This underscores the path-dependent force that largely determines a firm's technological trajectory and thus the direction of technological search behavior.

The third study reported in this dissertation examined how the formal structure of a firm influences its senior management's ability to coordinate knowledge diversity for technological innovation. After establishing the baseline hypotheses that there is a positive relation between firms' knowledge diversity and their innovation performance, this study finds that this baseline is negatively moderated by administrative intensity and positively moderated by the functional structure of top management teams. Furthermore, additional analysis of a sample that excludes large firms also shows that hierarchical structure has a positive moderation effect on the relationship between knowledge diversity and innovation performance. These results provide insights into the competing perspectives on the role of senior management in establishing coordination for knowledge exchange and recombination, and thereby in shaping organizational capabilities for innovation. Table 5.1 gives an overview of the hypotheses tested across the three studies in this dissertation and the empirical results obtained.

While each of the three studies focuses on a distinct research question, they all contribute to this dissertation's common research theme, namely how top managers influence innovation performance at their firm. The mechanisms underlying the managerial influence on technological innovation examined in these three studies are similar. In each study, the characteristics related to senior management (i.e., CEOs' aptitude and motivation for science and technology, executives' knowledge and skills, and management team structures) shape executives' strategic choices and actions, which in turn affect firms' technological search behavior and innovation performance. Moreover, the studies also explored the interdependencies between senior management characteristics and organizational contextual factors (e.g., firms' formal structure and diversification), as the organizational context impacts both the firm's strategic leadership process as well as its innovation processes.

Table 5.1: Overview of the three empirical studies

	Chapter 2	Chapter 3	Chapter 4
Title	CEO Research Orientation, Organizational Context, and Innovation.	Managerial Human Capital, Diversification, and Exploratory Search.	Knowledge Diversity, Innovation, and the Moderating Role of Formal Structure
Research question	What CEO characteristics positively impact firms' innovation outcomes, and when and how do they do so?	How does the managerial human capital that is available to the firm affect its propensity for exploratory search?	How does the formal structure of a firm influence senior management's ability to coordinate knowledge diversity for innovation?
Theory	Upper echelons perspective.	Resource-based view of the firm.	Organization design.
Dependent variable	Patent application count.	Exploratory patent citation ratio.	Citation-weighted patent count.
Explanatory variable	CEO research orientation (i.e., PhD degree; academic experience; R&D experience; patent holder).	Managerial human capital (i.e., TMT educational level; TMT industry experience; TMT company tenure).	Knowledge diversity.
Moderator variable(s)	CEO duality, slack resources, and firm age.	Firm diversification.	Administrative intensity, TMT hierarchical structure, and TMT functional structure.
Results	• CEO's exhibit considerable heterogeneity in their CEO research orientation (CEO RO). • CEO RO is positively related to firms' innovation outcomes. • CEO duality increases the positive relation between CEO RO and innovation. • Slack resources increase the positive relation between CEO RO and innovation. • R&D intensity partially mediates the positive relation between CEO RO and innovation. • CEO RO decreases the positive relation between R&D intensity and innovation.	• Exploring unfamiliar technology and exploring emerging technology are two distinct exploratory search behaviors. • Managerial human capital is positively related to a firm's propensity to explore emerging technologies. • A firm's level of diversification decreases the positive relation between managerial human capital and emerging technology. • Managerial human capital and its interplay with diversification do not significantly affect a firm's propensity to explore unfamiliar technologies.	• Knowledge diversity among a firm's inventors is positively related to the firm's innovation performance. • Administrative intensity decreases the relation between knowledge diversity and innovation. • TMT functional structure increases the relation between knowledge diversity and innovation. • In a sample excluding big pharma firms, TMT hierarchical structure increases the relation between knowledge diversity and innovation.

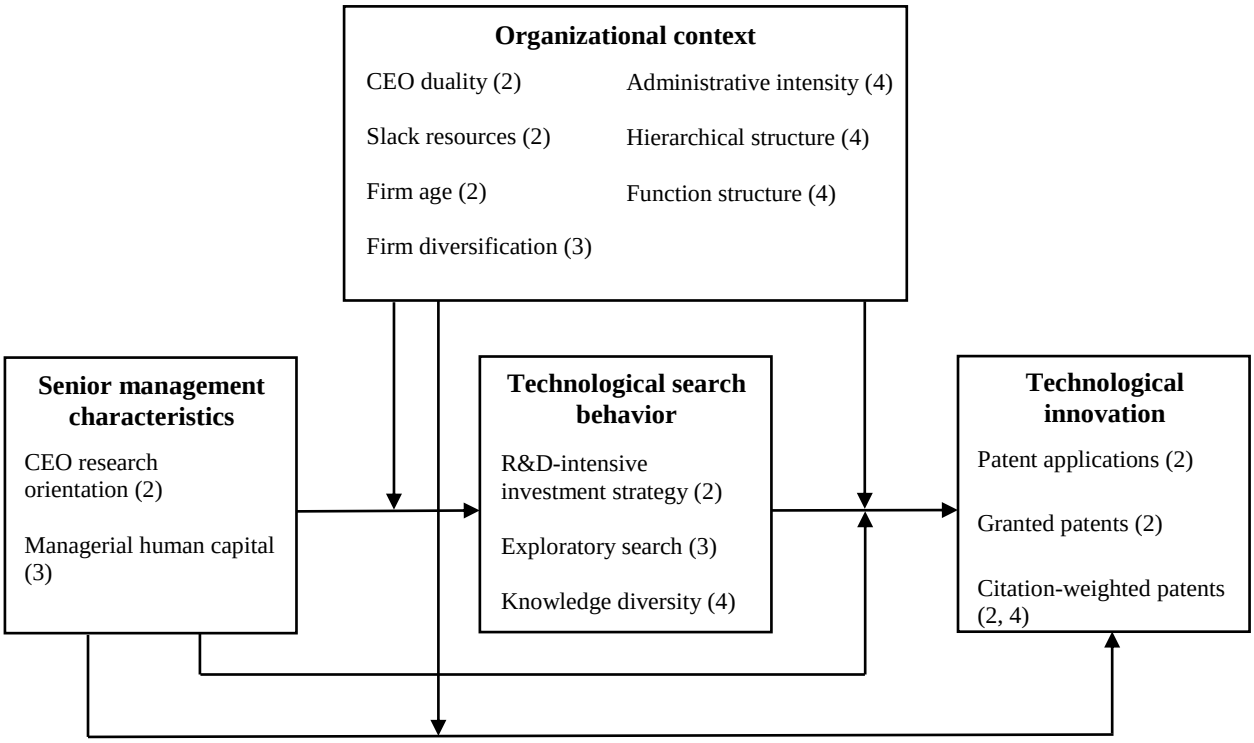
There are significant complementarities between the three studies. Each study explores a particular aspect of the causal chain that links senior management characteristics to technological innovation. While the first study sheds light on how the CEO, as the chief decision maker in a corporation, influences technological innovation, the second study focuses on how the human capital of all executives in a given management team affects such innovation. These two studies explain how senior management characteristics, through strategic choices and actions related to innovation strategy and search behavior, directly or indirectly influence technological innovation. The third study focuses on the later stage of the causal chain through which senior management influences technological innovation. It examines the moderating the role of senior management in the firm's innovation process, focusing on how TMT structure affects senior management's ability to resolve coordination problems that can arise from knowledge diversity.

Moreover, the three studies explain different performance indicators of technological innovation. The first study focuses on three measures of firms' innovative output by counting the number of patent applications, patents granted, and citations that a patent receives following its approval. The latter metric reflects the impact or novelty of a patent. The second study investigates how executives have an impact on a key strategic behavior for innovation, namely exploratory search. It observes search behavior in the outcomes of search processes by examining the citations of a firm's patents. The citation-weighted patent count, compared to the other two simpler patent counts, is the least directly controllable by senior management. The third study therefore examines the variation between firms in this performance measure of innovation by studying the contingent impact of senior management on the innovation process of translating knowledge diversity among a firm's inventors into new impactful technologies.

Another complementarity between the three studies is that they examine multiple contextual factors (i.e. moderator variables) at CEO, TMT, and firm level and their interdependencies with senior management characteristics in shaping firms' search behavior and subsequent innovative performance. The first and second study acknowledge that the organizational context impacts the firm's strategic leadership process. They therefore explore the interdependencies between senior management characteristics and organizational contextual factors in explaining differences between firms in search behavior and innovation performance. The third study acknowledges that the innovation process is embedded in the wider organizational context, of which strategic leadership and formal structure are important elements to consider, in explaining differences between firms in the management of innovation.

Together, the three studies provide valuable insights into how senior management characteristics impact technological innovation through managers' strategic choices and actions. These studies do so via a more inclusive set of ways and conditions than one study alone could achieve. As a result, this dissertation provides a deeper and more comprehensive understanding of the extent to which, in what specific ways, and under what conditions a firm's senior management influences the firm's strategic innovation-related behavior and how this behavior translates into technological innovation. Figure 5.1 depicts the conceptual framework presented in the Introduction of this dissertation, but here it is enriched with the main findings from the studies featured in this dissertation.

Figure 5.1: Detailed conceptual framework of this dissertation



Note: the number in parentheses indicates the relation of a concept to a chapter.

Contributions

This dissertation makes important contributions to the strategic management literature. One such contribution is the integration of the strategy and innovation literatures through the development and testing of a comprehensive framework focused on how senior management characteristics influence organizations' strategic behavior and innovation performance. Although in recent years scholars have taken the first steps toward showing that executives might influence technological innovation (Balsmeier & Buchwald, 2014; Cummings & Knott, 2018; Custódio et al., 2017), and despite immense efforts to understand the determinants of

technological innovation (Ahuja et al., 2008), surprisingly little is known about how executives specifically influence technological innovation. This dissertation recognizes the mutual relevance of the strategy and innovation literatures and combines theory from both of them to unravel the complex causal chain between the characteristics, strategic decisions, and actions of a firm's senior management on the one hand and the translation of these into concrete innovation activities and outcomes on the other hand.

Scholars increasingly argue that studying a direct relationship between senior management characteristics and organizational performance may be something of a stretch because such an approach overlooks the organizational processes and mechanisms that link those characteristics and related strategic choices to organizational activities and outcomes (Hambrick, 2007; Li et al., 2013; Liu et al., 2018; Talke et al., 2010). The three studies in this dissertation open up this proverbial black box of organizational processes through which executives' strategic choices and actions "cascade down" the organization and translate into a firm's technological innovation outcomes. The results indicate that senior management impacts technological innovation through its strategic choice for and implementation of an R&D-intensive investment strategy (Chapter 2), its strategic actions and the organizational processes that underpin the firm's innovation capabilities (Chapter 3), and its ability to coordinate in order to enable knowledge exchange and recombination among the firm's inventors (Chapter 4). As a result, this dissertation fills in an important gap between what happens at the upper echelons and how this affects activities at the lower echelons within the organization.

Through making such a contribution, the dissertation contributes to the wider debate on whether and how senior management impacts overall organizational performance. Some organizational theorists argue that executives' decisions and actions have little to no impact on the organizations that they lead because they face enormous constraints due to organizational inertia or institutional pressures to conform to social norms (DiMaggio & Powell, 1983; Hannan & Freeman, 1984). However, the findings of this dissertation show that top managers do matter when it comes to technological innovations. This insight highlights the pivotal role played by leaders in driving change and long-term success at their companies (Hambrick & Mason, 1984). This adds depth to our understanding of why some organizations adapt effectively to changing environmental circumstances while others do not.

This dissertation even moves beyond this debate by specifically addressing when senior management impacts firms' innovation performance (Liu et al., 2018). In a response to recent calls, this dissertation considers the conditions under which executives operate in explaining their strategic behavior and impact in relation to organizational performance in general

(Busenbark et al., 2016; Liu et al., 2018; Wowak et al., 2017) and innovation in particular (Simsek et al., 2015). As a result, it provides a more comprehensive view of how top executives, in their interplay with the organizational context, affect technological innovation at firms. The findings of the three studies not only demonstrate that the organizational context determines the degree of managerial discretion over the firm's innovation agenda (Chapter 2) but also reveal that the level of managerial resources available to the firm for innovation (Chapter 3) and senior management's ability to coordinate (Chapter 4) vary along with such a context.

The results of this dissertation contribute to the innovation literature by shedding more light on the microfoundations of firms' strategy and capabilities related to innovation. The findings suggest that differences between firms in terms of their ability and motivation to innovate result from the idiosyncrasies of their top managers. It is not only the human capital of CEOs (Chapter 2) and other top managers (Chapter 3) but also the formal structures related to management teams (Chapter 4) that serve as key antecedents of variation in firms' strategy choices and abilities to innovate as well as in the attendant performance consequences. Additionally, the results show that the influence of senior management on a firm's ability and motivation to innovate can be either enhanced or constrained by the organizational conditions under which the firm and its management operate. Taken as a whole, this dissertation contributes to research on firms' pursuit of new technologies and their success (Ahuja et al., 2008; Henderson, 1993), and it moves past the literature's traditional focus by highlighting the behavioral aspects of this pursuit (Eggers & Kaul, 2017).

Scholars have long acknowledged that firms develop capabilities and gain a competitive advantage through people (Pfeffer, 1994). Despite repeated calls for further examination of the role of the "human element" in the development of innovation capabilities (Li et al., 2013; Maggitti et al., 2013; O'Connor & McDermott, 2004), this area has been remarkably absent in the innovation literature. Instead, prior innovation research predominantly focused on firm-level factors such as organizational structures, processes, and routines to explain where innovation capabilities reside (e.g., Carnabuci & Operti, 2013; Grigoriou & Rothaermel, 2014). It is important to note here that such lack of attention to the individual is not to be found in the classical studies that underpin the literature on innovation (Chandler, 1977; Penrose, 1959; Schumpeter, 1950). Schumpeter (1950) makes it clear that it is the entrepreneur (or the entrepreneurial manager) who puts new combinations to work by directly assembling, allocating, and commanding the necessary resources. For Penrose (1959), the limits to a firm's growth and innovation are not bound by a production function but by the managerial talent and

experience that is available to the firm. The three studies in this dissertation highlight that the missing focus on individuals amounts to a substantial gap in the innovation literature by showing that executives and their human capital are important factors that shape firms' innovation capabilities alongside the relevant firm-level factors.

This dissertation also underscores the increasing awareness among innovation scholars that interfirm heterogeneity in technological innovation is driven by unobserved antecedents to innovation that can be found at different levels of analyses (Rothaermel & Hess, 2007; Slater, Mohr, & Sengupta, 2014; Talke et al., 2010). In most studies on firms' innovation activities and their associated performance outcomes, unexpected or unexplained findings are quite commonly attributed to "unobserved heterogeneity" (e.g., Phelps, 2010). A term that refers to the possibility that unmeasured differences among observationally equivalent firms affect their innovation performance. These differences may typically stem from unmeasured, systematic factors that will not be adequately captured by the standard controls—for example, firm age, size, and R&D intensity—that are typically used in most studies on innovation (Ahuja et al., 2008). This dissertation shows that senior management is a key source of unobserved heterogeneity in innovation strategies and innovation performance. Comparing the effect sizes of the empirical results in this dissertation even shows that CEO research orientation and managerial human capital have greater explanatory power than do other key explanatory variables for innovation, such as financial slack, financial performance, and R&D centralization.

Researchers also attribute differences in innovation performance to underlying differences in how firms execute innovation activities and other aspects of "project level" heterogeneity (Talke et al., 2010). In this respect, an often overlooked key aspect of the management of innovation is the distinction between the role of organizational conditions for innovation, the innovation execution process itself, and the interface between them. Van de Ven (1986, p. 598) stresses that this is "perhaps the most significant structural problem in managing complex organizations today, and innovation in particular." This dissertation takes a first step in integrating two streams in the innovation literature that have thus far mostly developed separately. The first of these is the execution-oriented, "project level" focused literature stream on the best practices for new product development and other innovation activities and processes (e.g., Kahn et al., 2012). The other stream comprises the literature on organizing for innovation through alignment of organizational conditions such as strategy, leadership, organizational structure, and culture (e.g., Danneels, 2008; O'Connor, 2008; Slater et al., 2014). This dissertation's research framework and its underlying mechanisms highlight the complex

interplay between the project-level elements and the organizational-level ones. This dissertation also reveals that achieving and maintaining alignment between these two sets of elements is crucial for achieving success in innovation.

Managerial implications

In addition to the managerial implications discussed in each study, there are two key takeaways related to this dissertation that inform how businesses could approach their activities in general. The first is that the strategic choices and actions of managers have important long-term consequences through their impact on organizations' success in technological innovation. That few companies are immune to the brutal forces of creative destruction is perhaps best revealed by the fact that the typical lifespan of a publicly traded company is about ten years only (Daepp, Hamilton, West, & Bettencourt, 2015). Moreover, the pace at which companies lose their market-leadership positions—if one uses inclusion in the S&P 500 as an indicator of such a position—is accelerating. Whereas the average lifespan of companies on the S&P 500 was thirty-three years in 1964, this period had narrowed to twenty-four years by 2016, and forecasts indicate that it will have shrunk to just twelve years by 2027 (Anthony, Viguerie, Schwartz, & Van Landeghem, 2018). This implies that about half of today's S&P 500 companies will be replaced by newcomers in the next ten years. These insights stress that today's globalized, digitalized, and fast-changing world requires organizations and their managers to continually search for new business opportunities, develop new technologies, and enter new markets. Leaders should give up on the idea of a sustainable competitive advantage and admit that any advantage is transient. Once they accept this idea, they will soon realize that the only winning strategy for organizations is one that centers on innovation. Only then will their organization survive and thrive in the future.

The second key takeaway of this dissertation is that companies can effectively organize for innovation and that human capital is an often overlooked yet very important element of the innovative organization—that is, an organization that integrates innovation and entrepreneurial activities into its strategy and business model to achieve and maintain a competitive advantage. While the allocation of financial capital has long been recognized as a critical driver of innovation performance, the value of the allocation and management of human capital is less widely recognized. Nonetheless, the importance of the latter has long been recognized by the world's leading innovators, as the following remark made two decades ago by Steve Jobs (1998) indicates: "Innovation has nothing to do with how many R&D dollars you have. When Apple came up with the Mac, IBM was spending at least 100 times more on R&D. It's not

about money. It's about the people you have, how you're led, and how much you get it." One of the key insights of this dissertation is therefore that increasing the firm's innovation performance may not stem from ongoing investments in R&D alone: consciously designing a firm's executive team and the supporting organizational context so that innovation can take place may be at least as important when it comes to reaping the full benefits of R&D investments and boosting a firm's innovation performance and future competitive advantage.

Limitations and future research

This dissertation has limitations that merit discussion and result in promising areas for future research. First, there is an exclusive focus on the generation of technological innovations throughout the studies in this dissertation. Certainly, technological innovation is the main engine of growth and an important creator of economic value. However, some important innovations may have little to do with new technology and may instead entail a change in business models and other organizational or management innovations. In addition, this dissertation conceptualizes innovation as an outcome, while innovation could also be understood as processes pertaining to the generation, development, and implementation of ideas (Garud et al., 2013) or as the adoption of new ideas rather than the creation of new ones (Cohen & Levinthal, 1990; Damanpour & Schneider, 2006). Indeed, the innovative performance of firms depends on both the creation of new technology and the commercialization of it. While this dissertation focuses on the creation of new technology, several other research opportunities arise from studying the role of senior management based on these alternative perspectives on innovation.

Second, the senior management characteristics examined in this dissertation are observable background characteristics such as formal education and work experiences. These characteristics serve as strong indicators of the skills and knowledge repertoire of managers in Chapter 3. However, such characteristics might be more noisy indicators of managers' cognitive attributes, values, and personalities, such as the research orientation of CEOs in Chapter 2. Although these indicators may contain more noise compared to pure psychological measures and are therefore less likely to yield significant findings, this drawback at the same time operates as a stringent test of the upper echelons perspective (Hambrick & Mason, 1984). Nevertheless, there have been repeated calls to use measurements of psychological constructs related to executives' motives, emotions, and behavior (e.g., speech and leadership styles) (Wowak et al., 2017). With recent developments in measures and with the emergence of complementary theories (Liu et al., 2018), there is ample opportunity for scholars to

supplement simplistic measures of demographic profiles with richer measures of mechanisms and processes that affect top managers' cognition, values, perceptions, and, consequently, strategic choices.

Third, this dissertation tries to unravel the complex causal chain that links senior management to technological innovation through the development of a comprehensive research framework. The core assumption here is that a given executive makes choices and acts, and in doing so he or she influences the firm's strategy and eventually its innovative performance. Yet, as is typical of many inquiries in the social sciences, this link is plagued with potential issues of reverse causality and endogeneity. Despite extensive efforts to control for and eliminate these issues, ranging from conscious study design to state-of-the-art econometrics, the findings still need to be interpreted with caution. In a sense, the best way to strengthen the causal claim in research frameworks such as the one in this dissertation is through the development and testing of detailed theoretical mechanisms and through focusing on the conditions under which these mechanisms vary to better tease out the working mechanisms. Such steps can be helpful in understanding the relationship between senior management and innovation insofar as the empirical results are in line with the theoretical predictions. Although this is largely the case in this dissertation, future research could further explore the link between processes and practices at the senior management level and organizational-level outcomes in order to further unravel this complex yet important causal chain.

Fourth, a core assertion of the strategic management literature is that organizational performance is the result of alignment between a firm's strategy, its organization, and its environment. This dissertation does consider the alignment between strategy and organization, but it lacks a detailed assessment of their alignment with the technological, legal, and competitive environments. The latter fall outside the scope of this dissertation as it focuses on the internal organization of technological innovation. This dissertation does treat the external environment as a background variable by controlling for macroeconomic and industry-specific variation using SIC and year dummies. This suffices here because the sampled firms and their managers face a fairly uniform external environment, as the research setting is publicly listed U.S. pharmaceutical firms. Moreover, even within a single industry, where managers face the same external environment, time-varying corporate effects associated with corporate-level managerial decisions are statistically significant (Adner & Helfat, 2003). Nevertheless, it would be interesting for future research to consider the role of the external environment in the current research framework. Prior research, for instance, shows that top managers significantly differ in their responses to external technological change and that the success of these responses

depends on whether they view such change as an opportunity rather than as a threat (Gilbert, 2006). Future research could thus examine how senior management's interpretation and awareness of the external environment affect their strategic behavior related to innovation.

Fifth, this dissertation assumes that a firm's top executives are responsible for and involved in strategic decision-making processes for technological innovation. However, it does not observe who is actually involved in this process and what an individual's specific contributions are. Another promising direction of future research would be to identify the subgroups who are primarily responsible for certain types of decisions or specific domains of action (Hambrick, 2007). For example, if a study tries to predict organizational outcomes related to technological innovation, it may make sense to consider the relevant decision body to consist of the CEO, CFO, VP of R&D, VP of marketing, and possibly R&D staff at lower levels of firms. But other executives, such as the COO or VP of communication, could be excluded. This is a promising line of thought that requires firsthand data about the involvement of various executives in specified decision domains and strategic situations. Despite such analytic challenges, the study of the varying involvement of different executives in different decision domains and strategic situations could be one of the next research frontiers for upper echelons scholars.

Finally, although the unique characteristics of the pharmaceutical industry (e.g., the strategic priority it attaches to innovation and the availability of detailed and reliable data on the sector) provide a strong research setting, they may limit the generalizability of this study's findings to other empirical settings. The complex scientific nature of innovation in the pharmaceutical industry involves interdisciplinary R&D activities and knowledge recombination across technological domains. The view of innovation as a process of searching and recombining existing knowledge elements has been adopted in several industries (for a review, see Savino et al., 2017). Hargadon and Sutton (1997), for instance, describe how a product design firm creates technological solutions and develops innovative products by combining ideas and technologies from various industries. Hence, the findings in this dissertation may be generalizable to other research-intensive industries and other environments where technology and human capital are core assets, but future research should examine whether this is the case.

REFERENCES

Adner, R., & Helfat, C. E. C. 2003. Corporate effects and dynamic managerial capabilities. *Strategic Management Journal*, 24(10): 1011–1025.

Aghion, P., Akcigit, U., & Howitt, P. W. 2014. What do we learn from Schumpeterian growth theory? *Handbook of Economic Growth* (pp. 515–563). Elsevier.

Aghion, P., & Howitt, P. W. 2008. *The economics of growth*. MIT press.

Aghion, P., Van Reenen, J., & Zingales, L. 2013. Innovation and institutional ownership. *American Economic Review*, 103(1): 277–304.

Ahuja, G., & Katila, R. 2001. Technological acquisition and the innovation performance of acquiring firms: A longitudinal study. *Strategic Management Journal*, 22(3): 197–220.

Ahuja, G., & 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.

Ahuja, G., Lampert, C. M., & Tandon, V. 2008. Moving beyond Schumpeter: Management research on the determinants of technological innovation. *The Academy of Management Annals*, 2(1): 1–98.

Ahuja, G., Lampert, C. M., & Tandon, V. 2014. Paradigm-changing vs. Paradigm-deepening innovation: How firm scope influences firm technological response to shocks. *Organization Science*, 25(3): 653–669.

Alcácer, J., & Gittelman, M. 2006. Patent citations as a measure of knowledge flows: The influence of examiner citations. *Review of Economics and Statistics*, 88(4): 774–779.

Amit, R., & Schoemaker, P. J. H. 1993. Strategic assets and organizational rent. *Strategic Management Journal*, 14(1): 33–46.

Andrew, J., Manget, J., Michael, M., Taylor, T., & Zablit, H. 2010. *Innovation 2010*.

Andrews, R., & Boyne, G. A. 2014. Task complexity, organization size, and administrative intensity: The case of UK universities. *Public Administration*, 92(3): 656–672.

Anthony, S. D., Viguerie, S. P., Schwartz, E. I., & Van Landeghem, J. 2018. *Corporate longevity forecast: Creative destruction is accelerating*.

Argyres, N. S., & Silverman, B. S. 2004. R&D, organization structure, and the development of corporate technological knowledge. *Strategic Management Journal*, 25(8–9): 929–958.

Arora, A., Belenzon, S., & Rios, L. A. 2014. Make, buy, organize: The interplay between research, external knowledge, and firm structure. *Strategic Management Journal*, 35: 317–337.

Arthur, M. B., Khapova, S. N., & Wilderom, C. P. M. 2005. Career success in a boundaryless career world. *Journal of Organizational Behavior*, 26(2): 177–202.

Audia, P. G., & Greve, H. R. 2006. Less likely to fail: Low performance, firm size, and factory expansion in the shipbuilding industry. *Management Science*, 52(1): 83–94.

Balsmeier, B., & Buchwald, A. 2014. Who promotes more innovations? Inside versus outside hired CEOs. *Industrial and Corporate Change*, 24(5): 1013–1045.

Bantel, K. A., & Jackson, S. 1989. Top management and innovations in banking: does the composition of the top team make a difference? *Strategic Management Journal*, 10: 107–124.

Barczak, G. 2016. Special issue: Best practices in new product development. *Journal of Product Innovation Management*, 2–2.

Barczak, G., Griffin, A., & Kahn, K. B. 2009. Perspective: Trends and drivers of success in NPD practices: Results of the 2003 PDMA best practices study. *Journal of Product Innovation Management*, 26(1): 3–23.

Barker, V., & Mueller, G. 2002. CEO characteristics and firm R&D spending. *Management Science*, 48(6): 782–801.

Barney, J. B. 1991. Firm resources and sustained competitive advantage. *Journal of Management*, 17(1): 99–120.

Barney, J. B. 1995. Looking inside for competitive advantage. *Academy of Management Perspectives*.

Barney, J. B., Foss, N. J., & Lyngsie, J. 2018. The role of senior management in opportunity formation: Direct involvement or reactive selection? *Strategic Management Journal*, 39(5): 1325–1349.

Baron, R. M., & Kenny, D. A. 1986. The moderator-mediator variable distinction in social the moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, 51(6): 1173–1182.

Baysinger, B. D., Kosnik, R. D., & Turk, T. A. 1991. Effects of board and ownership structure on corporate R&D strategy. *Academy of Management Journal*, 34(1): 205–214.

Beal, R., & Yasai-Ardekani, M. 2000. Performance implications of aligning CEO functional experiences with competitive strategies. *Journal of Management*, 26(4): 733–762.

Becker, G. S. 1964. *Human capital*. New York: Columbia University Press.

Beckman, C. M. 2006. The influence of founding team company affiliations on firm behavior. *Academy of Management Journal*, 49(4): 741–758.

Beckman, C. M., & Burton, M. D. 2008. Founding the future: Path dependence in the evolution of top management teams from founding to IPO. *Organization Science*, 19(1): 3–24.

Benner, M., & Tushman, M. 2002. Process management and technological innovation: A longitudinal study of the photography and paint industries. *Administrative Science Quarterly*, 47(4): 676–706.

Berg, J. M. 2016. Balancing on the creative highwire: Forecasting the success of novel ideas in organizations. *Administrative Science Quarterly*, 61(3): 433–468.

Berson, Y., Oreg, S., & Dvir, T. 2008. CEO values, organizational culture and firm outcomes. *Journal of Organizational Behavior*, 29(5): 615–633.

Bertrand, M. 2009. CEOs. *Annual Review of Economics*, 1(1): 121–150.

Bettis, R., & Gambardella, A. 2014. Quantitative empirical analysis in strategic management. *Strategic Management Journal*, 953(April): 949–953.

Blau, P. M., & Schoenherr, R. A. 1971. *The structure of organizations*. Basic Books (AZ).

Blundell, R., Griffith, R., & Van Reenen, J. 1995. Dynamic count data models of technological innovation. *The Economic Journal*, 333–344.

Blundell, R., Griffith, R., & Windmeijer, F. 2002. Individual effects and dynamics in count data models. *Journal of Econometrics*, 108(1): 113–131.

Boudreau, K. J., Guinan, E. C., Lakhani, K. R., & Riedl, C. 2016. Allocation in science looking across and looking beyond the knowledge frontier: Intellectual distance, novelty, and resource allocation in science. *Management Science*, 62(10): 2765–2783.

Bromiley, P., & Rau, D. 2016. Social, behavioral, and cognitive influences on upper echelons during strategy process: A literature review. *Journal of Management*, 42(1): 174–202.

Brown, S., & Eisenhardt, K. 1997. The art of continuous change: Linking complexity theory and time-paced evolution in relentlessly shifting organizations. *Administrative science quarterly*, 42(1): 1–34.

Burgelman, R. A. 1983a. Corporate entrepreneurship and strategic management: Insights from a process study. *Management Science*, 29(12): 1349–1364.

Burgelman, R. A. 1983b. A process model of internal corporate venturing in the diversified major firm. *Administrative Science Quarterly*, 28(2): 223–244.

Burgelman, R. A. 1991. Intraorganizational ecology of strategy making and organizational adaptation: theory and field research. *Organization Science*, 2(3): 239–262.

Burgelman, R. A., Floyd, S. W., Laamanen, T., Mantere, S., Vaara, E., & Whittington, R. 2018. Strategy processes and practices: Dialogues and intersections. *Strategic Management Journal*, 39(3): 531–558.

Burns, T., & Stalker, G. M. 1961. *The management of Innovation*. London: Tavistock.

Busenbark, J. R., Krause, R., Boivie, S., & Graffin, S. D. 2016. Toward a configurational perspective on the ceo:

A review and synthesis of the management literature. *Journal of Management*, 42(1): 234–268.

Caner, T., Cohen, S. K., & Pil, F. 2017. Firm heterogeneity in complex problem solving: A knowledge-based look at invention. *Strategic Management Journal*, 38: 1791–1811.

Cannella, A. A., Park, J. H., & Lee, H. U. 2008. Top management team functional background diversity and firm performance: Examining the roles of team member colocation and environmental uncertainty. *Academy of Management Journal*, 51(4): 768–784.

Capozzi, M., Gregg, B., & Howe, A. 2010. *Innovation and commercialization, 2010: McKinsey Global Survey results.*

Cardinal, L. 2001. Technological innovation in the pharmaceutical industry: The use of organizational control in managing research and development. *Organization Science*, 12(1): 19–36.

Carnabuci, G., & Operti, E. 2013. Where do firms' recombinant capabilities come from? Intraorganizational networks, knowledge, and firms' ability to innovate through technological recombination. *Strategic Management Journal*, 34: 1591–1613.

Carpenter, M. A. 2002. The implications of strategy and social context for the relationship between top management team heterogeneity and firm performance. *Strategic Management Journal*, 23(3): 275–284.

Carpenter, M. A., & Fredrickson, J. 2001. Top management teams, global strategic posture, and the moderating role of uncertainty. *Academy of Management journal*, 44(3): 533–545.

Carpenter, M. A., Geletkancz, M. A., & Sanders, W. G. 2004. Upper echelons research revisited: Antecedents, elements, and consequences of top management team composition. *Journal of Management*, 30(6): 749–778.

Castanias, R. P., & Helfat, C. E. 1991. Managerial resources and rents. *Journal of Management*, 17(1): 155–171.

Castanias, R. P., & Helfat, C. E. 2001. The managerial rents model: Theory and empirical analysis. *Journal of Management*, 27(6): 661–678.

Chandler, A. D. J. 1977. *The visible hand: The managerial revolution in american business*. Harvard University Press.

Chen, W. 2008. Determinants of firms' backward- and forward-looking R&D search behavior. *Organization Science*, 19(4): 609–622.

Chen, W., & Miller, K. D. 2007. Situational and institutional determinants of firms' R&D search intensity. *Strategic Management Journal*, 28: 369–381.

Child, J. 1972. Organization structure and strategies of control: A replication of the Aston study. *Administrative Science Quarterly*, 163–177.

Chin, M. K., Hambrick, D. C., & Trevino, L. K. 2013. Political ideologies of CEOs: The influence of executives' values on corporate social responsibility. *Administrative Science Quarterly*, 58(2): 197–232.

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

Christensen, C. M., & Bower, J. L. 1996. Customer power, strategic investment, and the failure of leading firm. *Strategic Management Journal*, 17(3): 197–218.

Cockburn, I. M., Henderson, R. M., & Stern, S. 2000. Untangling the origins of competitive advantage. *Strategic Management Journal*.

Coff, R., & Kryscynski, D. 2011. Drilling for micro-foundations of human capital-based competitive advantages. *Journal of Management*, 37(5): 1429–1443.

Cohen, W. M. 2010. Fifty years of empirical studies of innovative activity and performance. *Handbook of the Economics of Innovation* (pp. 129–213). Elsevier.

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

Cohen, W. M., & Levinthal, D. A. 1994. Fortune favors the prepared firm. *Management Science*, 40(2): 227–251.

Cohen, W. M., Nelson, R. R., & Walsh, J. P. 2000. *Protecting their intellectual assets: appropriability conditions and why U.S. manufacturing firms patent (or not)*. NBER Working Paper No. 7552.

Conti, R., Gambardella, A., & Mariani, M. 2014. Learning to be edison: Inventors, organizations, and breakthrough inventions. *Organization Science*, 25(3): 833–849.

Crook, T. R., Todd, S. Y., Combs, J. G., Woehr, D. J., & Ketchen, D. J. 2011. Does human capital matter? A meta-analysis of the relationship between human capital and firm performance. *Journal of Applied Psychology*, 96(3): 443–456.

Crossland, C., Zyung, J., Hiller, N. J., & Hambrick, D. C. 2014. CEO career variety: Effects on firm-level strategic and social novelty. *Academy of Management Journal*, 57(3): 652–674.

Cui, J., & Qian, G. 2007. Selection of working correlation structure and best model in GEE analyses of longitudinal data. *Communications in Statistics—Simulation and Computation*, 36(5): 987–996.

Cummings, T., & Knott, A. M. 2018. Outside CEOs and innovation. *Strategic Management Journal*, (January 2017): 1–25.

Custódio, C., Ferreira, M., & Matos, P. 2017. Do general managerial skills spur innovation? *Management Science*, 1–18.

Cyert, R., & March, J. 1963. A behavioral theory of the firm. *Englewood Cliffs, NJ*, 2: 169–187.

Daepp, M. I. G., Hamilton, M. J., West, G. B., & Bettencourt, L. M. A. 2015. The mortality of companies. *Journal of the Royal Society Interface*.

Damanpour, F., & Schneider, M. 2006. Phases of the adoption of innovation in organizations: Effects of environment, organization and top managers. *British Journal of Management*, 17(3): 215–236.

Danneels, E. 2008. Organizational antecedents of second-order competences. *Strategic Management Journal*, 29(5): 519–543.

Day, D. L. 1994. Raising for radicals: Corporate different ventures processes championing innovative. *Organization Science*, 5(2): 148–172.

Dietz, J. S., & Bozeman, B. 2005. Academic careers, patents, and productivity: Industry experience as scientific and technical human capital. *Research Policy*, 34(3): 349–367.

DiMaggio, P. J., & Powell, W. W. 1983. The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*, 48(2): 147.

Dosi, G. 1982. Technological paradigms and technological trajectories. A suggested interpretation of the determinants and directions of technical change. *Research Policy*, 11(3): 147–162.

Eggers, J. P., & Kaplan, S. 2009. Cognition and renewal: Comparing CEO and organizational effects on incumbent adaptation to technical change. *Organization Science*, 20(2): 461–477.

Eggers, J. P., & Kaul, A. 2017. Motivation and ability? A behavioral perspective on the pursuit of radical invention in multi-technology incumbents. *Academy of Management Journal*, 61(1): 67–93.

Eggers, J. P., & Park, K. F. 2018. Incumbent adaptation to technological change: The past, present, and future of research on heterogeneous incumbent response. *Academy of Management Annals*, 12(1): 357–389.

Eisenhardt, K. 1989. Making fast strategic decisions in high-velocity environments. *Academy of Management Journal*, 32(3): 543–576.

Elenkov, D. S., Judge, W., & Wright, P. 2005. Strategic leadership and executive innovation influence: An international multi-cluster comparative study. *Strategic Management Journal*, 26(7): 665–682.

Elenkov, D. S., & Manev, I. M. 2005. Top management leadership and influence on innovation: The role of sociocultural context. *Journal of Management*, 31(3): 381–402.

Felix, B., & Bistrova, J. 2015. Many CEOs aren't breakthrough innovators (and that's OK). *Harvard Business Review*.

Finkelstein, S., Hambrick, D. C., & Cannella, A. A. 2009. *Strategic leadership: Theory and research on executives, top management teams, and boards*. Strategic Management (Oxford University Press).

Flammer, C., & Ioannou, I. 2018. *To save or to invest? Strategic management during the financial crisis*. *SSRN*.

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

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

Galbraith, J. R. 1974. Organization design: An information processing view. *Interfaces*, 4(3): 28–36.

Galvin, B. M., Lange, D., & Ashforth, B. E. 2015. Narcissistic organizational identification: Seeing oneself as central to the organization's identity. *Academy of Management Review*, 40(2): 163–181.

Gambardella, A., Panico, C., & Valentini, G. 2015. Strategic incentives to human capital. *Strategic Management Journal*, 36: 37–52.

Garcia-Macia, D., Hsieh, C.-T., & Klenow, P. J. 2018. *How destructive is innovation? SSRN*.

Garud, R., Tuertscher, P., & Van de Ven, A. H. 2013. Perspectives on innovation processes. *The Academy of Management Annals*, 7(March 2015): 775–819.

Gavetti, G. 2012. PERSPECTIVE—Toward a behavioral theory of strategy. *Organization Science*, 23(1): 267–285.

Gavetti, G., Greve, H. R., Levinthal, D. A., & Ocasio, W. 2012. The behavioral theory of the firm: Assessment and prospects. *The Academy of Management Annals*, 6(1): 1–40.

Gavetti, G., & Levinthal, D. 2000. Looking forward and looking backward: Cognitive and experiential search. *Administrative Science Quarterlycience quarterly*, 45(1): 113–137.

Gerstner, W.-C., Konig, A., Enders, A., & Hambrick, D. C. 2013. CEO narcissism, audience engagement, and organizational adoption of technological discontinuities. *Administrative Science Quarterly*, 58(2): 257–291.

Giberson, T. R., Resick, C. J., Dickson, M. W., Mitchelson, J. K., Randall, K. R., & Clark, M. A. 2009. Leadership and organizational culture: Linking CEO characteristics to cultural values. *Journal of Business and Psychology*, 24(2): 123–137.

Gilbert, C. G. 2006. Change in the presence of residual fit: Can competing frames coexist? *Organization Science*, 17(1): 150–167.

Gilsing, V., Nooteboom, B., Vanhaverbeke, W., Duysters, G., & van den Oord, A. 2008. Network embeddedness and the exploration of novel technologies: Technological distance, betweenness centrality and density. *Research Policy*, 37(10): 1717–1731.

Grant, R. 1996. Toward a knoweldge-based theory of the firm. *Strategic Management Journal*, 17: 109–122.

Greve, H. 2003. A behavioral theory of R&D expenditures and innovations: Evidence from shipbuilding. *Academy of Management Journal*, 46(6): 685–702.

Greve, H. R., & Taylor, A. 2000. Innovations as catalysts for organizational change: Shifts in organizational cognition and search. *Administrative Science Quarterly*, 45(1): 54–80.

Grigoriou, K., & Rothaermel, F. 2017. Organizing for knowledge generation: Internal knowledge networks and the contingent effect of external knowledge sourcing. *Strategic Management Journal*, 38: 395–414.

Grigoriou, K., & Rothaermel, F. T. 2014. Structural microfoundations of innovation: The role of relational stars. *Journal of Management*, 40(2): 586–615.

Griliches, Z. 1990. Patent statistics as economic indicators: A survey. *Journal of Economic Literature*, 28(4): 1661–1707.

Gruber, M., Harhoff, D., & Hoisl, K. 2013. Knowledge recombination across technological boundaries: Scientists vs. engineers. *Management Science*, 59(4): 837–851.

Gupta, A., & Govindarajan, V. 1984. Business unit strategy, managerial characteristics, and business unit effectiveness at strategy implementation. *Academy of Management journal*, 27(1): 25–41.

Hagedoorn, J., & Cloodt, M. 2003. Measuring innovative performance: is there an advantage inusing multiple indicators? *Research Policy*, 32(8): 1365–1379.

Hall, B. H., Griliches, Z., & Hausman, J. A. 1986. *Patents and R and D: Is There a Lag?*

Hall, B. H., Jaffe, A., & Trajtenberg, M. 2005. Market value and patent citations. *The RAND Journal of Economics*, 36(1): 16–38.

Hambrick, D. C. 2007. Upper echelons theory: An update. *Academy of Management Review*, 32(2): 334–343.

Hambrick, D. C., & Cannella, A. A. 2004. CEOs who have COOs: Contingency analysis of an unexplored structural form. *Strategic Management Journal*, 25(10): 959–979.

Hambrick, D. C., & Finkelstein, S. 1987. Managerial discretion: A bridge between polar views of organizational outcomes. *Research in Organizational Behavior*.

Hambrick, D. C., Finkelstein, S., Mooney, A. C., Hambrick, D. C., Finkelstein, S., & Mooney, A. N. N. C. 2005. Executive job demands: New insights for explaining strategic decisions and leader behaviors. *Academy of Management Review*, 30(3): 472–491.

Hambrick, D. C., & Fukutomi, G. 1991. The seasons of a CEO's tenure. *Academy of Management Review*, 16(4): 719–742.

Hambrick, D. C., Humphrey, S. E., & Gupta, A. 2014. Structural interdependence within top management teams: A key moderator of upper echelons predictions. *Strategic Management Journal*, 36(3): 449–461.

Hambrick, D. C., & Mason, P. A. 1984. Upper echelons: The organization as a reflection of its top managers. *Academy of Management Review*, 9(2): 193–206.

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

Hargadon, A., & Sutton, R. 1997. Technology brokering and innovation in a product development firm. *Administrative Science Quarterly*, 42(4): 716.

Hausman, J., Hall, B. H., & Griliches, Z. 1984. Econometric models for count data with an application to the patents-R&D relationship. *Econometrica*, 52(4): 909–938.

Helfat, C. E. 1994. Firm-specificity in corporate applied research-and-development. *Organization Science*, 5(2): 173–184.

Helfat, C. E., & Martin, J. A. 2015. Dynamic managerial capabilities: Review and assessment of managerial impact on strategic change. *Journal of Management*, 41(5): 1281–1312.

Henderson, A. D., & Fredrickson, J. 1996. Information-processing demands as a determinant of CEO compensation. *Academy of Management Journal*, 39(3): 575–606.

Henderson, R. 1993. Underinvestment and incompetence as response to radical innovation: Evidence from the semiconductor photolithographic alignment equipment industry. *RAND Journal of Economics*, 24(2): 248–270.

Henderson, R., & Clark, K. 1990. Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. *Administrative Science Quarterly*, 35(1): 9–30.

Henderson, R., & Cockburn, I. 1994. Measuring competence? Exploring firm effects in pharmaceutical research. *Strategic Management Journal*, 15(Special Issue: Competitive Organizational Behavior): 63–84.

Henderson, R. M., & Cockburn, I. M. 1996. Scale, scope, and spillovers: The determinants of research productivity in drug discovery. *RAND Journal of Economics*, 27(1): 32–59.

Hitt, M. 1990. Mergers and acquisitions and managerial commitment to innovation in M-form firms. *Strategic Management …*, 11: 29–47.

Hitt, M. A., Bierman, L., Shimizu, K., & Kochhar, R. 2001. Direct and moderating effects of human capital on strategy and performance in professional service firms: A resource-based perspective. *Academy of Management Journal*, 44(1): 13–28.

Hitt, M. A., Bierman, L., Uhlenbruck, K., & Shimizu, K. 2006. The importance of resources in the internationalization of professional service firms: The good, the bad, and the ugly. *Academy of Management Journal*.

Hoisl, K., Gruber, M., & Conti, A. 2017. R&D team diversity and performance in hypercompetitive environments. *Strategic Management Journal*, 38(7): 1455–1477.

Horwitz, S. K., & Horwitz, I. B. 2007. The effects of team diversity on team outcomes: A meta-analytic review of team demography. *Journal of Management*.

Hughes, J. P., Rees, S. S., Kalindjian, S. B., & Philpott, K. L. 2011. Principles of early drug discovery. *British Journal of Pharmacology*, 162(6): 1239–1249.

Jansen, J. J. P., Tempelaar, M. P., van den Bosch, F. A. J., & Volberda, H. W. 2009. Structural differentiation and ambidexterity: The mediating role of integration mechanisms. *Organization Science*, 20(4): 797–811.

Jensen, M. C., & Meckling, W. H. 1976. Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, 3(4): 305–360.

Judge, T. A., Cable, D. M., Boudreau, J. W., & Bretz, R. D. 1995. An empirical-investigation of the predictors of executive career success. *Personnel Psychology*, 48(3): 485–519.

Jung, H. J., & Lee, J. J. 2016. The quest for originality: A new typology of knowledge search and breakthrough inventions. *Academy of Management Journal*, 59(5): 1725–1753.

Kahn, K. B., Barczak, G., & Moss, R. 2006. Perspective: Establishing an NPD best practices framework. *Journal of Product Innovation Management*, 23(Dialogue on Best Practices in New Product Development): 106–116.

Kahn, K. B., Barczak, G., Nicholas, J., Ledwith, A., & Perks, H. 2012. An examination of new product development best practice. *Journal of Product Innovation Management*, 29(2): 180–192.

Kalnins, A. 2018. Multicollinearity: How common factors cause type 1 errors in multivariate regression. *Strategic Management Journal*, 39(8): 2362–2385.

Kaplan, S. 2008. Cognition, capabilities, and incentives: assessing firm response to the fiber-optic revolution. *Academy of Management Journal*, 51(4): 672–695.

Kaplan, S., Murray, F., & Henderson, R. 2003. Discontinuities and senior management: Assessing the role of recognition in pharmaceutical firm response to biotechnology. *Industrial and Corporate Change*, 12(4): 203–233.

Kaplan, S., & Tripsas, M. 2008. Thinking about technology: Applying a cognitive lens to technical change. *Research Policy*, 37(5): 790–805.

Kaplan, S., & Vakili, K. 2015. The double-edge sword of recombination in breakthrough innovation. *Strategic Management Journal*, 36: 1435–1457.

Kapoor, R., & Klueter, T. 2015. Decoding the adaptability–rigidity puzzle: Evidence from pharmaceutical incumbents' pursuit of gene therapy and monoclonal antibodies. *Academy of Management Journal*, 58(4): 1180–1207.

Katila, R. 2002. New product search over time: past ideas in their prime? *Academy of Management Journal*, 45(5): 995–1010.

Katila, R., & Ahuja, G. 2002. Something old, something new: A longitudinal study of search behavior and new product introduction. *Academy of Management Journal*, 45(6): 1183–1194.

Katila, R., Thatchenkery, S., Christensen, M., & Zenios, S. 2017. Is there a doctor in the house? Expert product users, organizational roles, and innovation. *Academy of Management Journal*, 21(1): 1–52.

Kim, S. K., Arthurs, J., Sahaym, A., & Cullen, J. B. 2013. Search behavior of the diversified firm: The impact of fit on innovation. *Strategic Management Journal*, 34: 999–1009.

Kirkpatrick, D. 1998. The second coming of apple through a magical fusion of man--Steve Jobs--and company, apple is becoming itself again: The little anticompany that could. *Fortune Magazine*. Retrieved from http://archive.fortune.com/magazines/fortune/ fortune_archive/1998/11/09/250834/index.htm

Kogan, L., Papanikolaou, D., Seru, A., & Stoffman, N. 2017. Technological innovation, resource allocation, and growth. *Quarterly Journal of Economics*, 132(2): 665–712.

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

Kogut, B., & Zander, U. 1996. What firms do? Coordination, identify, and learning. *Organization Science*, 7(5):

502–518.

Kor, Y., & Mesko, A. 2013. Research notes and commentaries: Dynamic managerial capabilities: configuration and orchestration of top executives' capabilities and the firm's dominant logic. *Strategic Management Journal*, 244(June 2012): 233–244.

Kor, Y. Y. 2003. Experience-based top management team competence and sustained growth. *Organization Science*, 14(6): 707–719.

Kor, Y. Y. 2006. Direct and interaction effects of top management team and board compositions on R&D investment strategy. *Strategic Management Journal*, 27(11): 1081–1099.

Kor, Y. Y., & Leblebici, H. 2005. How do interdependences among human-capital deployment, development, and diversification strategies affect firms' financial performance? *Strategic Management Journal*, 26(10): 967–985.

Kor, Y. Y., & Mahoney, J. T. 2005. How dynamics, management, and governance of resource deployments influence firm-level performance. *Strategic Management Journal*, 26(5): 489–496.

Krause, R., Semadeni, M., & Cannella, A. A. 2014. CEO duality: A review and research agenda. *Journal of Management*, 40(1): 256–286.

Lakdawalla, D. 2018. Economics of the pharmaceutical industry. *Journal of Economic Literature*, 56(2): 397–449.

Laloux, F. 2014. *Reinventing organizations: A guide to creating organizations inspired by the next stage of human consciousness*. Nelson parker.

Lavie, D., Stettner, U., & Tushman, M. L. 2010. Exploration and exploitation within and across organizations. *Academy of Management Annals*, 4(1): 109–155.

Lawrence, P. R., & Lorsch, J. W. 1967a. New management job: the integrator. *Harvard Business Review*, (1): 41–46.

Lawrence, P. R., & Lorsch, J. W. 1967b. Differentiation and integration in complex organizations. *Administrative Science Quarterly*, 12(1): 1–47.

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

Levinthal, D. A., & March, J. 1993. The myopia of learning. *Strategic Management Journal*, 14: 95–112.

Li, G. C., Lai, R., D'Amour, A., Doolin, D. M., Sun, Y., Torvik, V. I., Yu, A. Z., & Lee, F. 2014. Disambiguation and co-authorship networks of the US patent inventor database (1975-2010). *Research Policy*, 43(6): 941–955.

Li, Q., Maggitti, P., Smith, K., Tesluk, P., & Katila, R. 2013. Top management attention to innovation: The role of search selection and intensity in new product introductions. *Academy of Management Journal*, 56(3): 893–916.

Liang, K.-Y., & Zeger, S. 1986. Longitudinal data analysis using generalized linear models. *Biometrika*, 73: 13–22.

Liu, D., Fisher, G., & Chen, G. 2018. CEO attributes and firm performance: A sequential mediation process model. *Academy of Management Annals*, 12(2): 789–816.

Lungeanu, R., Stern, I., & Zajac, E. J. 2016. When do firms change technology-sourcing vehicles? The role of poor innovative performance and finanicial slack. *Strategic Management Journal*, 37(5): 855–869.

Maggitti, P. G., Smith, K. G., & Katila, R. 2013. The complex search process of invention. *Research Policy*, 42(1): 90–100.

Manso, G. 2011. Motivating innovation. *Journal of Finance*, 66(5): 1823–1860.

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

Menz, M. 2012. Functional top management team members: A review, synthesis, and research agenda. *Journal of Management*, 38(1): 45–80.

Michel, J., & Hambrick, D. C. 1992. Diversification posture and top management team characteristics. *Academy of Management Journal*, 35(1): 9–37.

Miller, D. 1991. Stale in the saddle: CEO tenure and the match between organization and environment. *Management Science*, 37(1): 34–52.

Miller, D. J. 2006. Technological diversity, related diversification, and firm performance. *Strategic Management Journal*.

Mintzberg, H. 1979. *The structuring of organizations*. Englewood Cliffs.

Mitchell, W., & Singh, K. 1993. Death of the lethargic: Effects of expansion into new technical subfields on performance in a firm's base business. *Organization Science*, 4(2): 152–180.

Morris, M., Kuratko, D., & Covin, J. 2010. *Corporate entrepreneurship & innovation* (3rd ed.). Cengage Learning.

Munos, B. 2009. Lessons from 60 years of pharmaceutical innovation. *Nature reviews Drug discovery*, 8(12): 959–968.

Nadkarni, S., & Chen, J. 2014. Bridging yesterday, today, and tomorrow: CEO temporal focus, environmental dynamism, and rate of new product introduction. *Academy of Management Journal*, 57(6): 1810–1833.

Nahapiet, J., & Ghoshal, S. 1998. Social capital, intellectual capital, and the organizational advantage. *Academy of Management Review*, 23(2): 242–266.

Narayanan, V. K., Zane, L. J., & Kemmerer, B. 2011. The cognitive perspective in strategy: An integrative review. *Journal of Management*, 37(1): 305–351.

Nelson, R. R., & Winter, S. G. 1982. *An evolutionary theory of economic change*. *The Economic Journal* (Vol. 93).

Nohria, N., & Gulati, R. 1996. Is slack good or bad for innovation? *Academy of Management Journal*, 39(5): 1245–1264.

Nunnally, J. 1978. *Psychometric Theory*. New York: McGraw-Hill.

Nyberg, A. J., Moliterno, T. P., Hale, D., & Lepak, D. P. 2014. Resource-Based Perspectives on Unit-Level Human Capital: A Review and Integration. *Journal of Management*, 40(1): 316–346.

O'Connor, G. C. 2008. Major innovation as a dynamic capability: A system approach. *Journal of product innovation management*, 25(4): 313–330.

O'Connor, G. C., & McDermott, C. 2004. The human side of radical innovation. *Journal of Engineering and Technology …*, 21(1–2): 11–30.

O'Reilly, C., & Tushman, M. 2013. Organizational ambidexterity: Past, present and future. *The Academy of Management Perspectives*, 27(4): 324–338.

O'Reilly III, C. A., Caldwell, D. F., Chatman, J. A., & Doerr, B. 2014. The promise and problems of organizational culture: CEO personality, culture, and firm performance. *Group & Organization Management*, 39(6): 595–625.

Ocasio, W. 1997. Towards an attention-based view of the firm. *Strategic Management Journal*, 18(S1): 187–206.

Ostroff, F. 1999. The horizontal organization: What the organization of the future actually looks like and how it delivers value to customers. *Academy of Management Perspectives*, 13(2): 97–98.

Palepu, K. 1985. Diversification strategy, profit performance and the entropy measure. *Strategic Management Journal*, 6(3): 239–255.

Pan, Y. 2015. The determinants and impact of executive-firm matches. *Management Science*, 63(1): 185–200.

Papke, L. E., & Wooldridge, J. M. 2008. Panel data methods for fractional response variables with an application to test pass rates. *Journal of Econometrics*.

Paruchuri, S. 2010. Intraorganizational networks, interorganizational networks, and the impact of central inventors: A longitudinal study of pharmaceutical firms. *Organization Science*, 21(May 2017): 63–80.

Penrose, E. 1959. *Theory of the growth of the firm*. New York: Sharpe.

Pfeffer, J. 1994. *Competitive advantage through people*. Harvard Business School Press.

Phelps, C. 2010. A longitudinal study of the influence of alliance network structure and composition on firm exploratory innovation. *Academy of Management Journal*, 53(4): 890–913.

Pisano, G. P. 2006. *Science business: the promise, the reality, and the future of biotech.* (Vol. 13). Harvard Business School Press.

Ployhart, R. E., Nyberg, A. J., Reilly, G., & Maltarich, M. A. 2014. Human capital is dead; Long live human capital resources! *Journal of Management*, 40(2): 371–398.

Powell, T., Lovallo, D., & Fox, C. 2011. Behavioral Strategy. *Strategic Management Journal*, 32(2): 1369–1386.

Prahalad, C. K., & Bettis, R. A. 1986. The dominant logic: A new linkage between diversity and performance. *Strategic Management Journal*.

Quigley, T. J., & Hambrick, D. C. 2015. Has the "CEO effect" increased in recent decades? A new explanation for the great rise in america's attention to corporate leaders. *Strategic Management Journal*, 36: 812–830.

Rigby, D. K., Sutherland, J., & Takeuchi, H. 2016. Embracing agile. *Harvard Business Review*.

Ringel, M., Grassl, F., Möller, C., Zablit, H., & Manly, J. 2018. *The most innovative companies 2018*.

Roach, M., & Cohen, W. M. 2013. Lens or prism? Patent citations as a measure of knowledge flows from public research. *Management Science*, 59(2): 504–525.

Roach, M., & Sauermann, H. 2010. A taste for science? PhD scientists' academic orientation and self-selection into research careers in industry. *Research Policy*, 39(3): 422–434.

Roberts, P. W. 1999. Product innovation, product-market competition and persistent profitability in the U.S. pharmaceutical industry. *Strategic Management Journal*, 20(7): 655–670.

Robertson, B. J. 2015. *Holacracy: The new management system for a rapidly changing world*. New York: Henry Holt and Company.

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

Rothaermel, F. T., & Hess, A. M. 2007. Building dynamic capabilities: Innovation driven by individual-, firm-, and network-level effects. *Organization Science*, 18(6): 898–921.

Sanders, W., & Carpenter, M. A. 1998. Internationalization and firm governance: The roles of CEO compensation, top team composition, and board structure. *Academy of Management Journal*, 41(2): 158–178.

Savino, T., Messeni Petruzzelli, A., & Albino, V. 2017. Search and recombination process to innovate: A review of the empirical evidence and a research agenda. *International Journal of Management Reviews*, 19(1): 54–75.

Scannell, J. W., Blanckley, A., Boldon, H., & Warrington, B. 2012. Diagnosing the decline in pharmaceutical R&D efficiency. *Nature reviews Drug discovery*, 11(3): 191–200.

Schneider, A., Erden, Z., Widmer, H., Koch, G., Billy, C., & Von Krogh, G. 2012. Rethinking leadership in drug discovery projects. *Drug Discovery Today*, 17(23–24): 1258–1262.

Schumpeter, J. A. 1934. *The theory of economic development*. Cambridge, MA: Harvard University Press.

Schumpeter, J. A. 1950. *Capitalism, socialism and democracy*. New York: Harper Brothers.

Shane, S. 2000. Prior knowledge and the discovery of entrepreneurial opportunities. *Organization Science*, 11(4): 448–469.

Silverman, B. S. 1999. Technological resources and the direction of corporate diversification: Toward an integration of the resource-based view and transaction cost economics. *Management Science*, 45(8): 1109–1124.

Simsek, Z., Jansen, J. J. P., Minichilli, A., & Escriba-Esteve, A. 2015. Strategic leadership and leaders in entrepreneurial contexts: A nexus for innovation and impact missed? *Journal of Management Studies*, 52(4): 463–478.

Sine, W. D., Mitsuhashi, H., & Kirsch, D. a. 2006. Revisiting Burns and Stalker: Formal structure and new venture

performance in emerging economic sectors. *Academy of Management Journal*, 49(1): 121–132.

Slater, S. F., Mohr, J. J., & Sengupta, S. 2014. Radical product innovation capability: Literature review, synthesis, and illustrative research propositions. *Journal of Product Innovation Management*, 31(3): 552–566.

Smith, K. G., Collins, C. J., & Clark, K. D. 2005. Existing knowledge, knowledge creation capability, and the rate of new product introduction in high-technology firms. *Academy of Management Journal*, 48(2): 346–357.

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

Stettner, U., & Lavie, D. 2014. Ambidexterity under scrutiny: Exploration and exploitation via internal organization, alliances, and acquisitions. *Strategic Management Journal*, 35: 1903–1929.

Stock, J. H., & Yogo, M. 2005. Testing for weak instruments in Linear IV regression. *Andrews DWK Identification and Inference for Econometric Models* (pp. 80–108). New York: Cambridge University Press.

Sullivan, S. E., & Baruch, Y. 2009. Advances in career theory and research: A critical review and agenda for future exploration. *Journal of Management*, 35(6): 1542–1571.

Talke, K., Salomo, S., & Rost, K. 2010. How top management team diversity affects innovativeness and performance via the strategic choice to focus on innovation fields. *Research Policy*, 39(7): 907–918.

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

Teece, D. 1986. Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research Policy*, 15: 285–305.

Teece, D. J. 1996. Firm organization, industrial structure, and technological innovation. *Journal of Economic Behavior and Organization*, 31(2): 193–224.

Teece, D. J. 2007. Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, 28(13): 1319–1350.

Teece, D. J., & Dosi, G. 1988. Technological change and the nature of the firm. *Technical change and economic theory*.

Terjesen, S., & Patel, P. C. 2017. In search of process innovations: The role of search depth, search breadth, and the industry environment. *Journal of Management*, 43(5): 1421–1446.

Thompson, J. D. 1967. *Organizations in action: Social science bases of administration*.

Trajtenberg, M., Henderson, R., & Jaffe, A. 1997. University versus corporate patents: A window on the basicness of invention. *Economics of Innovation and New Technology*, 5(1): 19–50.

Tripsas, M., & Gavetti, G. 2000. Capabilities, cognition, and inertia: Evidence from digital imaging. *Strategic Management Journal*, 21(10): 1147–1161.

Tushman, M., & Anderson, P. 1986. Technological discontinuities and organizational environments. *Administrative Scienece Quaterly*, 31(3): 439–465.

Tushman, M. L., & Nadler, D. A. 1978. Information processing as an integrating concept in organizational design. *Academy of Management Review*, 3(3): 613–624.

Tushman, M., & Nadler, D. 1986. Organizing for innovation. *California Management Review*, 28(3): 74–92.

Tversky, A., & Kahneman, D. 1974. Judgment under uncertainty: Heuristics and biases. *Science*, 185(4157): 1124–1131.

Tyler, B., & Steensma, H. 1998. The effects of executives' experiences and perceptions on their assessment of potential technological alliances. *Strategic Management Journal*, 19(10): 939–965.

Van de Ven, A. H. 1986. Central problems in the management of innovation. *Organization Design*, 32(5): 590–607.

Van de Ven, A. H., Ganco, M., & Hinings, C. R. 2013. Returning to the frontier of contingency theory of organizational and institutional designs. *Academy of Management Annals*, 7(1): 393–440.

Vermeulen, F., & Barkema, H. 2001. Learning through acquisitions. *Academy of Management Journal*, 44(3):

457–476.

Verona, G. 1999. A resource-based view of product development. *Academy of Management Review*, 24(1): 132–142.

Villalonga, B., & Mcgahan, A. M. 2005. The choice among acquisitions, alliances, and divestitures. *Strategic Management Journal*, 26(13): 1183–1208.

Wal, T. V., & Gray, D. 2014. *The connected company*. O'Reilly Media, Inc.

Walrave, B., Romme, A. G. L., van Oorschot, K. E., & Langerak, F. 2017. Managerial attention to exploitation versus exploration: Toward a dynamic perspective on ambidexterity. *Industrial and Corporate Change*, 26(6): 1145–1160.

Walrave, B., van Oorschot, K. E., & Romme, A. G. L. 2011. Getting trapped in the suppression of exploration: A simulation model. *Journal of Management Studies*, 48(8): 1727–1751.

Wasserman, N., Nohria, N., & Anand, B. 2010. When does leadership matter? A contingent opportunities view of ceo leadership. *Handbook of leadership theory and practice*. Harvard Business Press.

Wiersema, M. F., & Bantel, K. A. 1992. Top management team demography and corporate strategic change. *Academy of Management Journal*, 35(1): 91–121.

Williams, C., Chen, P. L., & Agarwal, R. 2017. Rookies and seasoned recruits: How experience in different levels, firms, and industries shapes strategic renewal in top management. *Strategic Management Journal*, 38(7): 1391–1415.

Wowak, A. J., Gomez-Mejia, L. R., & Steinbach, A. L. 2017. Inducements and motives at the top: A holistic perspective on the drivers of executive behavior. *Academy of Management Annals*, 11(2): 669–702.

Wu, S., Levitas, E., & Priem, R. R. L. 2005. CEO tenure and company invention under differing levels of technological dynamism. *Academy of Management Journal*, 48(5): 859–873.

Yadav, M. S., Prabhu, J. C., & Chandy, R. K. 2007. Managing the future: CEO attention and innovation outcomes. *Journal of Marketing*, 71(4): 84–101.

Zucker, L. G., & Darby, M. R. 1997. Present at the biotechnological revolution: transformation of technological identity for a large incumbent pharmaceutical firm. *Research Policy*, 26: 429–446.

Zucker, L. G., Darby, M. R., & Brewer, M. B. 1998. Intellectual human capital and the birth of U.S. biotechnology enterprises. *The American Economic Review*, 88(1): 290–306.

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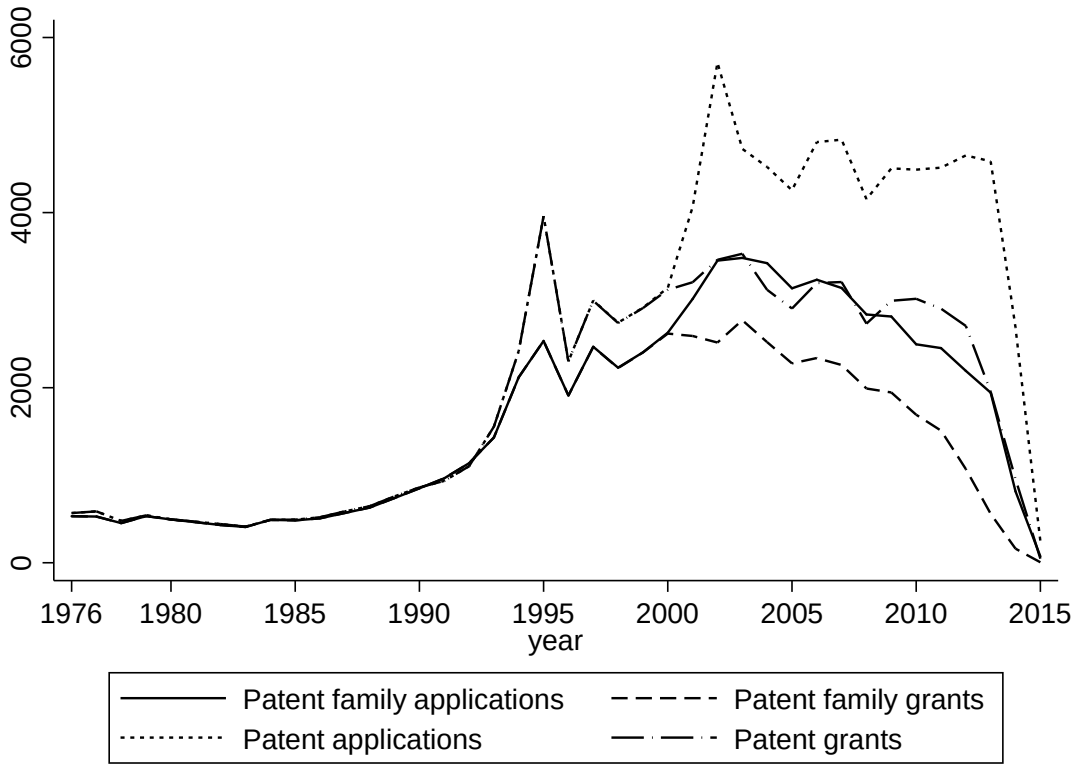
Appendix 1.1: Downloading and matching patent and SDC data

Download

This dissertation's measure of technological innovation relies on using information on patents created by firms. Patents in the United States are granted by the USPTO. All U.S. patent documents were downloaded from the official ReedTech website (https://patents.reedtech.com/pgrbft.php). Over 10 million patent files were found and downloaded using an automation script. However, the oldest patent filings had to be downloaded, parsed and cleaned manually. After this process, all available USPTO data were downloaded, which resulted in a dataset covering patents granted between 1976 and 2015 and patent applications between 2001 and 2015. Figure A displays the time trends of the number of patent applications and grants in the USPTO database. It also reveals the impact of correcting for patent families—that is, those patents combining multiple patents related to the same invention, also known as continuation-in-part applications and divisional patent filings.

Figure A: Number of patents over time



Matching patents to firms

Patents in the USPTO data were matched to the 195 sampled firms by incorporating the data of the detailed family trees, such as time-varying parent-subsidiary ownership structures, historical company names, and alternative company names and its abbreviations. In some

cases, a subsidiary applied for a patent that later was assigned to the parent organization. I therefore first used applicant data for matching patents to firms because the applicant of a patent (potentially a subsidiary) is more closely related to the innovative activity than the eventual assignee (potentially a parent). When applicant data were missing (there were 35.936 applicant names versus 827.941 assignee names), I used assignee data to match patents to firms. This is the most fine-grained matching procedure that could be applied with the data available.

Before matching, a name cleaning algorithm standardized company names in both the company names in the family trees as well as those in the USPTO data. The algorithm used both automated rules as well as manual inputs. As a final check, a "level 2" form of company names was made that removed conjunctions (and, et, und etc.) and preserved the alphanumerical characters only. For example, "Abbott GmbH & Co. KG" becomes "Abbott" with legal form "GmbH & Co.KG" and 'level 2-name' was "Abbott". In short, the first step was to apply a name cleaning algorithm to the focal, applicant and assignee names:

- Clean diacritics (e.g., characters such as ë, ê, é, è are transformed into e)
- Remove the legal form ("Inc.", "Ltd.", "B.V."); but keep this information in another variable in harmonized form (e.g. both "Ltd." and "Limited" are saved as "Ltd.").
- Strip the leading "The" and other extraneous characters and strings from the name.
- Remove leading, trailing and double spaces.

A substantial part of the company list contained foreign company names of subsidiaries located outside U.S. borders. Incorporating the substantial variation in company names and legal forms across countries was accomplished in two steps. First, I validated and corrected non-English company names through manual verification using Google searches, and later manually checked patent matches for these foreign firms. Secondly, I incorporated a list of legal forms, gathered from Wikipedia, into the matching procedure. The legal form (e.g., "Inc.", "Ltd.", and "Plc.") were removed from the company names and saved in another file in harmonized form. For example, both "Ltd." and "Limited" are saved as "Ltd." and typos such as "Incoporated" and "Coproration" were corrected. These words are of importance in the name matching procedure as they help to indicate whether a company is a subsidiary or a parent.

The cleaned company names were used to match patents to firms. I created targeted search queries by manually creating regular expressions for each firm. The regular expression for "Abbott Laboratories" was "Ab{1,2}ot{1,2} Lab". This search retrieved "Abott Laboratories" and "Abbott Laboratoires", but not "Abbottt Labs". In creating the regular expressions, I generally cut off the name at the end and applied wildcards to parts of the name where a typo is more likely to be made. An automated script ran all search queries and used a Levenshtein

distance (i.e., the number of edits required to make one string match another string, where an edit is inserting, deleting, or substituting one character) function to capture those typos. The twelve indicators used to determine the quality of a match between USPTO name and company name in family tree were: (1) Levenshtein distance between names, (2) length of USPTO name, (3) length of company name, (4) difference between names in length, (5) Levenshtein relative to length of company name, (6) number of words in USPTO, (7) name number of words in company name, (8) difference between names in number of words, (9) same country, (10) same legal form, (11) number of words in legal form, and (12) length of legal form.

Results were saved in three tables: exact matches, approximate matches, and a so called "garbage" table. What followed was a manual control of the matches in these tables. Visual inspection of the exact and approximate matches confirmed few mistakes in the matching. For the "garbage" table, I mostly focused on those matches that have a high patent count because this could indicate errors or (foreign) names that were difficult to match using the algorithm. In the end, extensive manual effort was expended to resolve ambiguities and to control the resulting patent scores by performing actual checks of patent data and web searches. These checks underscored the high quality of the matching procedure.

Matching SDC records to firms

The same name cleaning and name matching procedures were followed to match Securities Data Company (SDC) Platinum records to firm data in the family trees. Since two or more participants of a joint venture or alliance were not listed separately, I first separated and cleaned all participants. Moreover, SDC lists the parent company and ultimate parent company of each company involved in a divestiture, strategic alliance, joint venture, or acquisition where data is available. Given I constructed a detailed family tree for each sampled firm, I incorporated the parent-subsidiary relationship of the SDC data in the matching procedure by matching the full 12 matching indicators mentioned above for all company names (i.e., ultimate parent, parent, and subsidiary). In addition, I matched SDC records to firms in the family trees based on the CUSIP number as a firm identifier when these data were available.

Appendix 2.1: Reliability and factor analysis of CEO research orientation

Cronbach's alpha applied to the four items of the research orientation index equals .87, which is well above the threshold of .70 recommended for evaluating the reliability of new constructs (Nunnally, 1978). The tetrachoric correlations among the indicators were high and all positive, ranging from .62 to .94 ($p < .01$). I used tetrachoric correlations because correlations among binary variables are much lower than the correlations among continuous variables, which makes the use of Pearson correlations problematic. To further confirm the coherence among indicators, I conducted an exploratory factor analysis, again using tetrachoric correlations. With a principal component factoring procedure, all four indicators loaded on a single factor (with loadings ranging from .87 to .99) that had an eigenvalue of 3.48, explaining 87.1 of the variance.

Tetrachoric Correlations of CEO Research Orientation Items

		1	2	3
1	PhD engineering/science			
2	Patent holder	0.78		
3	R&D experience	0.94	0.86	
4	Academic experience	0.82	0.62	0.92

Factor Loading of Exploratory Factor Analysis

Variable	Factor 1
PhD engineering/science	0.953
Patent holder	0.872
R&D experience	0.999
Academic experience	0.904

Appendix 2.2: Endogeneity control

Following research in pharmaceutical innovation and upper echelons research (Gerstner et al., 2013), I explored a broad set of possible predictors of CEO research orientation to address potential concerns that result from the possibility that research-oriented CEOs might be attracted by and selected in contexts that match their orientation. I did so by regressing my 109 CEOs against a set of carefully selected variables that potentially drive a CEO selection effect. In various regression analyses, I included (combinations of) the following variables measured at the year of appointment and/or at the year prior to appointment: CEO insider, CEO age, CEO appointment year, calendar year of appointment, the number of years since the establishment of the pharmaceutical industry (around 1972/1976), firm age, firm patent propensity, firm R&D investment stock, firm patent stock, firm R&D intensity, industry age, industry R&D intensity, and SIC codes.

Only firm age prior to appointment and CEO insider significantly predicted CEO research orientation with an overall model R-squared of .12 (F = 2.35, p = .036). As an alternative to OLS regression, I also ran an ordered probit regression predicting the research orientation score of the CEO because 65 CEOs had a research orientation score of zero. The overall model reported a McFadden's pseudo R-squared of .06 (LR chi^2 = 15.50, p = .030) and the findings were the same as those reported in the OLS regression here. I then used the regression coefficients for these variables to calculate each CEO's predicted research orientation score and include that value as an "endogeneity control" in all analyses. However, since only two variables predicted CEO research orientation, I decided that the quality of the constructed endogeneity control was too low and therefore included firm age and CEO insider as control variables in all my analyses.

Appendix 3.1: Analysis using strategic portfolio diversification

	Emerging technology			Unfamiliar technology		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Managerial human capital		0.104**	0.146**		-0.106	-0.028
		(0.052)	(0.060)		(0.155)	(0.172)
Managerial human capital*Strategic diversification			-0.082*			-0.111
			(0.047)			(0.125)
Strategic diversification		0.003	0.000		0.080	0.069
		(0.024)	(0.023)		(0.091)	(0.080)
Firm diversification	-0.057	-0.047	-0.049	0.001	-0.011	-0.011
	(0.042)	(0.042)	(0.040)	(0.109)	(0.113)	(0.115)
Firm size	-0.001	-0.004	-0.001	-0.071	-0.072	-0.066
	(0.029)	(0.029)	(0.029)	(0.074)	(0.074)	(0.072)
Firm age	-0.000	-0.000	-0.000	-0.002	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Performance	0.032	0.042	0.049	-0.370	-0.359	-0.359
	(0.089)	(0.090)	(0.089)	(0.244)	(0.243)	(0.243)
Financial slack	0.003	0.003	0.003	0.008	0.009	0.009
	(0.003)	(0.003)	(0.003)	(0.015)	(0.015)	(0.015)
R&D intensity	-0.000	-0.000	-0.000	-0.001*	-0.001*	-0.001*
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Acquisitions	0.036**	0.034**	0.038**	0.114*	0.082*	0.090*
	(0.016)	(0.017)	(0.017)	(0.062)	(0.048)	(0.052)
Institutional ownership	-0.047	-0.090	-0.107	0.352	0.373	0.344
	(0.102)	(0.098)	(0.098)	(0.346)	(0.346)	(0.341)
Board independence	-0.603***	-0.601***	-0.606***	1.054	1.069	1.069
	(0.210)	(0.205)	(0.203)	(0.855)	(0.856)	(0.852)
Presample patent stock	0.001	0.001	0.001*	0.003*	0.003*	0.003*
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
R&D centralization	0.109	0.100	0.094	-0.302	-0.284	-0.287
	(0.082)	(0.084)	(0.084)	(0.215)	(0.218)	(0.223)
Knowledge diversity	-0.031	-0.039	-0.041	-0.060	-0.057	-0.065
	(0.041)	(0.041)	(0.040)	(0.180)	(0.182)	(0.178)
Senior team size	0.013	0.009	0.008	-0.010	-0.009	-0.010
	(0.011)	(0.011)	(0.011)	(0.033)	(0.032)	(0.034)
Senior management age	0.007	0.005	0.004	-0.008	-0.004	-0.003
	(0.006)	(0.006)	(0.006)	(0.020)	(0.021)	(0.021)
Gender composition	0.562***	0.565***	0.543***	-0.256	-0.212	-0.245
	(0.190)	(0.193)	(0.197)	(0.572)	(0.553)	(0.561)
Functional heterogeneity	-0.880*	-0.711	-0.679	3.437**	3.174**	3.212**
	(0.502)	(0.497)	(0.496)	(1.717)	(1.590)	(1.608)
Tenure heterogeneity	-0.028***	-0.023**	-0.022**	-0.058	-0.062	-0.062
	(0.009)	(0.010)	(0.010)	(0.047)	(0.047)	(0.047)
Founders	0.002	0.009	0.009	-0.134	-0.137	-0.135
	(0.039)	(0.038)	(0.037)	(0.135)	(0.136)	(0.137)
CEO research orientation	0.017	0.009	0.011	0.101	0.105	0.107
	(0.017)	(0.017)	(0.017)	(0.071)	(0.074)	(0.074)
Constant	-0.500	-0.383	-0.394	-4.152***	-4.224***	-4.293***
	(0.487)	(0.495)	(0.499)	(1.413)	(1.397)	(1.454)
Observations	1108	1108	1108	1108	1108	1108
Wald chi-square	242.91***	247.21***	248.26***	206.55***	209.82***	208.67***

Note: Table shows coefficients and robust standard errors (in parentheses) clustered by firms. All models include SIC and time dummies. Significance levels of two-tailed tests: * p <.10; ** p<.05; *** p<.01.

Appendix 3.2: Individual indicators of human capital predicting unfamiliar technology

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
TMT educational level		0.272***	0.275**	0.277***	0.272***	0.285***
		(0.097)	(0.110)	(0.095)	(0.097)	(0.108)
TMT industry experience		-0.069**	-0.069**	-0.085**	-0.069**	-0.086**
		(0.029)	(0.029)	(0.034)	(0.029)	(0.034)
TMT company tenure		-0.064**	-0.064**	-0.058*	-0.065	-0.067
		(0.030)	(0.030)	(0.032)	(0.052)	(0.052)
TMT educational level*Diversification			-0.005			-0.010
			(0.091)			(0.085)
TMT industry experience*Diversification				0.022		0.023
				(0.021)		(0.022)
TMT company tenure*Diversification					0.001	0.006
					(0.021)	(0.024)
Diversification	0.001	-0.016	0.007	-0.096	-0.018	-0.066
	(0.109)	(0.086)	(0.429)	(0.125)	(0.108)	(0.436)
Firm size	-0.071	-0.076	-0.076	-0.083	-0.075	-0.082
	(0.074)	(0.078)	(0.077)	(0.077)	(0.079)	(0.078)
Firm age	-0.002	0.002	0.002	0.002	0.002	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Financial performance	-0.370	-0.371	-0.371	-0.403	-0.371	-0.402
	(0.244)	(0.281)	(0.284)	(0.292)	(0.282)	(0.296)
Financial slack	0.008	0.006	0.006	0.005	0.006	0.005
	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
R&D intensity	-0.001*	-0.001*	-0.001*	-0.001*	-0.001*	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Acquisitions	0.114*	0.124**	0.124**	0.126**	0.123*	0.123*
	(0.062)	(0.061)	(0.061)	(0.060)	(0.066)	(0.065)
Institutional ownership	0.352	0.319	0.319	0.345	0.318	0.346
	(0.346)	(0.334)	(0.338)	(0.326)	(0.334)	(0.327)
Board independence	1.054	1.126	1.126	1.157	1.126	1.166
	(0.855)	(0.825)	(0.825)	(0.842)	(0.824)	(0.846)
Presample patents	0.003*	0.002	0.002	0.002	0.002	0.002
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
R&D centralization	-0.302	-0.272	-0.271	-0.260	-0.272	-0.254
	(0.215)	(0.204)	(0.208)	(0.201)	(0.207)	(0.208)
Knowledge diversity	-0.060	-0.080	-0.080	-0.086	-0.080	-0.090
	(0.180)	(0.185)	(0.187)	(0.188)	(0.188)	(0.194)
TMT size	-0.010	-0.001	-0.001	0.000	-0.001	0.001
	(0.033)	(0.028)	(0.028)	(0.029)	(0.028)	(0.029)
TMT age	-0.008	0.011	0.012	0.015	0.011	0.016
	(0.020)	(0.023)	(0.022)	(0.021)	(0.023)	(0.021)
Gender composition	-0.256	-0.158	-0.158	-0.177	-0.156	-0.163
	(0.572)	(0.537)	(0.538)	(0.533)	(0.527)	(0.522)
Functional heterogeneity	3.437**	3.755**	3.755**	3.845**	3.755**	3.848**
	(1.717)	(1.546)	(1.552)	(1.584)	(1.547)	(1.596)
Tenure heterogeneity	-0.058	-0.096*	-0.096*	-0.100*	-0.096*	-0.099*
	(0.047)	(0.052)	(0.052)	(0.052)	(0.054)	(0.054)
Founders	-0.134	-0.119	-0.119	-0.118	-0.119	-0.120
	(0.135)	(0.122)	(0.122)	(0.121)	(0.122)	(0.121)
CEO research orientation	0.101	0.096	0.096	0.093	0.096	0.093
	(0.071)	(0.066)	(0.066)	(0.067)	(0.067)	(0.067)
Constant	-4.152***	-6.250***	-6.268***	-6.433***	-6.249***	-6.479***
	(1.413)	(1.569)	(1.500)	(1.563)	(1.573)	(1.500)
Observations	1108	1108	1108	1108	1108	1108

Note: Table shows coefficients and robust standard errors (in parentheses) clustered by firms. All models include SIC and time dummies. Significance levels of two-tailed tests: * p <.10; ** p<.05; *** p<.01.

Appendix 3.3: Panel linear regression using robust standard errors

Dependent variable:	Emerging technology			Unfamiliar technology		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Managerial human capital		0.018*	0.036***		-0.004	-0.003
		(0.010)	(0.013)		(0.005)	(0.006)
Managerial human capital*Firm diversification			-0.023**			-0.001
			(0.011)			(0.005)
Firm diversification	-0.010	-0.009	-0.010	0.000	-0.000	-0.000
	(0.007)	(0.007)	(0.006)	(0.003)	(0.004)	(0.003)
Firm size	0.001	0.000	0.000	-0.001	-0.000	-0.000
	(0.005)	(0.005)	(0.005)	(0.002)	(0.002)	(0.003)
Firm age	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Performance	0.009	0.011	0.014	-0.006	-0.007	-0.006
	(0.017)	(0.018)	(0.017)	(0.005)	(0.005)	(0.006)
Financial slack	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R&D intensity	-0.000**	-0.000**	-0.000*	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Acquisitions	0.008**	0.008**	0.008**	0.003	0.003	0.003
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Institutional ownership	-0.012	-0.019	-0.023	0.006	0.008	0.008
	(0.020)	(0.020)	(0.019)	(0.007)	(0.008)	(0.008)
Board independence	-0.114***	-0.115***	-0.114***	0.025	0.025	0.025
	(0.044)	(0.044)	(0.043)	(0.030)	(0.030)	(0.030)
Presample patent stock	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Centralized R&D	0.020	0.018	0.017	-0.013	-0.012	-0.012
	(0.016)	(0.016)	(0.016)	(0.010)	(0.010)	(0.010)
Knowledge diversity	-0.007	-0.009	-0.009	-0.001	-0.001	-0.001
	(0.008)	(0.008)	(0.008)	(0.005)	(0.005)	(0.006)
Senior team size	0.002	0.002	0.002	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Senior management age	0.001	0.001	0.001	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Gender composition	0.110***	0.110***	0.106**	-0.003	-0.003	-0.004
	(0.042)	(0.042)	(0.043)	(0.013)	(0.013)	(0.012)
Functional heterogeneity	-0.161	-0.136	-0.125	0.076	0.068	0.069
	(0.104)	(0.103)	(0.103)	(0.059)	(0.057)	(0.058)
Tenure heterogeneity	-0.006***	-0.005**	-0.005**	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Founders	0.001	0.002	0.003	-0.004	-0.004	-0.004
	(0.008)	(0.008)	(0.008)	(0.003)	(0.003)	(0.003)
CEO research orientation	0.003	0.002	0.001	0.002	0.002	0.002
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
Constant	0.249**	0.271***	0.269**	-0.009	-0.014	-0.014
	(0.102)	(0.103)	(0.105)	(0.037)	(0.038)	(0.038)
Observations	1108	1108	1108	1108	1108	1108

Note: Table shows coefficients and robust standard errors (in parentheses). All models include SIC and time dummies. Significance levels of two-tailed tests: * p <.10; ** p<.05; *** p<.01.

GEE estimations specifying an identity link, a Gaussian distribution and an exchangeable within-group correlation structure

Dependent variable:	Emerging technology			Unfamiliar technology		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Managerial human capital		0.018*	0.036***		-0.005	-0.005
		(0.010)	(0.013)		(0.005)	(0.006)
Managerial human capital*Firm diversification			-0.023**			-0.000
			(0.011)			(0.005)
Firm diversification	-0.010	-0.009	-0.010	0.000	-0.000	-0.000
	(0.007)	(0.007)	(0.006)	(0.003)	(0.003)	(0.003)
Firm size	0.001	0.000	0.000	-0.000	-0.000	-0.000
	(0.005)	(0.005)	(0.005)	(0.002)	(0.003)	(0.003)
Firm age	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Performance	0.009	0.011	0.014	-0.005	-0.006	-0.006
	(0.017)	(0.018)	(0.017)	(0.005)	(0.005)	(0.006)
Financial slack	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R&D intensity	-0.000**	-0.000**	-0.000*	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Acquisitions	0.008**	0.008**	0.008**	0.004	0.004	0.004
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Institutional ownership	-0.012	-0.019	-0.023	0.004	0.006	0.006
	(0.020)	(0.020)	(0.019)	(0.007)	(0.008)	(0.008)
Board independence	-0.114***	-0.115***	-0.114***	0.029	0.030	0.030
	(0.044)	(0.044)	(0.043)	(0.033)	(0.033)	(0.033)
Presample patent stock	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Centralized R&D	0.020	0.018	0.017	-0.013	-0.012	-0.012
	(0.016)	(0.016)	(0.016)	(0.011)	(0.010)	(0.010)
Knowledge diversity	-0.007	-0.009	-0.009	-0.002	-0.001	-0.001
	(0.008)	(0.008)	(0.008)	(0.006)	(0.006)	(0.006)
Senior team size	0.002	0.002	0.002	-0.001	-0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Senior management age	0.001	0.001	0.001	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Gender composition	0.110***	0.110***	0.106**	-0.007	-0.007	-0.007
	(0.042)	(0.042)	(0.043)	(0.016)	(0.016)	(0.016)
Functional heterogeneity	-0.161	-0.136	-0.125	0.079	0.070	0.071
	(0.104)	(0.103)	(0.103)	(0.059)	(0.057)	(0.057)
Tenure heterogeneity	-0.006***	-0.005**	-0.005**	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Founders	0.001	0.002	0.003	-0.003	-0.003	-0.003
	(0.008)	(0.008)	(0.008)	(0.003)	(0.003)	(0.003)
CEO research orientation	0.003	0.002	0.001	0.001	0.002	0.002
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
Constant	0.249**	0.271***	0.269**	-0.014	-0.020	-0.020
	(0.102)	(0.103)	(0.105)	(0.036)	(0.037)	(0.037)
Observations	1108	1108	1108	1108	1108	1108

Note: Table shows coefficients and robust standard errors (in parentheses) clustered by firms. All models include SIC and time dummies. Significance levels of two-tailed tests: * p <.10; ** p<.05; *** p<.01.

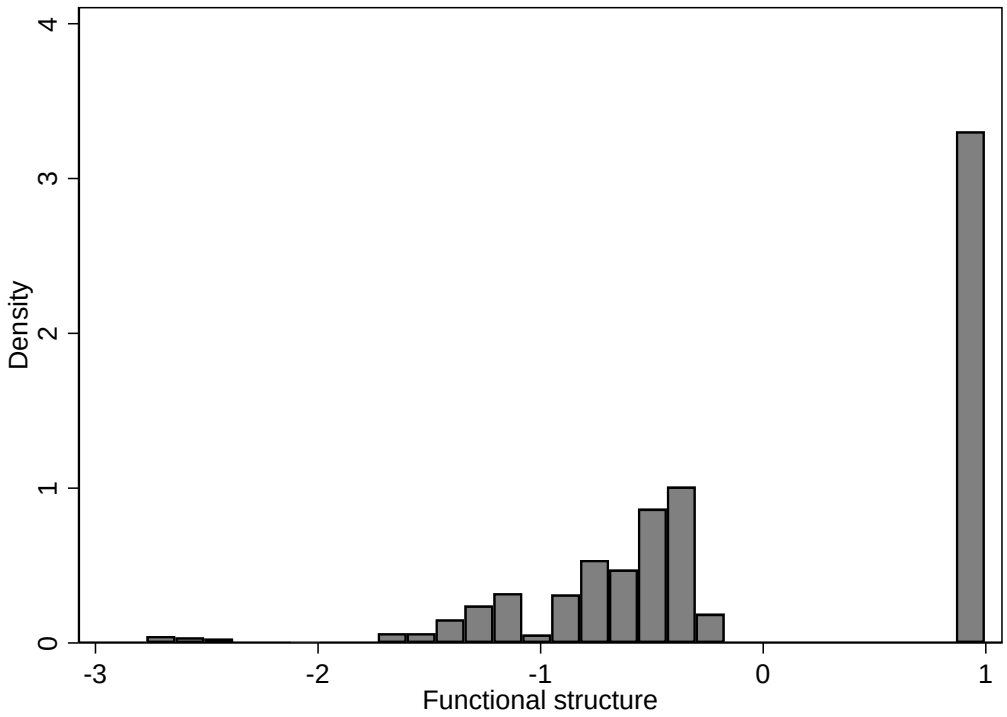
Appendix 3.4: Specification of autocorrelation structure

Dependent variable:	Emerging technology			Unfamiliar technology		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Managerial human capital		0.019*	0.037**		-0.006	-0.004
		(0.011)	(0.015)		(0.005)	(0.007)
Managerial human capital*Firm diversification			-0.023**			-0.003
			(0.011)			(0.005)
Firm diversification	-0.009	-0.007	-0.009	-0.000	-0.000	-0.001
	(0.008)	(0.008)	(0.007)	(0.004)	(0.004)	(0.004)
Firm size	0.002	0.002	0.001	-0.002	-0.002	-0.002
	(0.007)	(0.007)	(0.007)	(0.002)	(0.002)	(0.002)
Firm age	-0.000	-0.000	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Performance	0.026	0.028	0.031	-0.005	-0.006	-0.005
	(0.022)	(0.022)	(0.022)	(0.006)	(0.006)	(0.007)
Financial slack	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R&D intensity	0.000	0.000	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Acquisitions	0.008**	0.008**	0.008**	0.003	0.003	0.004
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Institutional ownership	-0.016	-0.024	-0.027	0.009	0.011	0.011
	(0.025)	(0.024)	(0.024)	(0.008)	(0.009)	(0.009)
Board independence	-0.106**	-0.106**	-0.103**	-0.000	-0.001	-0.001
	(0.048)	(0.047)	(0.046)	(0.017)	(0.017)	(0.016)
Presample patent stock	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D centralization	0.020	0.018	0.017	-0.009	-0.007	-0.007
	(0.017)	(0.018)	(0.018)	(0.009)	(0.008)	(0.008)
Knowledge diversity	-0.012	-0.014	-0.013	0.003	0.003	0.003
	(0.011)	(0.011)	(0.010)	(0.003)	(0.004)	(0.004)
Senior team size	0.003	0.003	0.003	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Senior management age	0.001	0.000	0.001	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Gender composition	0.118***	0.119***	0.114***	-0.011	-0.011	-0.012
	(0.041)	(0.042)	(0.042)	(0.011)	(0.011)	(0.011)
Functional heterogeneity	-0.214*	-0.190	-0.182	0.092	0.080	0.081
	(0.116)	(0.116)	(0.117)	(0.064)	(0.062)	(0.062)
Tenure heterogeneity	-0.006***	-0.005**	-0.005**	-0.001	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Founders	0.003	0.004	0.005	-0.003	-0.004	-0.003
	(0.009)	(0.009)	(0.009)	(0.003)	(0.003)	(0.004)
CEO research orientation	0.000	-0.001	-0.001	0.002	0.003	0.003
	(0.004)	(0.004)	(0.004)	(0.002)	(0.003)	(0.003)
Constant	0.279**	0.301**	0.294**	-0.008	-0.013	-0.014
	(0.128)	(0.127)	(0.126)	(0.038)	(0.038)	(0.038)
Observations	992	992	992	992	992	992

Note: Table shows coefficients and robust standard errors (in parentheses) clustered by firms. All models include SIC and time dummies. Significance levels of two-tailed tests: * p <.10; ** p<.05; *** p<.01.

Appendix 4.1: Analysis using TMT horizontal interdependence structure index variable

Distribution of TMT horizontal interdependence structure index variable



GEE negative binomial analyses for innovation performance

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Knowledge diversity		0.484***	1.102***	0.499***	0.337**	0.985***	0.580**
		(0.158)	(0.246)	(0.157)	(0.163)	(0.275)	(0.268)
Knowledge diversity* Administrative intensity			-1.641***			-1.628***	-0.550
			(0.342)			(0.400)	(0.378)
Knowledge diversity* Hierarchical structure				0.095		0.191	0.257**
				(0.110)		(0.116)	(0.116)
Knowledge diversity* Functional structure					0.234**	0.219**	-0.001
					(0.110)	(0.105)	(0.089)
Administrative intensity	-1.198***	-0.831*	1.394**	-0.788*	-0.861*	1.444**	0.207
	(0.409)	(0.431)	(0.593)	(0.439)	(0.452)	(0.704)	(0.651)
Hierarchical structure	-0.065	-0.067	-0.096	-0.270	-0.069	-0.504*	-0.577**
	(0.073)	(0.072)	(0.075)	(0.253)	(0.073)	(0.273)	(0.254)
Functional structure	-0.050	-0.041	-0.067	-0.042	-0.522**	-0.519**	-0.174
	(0.067)	(0.068)	(0.063)	(0.067)	(0.242)	(0.229)	(0.189)
Firm size	0.278***	0.273***	0.207***	0.272***	0.250***	0.187***	-0.005
	(0.079)	(0.078)	(0.073)	(0.078)	(0.076)	(0.071)	(0.062)
Firm age	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.024***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)
Financial performance	-0.105	-0.122	-0.125	-0.126	-0.085	-0.102	-0.011
	(0.228)	(0.235)	(0.239)	(0.233)	(0.228)	(0.225)	(0.204)
Financial slack	0.003	0.003	0.003	0.003	0.001	0.002	0.000
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.005)

R&D intensity	0.001*	0.001	0.001	0.001	0.001*	0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D centralization	0.341	0.336	0.326	0.344	0.354	0.348	0.215
	(0.234)	(0.242)	(0.232)	(0.245)	(0.236)	(0.229)	(0.184)
Acquisitions	-0.016	-0.012	-0.009	-0.012	-0.015	-0.013	-0.027
	(0.030)	(0.030)	(0.031)	(0.030)	(0.030)	(0.030)	(0.040)
Diversification	-0.050	-0.051	-0.015	-0.054	-0.041	-0.015	-0.062
	(0.092)	(0.094)	(0.096)	(0.095)	(0.092)	(0.095)	(0.086)
Institutional ownership	0.119	0.160	0.025	0.175	0.233	0.110	0.475**
	(0.245)	(0.237)	(0.227)	(0.237)	(0.239)	(0.228)	(0.197)
Board independence	-0.835	-0.801	-1.041*	-0.813	-0.890*	-1.158**	-1.573***
	(0.527)	(0.525)	(0.594)	(0.515)	(0.530)	(0.569)	(0.514)
CEO research	0.044	0.043	0.024	0.045	0.051	0.032	0.001
	(0.042)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.036)
Founders	-0.033	-0.025	-0.012	-0.027	-0.013	-0.010	-0.087
	(0.075)	(0.074)	(0.071)	(0.075)	(0.073)	(0.071)	(0.066)
TMT size	0.086**	0.081**	0.075**	0.080**	0.089***	0.076**	0.011
	(0.034)	(0.033)	(0.032)	(0.034)	(0.033)	(0.032)	(0.031)
TMT age	-0.030	-0.030	-0.024	-0.030	-0.030	-0.024	-0.011
	(0.019)	(0.019)	(0.017)	(0.019)	(0.018)	(0.017)	(0.017)
Gender composition	0.568	0.599	0.720	0.585	0.648	0.739	1.019**
	(0.527)	(0.544)	(0.583)	(0.538)	(0.550)	(0.579)	(0.451)
Functional heterogeneity	-2.265	-2.225	-1.543	-2.152	-2.360	-1.548	-0.523
	(1.911)	(1.887)	(1.886)	(1.923)	(1.890)	(1.920)	(1.283)
Tenure heterogeneity	0.044	0.036	0.039	0.036	0.043	0.047	0.103***
	(0.036)	(0.036)	(0.038)	(0.036)	(0.035)	(0.038)	(0.035)
Proportion PhDs	-0.134	-0.122	-0.055	-0.115	-0.274	-0.174	-0.260
	(0.336)	(0.331)	(0.330)	(0.336)	(0.336)	(0.337)	(0.290)
Company tenure	-0.028	-0.026	-0.022	-0.026	-0.029	-0.025	-0.057**
	(0.019)	(0.019)	(0.018)	(0.019)	(0.019)	(0.018)	(0.024)
Inventors	-0.000	-0.000	0.000	-0.000	-0.000	0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Classes	0.013*	0.000	-0.014	0.000	0.007	-0.007	-0.005
	(0.008)	(0.009)	(0.009)	(0.008)	(0.009)	(0.010)	(0.011)
Granted patents	0.011***	0.011***	0.012***	0.011***	0.011***	0.012***	0.071***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)
Presample patent stock	0.000	0.000	0.000	0.000	0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	5.059***	4.082**	3.121**	3.992**	4.591***	3.489**	4.385***
	(1.635)	(1.591)	(1.568)	(1.606)	(1.635)	(1.640)	(1.425)
Observations	862	862	862	862	862	862	772

Note: Table shows coefficients and robust standard errors (in parentheses) clustered by firms. All models include SIC and time dummies. Significance levels of two-tailed tests: * p <.10; ** p<.05; *** p<.01.

Appendix 4.2: Analysis using orthogonalized variables

Descriptive statistics

		Mean	SD	Min	Median	Max
1	Innovation performance	325.97	1,466.65	0.00	34.00	17,961.00
2	Knowledge diversity	2.13	0.62	0.00	2.12	4.08
3	Administrative intensity	0.22	0.24	0.00	0.15	1.60
4	Hierarchical structure	0.00	0.69	-1.45	0.29	1.29
5	Functional structure	0.87	0.16	0.14	0.89	1.00
6	Firm size[i]	8,969.18	2,2251.38	15.00	575.00	122,200.00
7	Firm age	26.23	36.19	0.00	14.00	161.00
8	Financial performance	-0.12	0.29	-1.33	-0.04	0.76
9	Financial slack	5.84	6.61	0.37	3.78	64.14
10	R&D intensity	155.12	151.03	0.65	119.71	1,285.52
11	R&D centralization	0.84	0.24	0.00	1.00	1.00
12	Acquisitions	0.47	1.04	0.00	0.00	8.00
13	Diversification	0.70	0.87	0.00	0.39	3.66
14	Institutional ownership	0.66	0.24	0.01	0.68	1.00
15	Board independence	0.82	0.09	0.50	0.85	1.00
16	CEO research orientation	1.49	1.47	0.00	1.00	4.00
17	Founders	0.39	0.68	0.00	0.00	4.00
18	TMT size	8.43	2.95	3.00	8.00	23.00
19	TMT age	50.01	3.52	38.60	50.00	60.50
20	Gender composition	0.11	0.12	0.00	0.11	0.63
21	Functional heterogeneity	0.81	0.07	0.48	0.82	0.95
22	Tenure heterogeneity	3.79	1.83	0.00	3.68	11.36
23	Proportion PhDs	0.41	0.20	0.00	0.40	1.00
24	Company tenure	7.70	3.75	1.00	7.13	31.00
25	Inventors[i]	245.93	551.24	5.00	50.00	3,801.00
26	Classes[i]	21.50	28.58	1.00	12.00	186.00
27	Granted patents	26.68	69.07	0.00	5.00	557.00
28	Presample patent stock[i]	137.83	266.90	0.48	34.36	1,582.67

Note: Observations = 862. [i] Orthogonalized variable but original values reported here.

Correlation matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Innovation performance															
2	Knowledge diversity	0.43														
3	Administrative intensity	-0.18	-0.61													
4	Hierarchical structure	-0.26	-0.16	0.15												
5	Functional structure	-0.55	-0.45	0.12	0.13											
6	Firm size	-0.22	0.13	-0.17	0.01	-0.11										
7	Firm age	0.43	0.50	-0.31	-0.19	-0.42	0.30									
8	Financial performance	0.16	0.25	-0.04	0.02	-0.26	0.44	0.32								
9	Financial slack	-0.11	-0.19	0.15	0.13	0.14	-0.29	-0.24	-0.06							
10	R&D intensity	-0.13	-0.22	0.02	0.07	0.26	-0.43	-0.26	-0.51	0.21						
11	R&D centralization	-0.41	-0.30	0.13	0.11	0.40	-0.15	-0.37	-0.24	0.19	0.19					
12	Acquisitions	0.45	0.41	-0.20	-0.12	-0.41	0.12	0.47	0.23	-0.17	-0.14	-0.44				
13	Diversification	0.31	0.54	-0.24	-0.10	-0.51	0.44	0.55	0.47	-0.32	-0.45	-0.35	0.45			
14	Institutional ownership	-0.05	0.07	-0.10	0.05	0.08	0.28	-0.01	0.27	0.01	0.01	-0.05	0.00	0.11		
15	Board independence	0.01	0.20	-0.17	-0.10	0.06	-0.09	0.09	-0.03	-0.06	0.04	0.03	0.01	0.10	0.00	
16	CEO research orientation	-0.15	-0.15	-0.08	-0.01	0.17	-0.18	-0.27	-0.26	0.23	0.24	0.16	-0.14	-0.29	-0.26	0.05
17	Founders	-0.10	-0.17	0.11	0.01	0.06	-0.16	-0.26	-0.33	0.16	0.11	0.13	-0.16	-0.28	-0.05	-0.15
18	TMT size	0.34	0.52	-0.30	0.00	-0.38	0.30	0.50	0.23	-0.19	-0.08	-0.27	0.40	0.44	0.18	0.12
19	TMT age	0.11	0.12	-0.15	0.00	-0.07	0.18	0.32	0.04	-0.26	-0.08	-0.17	0.14	0.19	0.03	0.04
20	Gender composition	0.09	0.04	-0.07	-0.19	-0.01	-0.06	0.13	-0.02	-0.08	0.12	-0.01	0.04	0.02	0.03	0.14
21	Functional heterogeneity	0.22	0.40	-0.16	0.05	-0.29	0.38	0.40	0.25	-0.17	-0.09	-0.24	0.30	0.35	0.25	0.09
22	Tenure heterogeneity	0.01	0.06	-0.06	0.02	-0.08	0.16	0.12	0.11	0.02	-0.13	-0.08	0.02	0.01	0.07	-0.15
23	Proportion PhDs	-0.21	-0.23	-0.06	0.08	0.26	-0.30	-0.33	-0.29	0.27	0.39	0.23	-0.19	-0.40	-0.12	-0.11
24	Company tenure	0.19	0.30	-0.21	-0.11	-0.26	0.31	0.55	0.27	-0.15	-0.26	-0.20	0.28	0.36	0.02	-0.07
25	Inventors	0.71	0.61	-0.36	-0.30	-0.53	0.00	0.78	0.27	-0.21	-0.21	-0.46	0.61	0.51	-0.04	0.13
26	Classes	0.22	0.55	-0.22	-0.02	-0.30	0.00	-0.01	0.13	-0.09	-0.18	-0.05	0.03	0.33	0.08	0.08
27	Granted patents	0.83	0.58	-0.30	-0.28	-0.55	-0.08	0.65	0.24	-0.18	-0.19	-0.44	0.52	0.45	-0.06	0.09
28	Presample patent stock	0.10	-0.01	-0.02	-0.04	-0.01	0.00	0.04	-0.05	0.02	0.01	0.09	-0.07	-0.07	-0.06	-0.01

Correlation matrix (continued)

		16	17	18	19	20	21	22	23	24	25	26	27
17	Founders	0.14											
18	TMT size	-0.21	-0.20										
19	TMT age	-0.13	-0.24	0.13									
20	Gender composition	0.12	-0.08	0.15	0.01								
21	Functional heterogeneity	-0.28	-0.20	0.83	0.12	0.14							
22	Tenure heterogeneity	-0.02	0.00	-0.02	0.26	-0.14	0.01						
23	Proportion PhDs	0.53	0.11	-0.25	-0.09	0.07	-0.39	0.06					
24	Company tenure	-0.13	-0.10	0.23	0.37	-0.04	0.17	0.54	-0.12				
25	Inventors	-0.22	-0.19	0.54	0.24	0.18	0.39	0.02	-0.26	0.39			
26	Classes	-0.10	-0.06	0.15	-0.07	-0.08	0.13	0.02	-0.23	0.04	0.00		
27	Granted patents	-0.19	-0.16	0.47	0.19	0.15	0.33	0.01	-0.23	0.35	0.91	0.14	
28	Presample patent stock	0.09	-0.02	0.02	-0.08	0.17	0.02	-0.11	-0.03	0.07	0.00	0.00	0.07

Note: Correlations greater than 0.07 are significant at $p < 0.05$ and those greater than 0.09 are significant at $p < 0.01$.

GEE negative binomial analyses for innovation performance

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7 [i]
Knowledge diversity		0.475***	1.077***	0.490***	-1.001*	-0.188	0.636
		(0.158)	(0.248)	(0.157)	(0.537)	(0.651)	(0.587)
Knowledge diversity* Administrative intensity			-1.580***			-1.535***	-0.528
			(0.349)			(0.405)	(0.374)
Knowledge diversity* Hierarchical structure				0.103		0.181	0.254**
				(0.111)		(0.116)	(0.115)
Knowledge diversity* Functional structure					1.514***	1.297**	-0.051
					(0.555)	(0.558)	(0.489)
Administrative intensity	-1.169***	-0.811*	1.335**	-0.765*	-0.831*	1.345*	0.207
	(0.409)	(0.426)	(0.607)	(0.435)	(0.437)	(0.711)	(0.643)
Hierarchical structure	-0.045	-0.051	-0.076	-0.272	-0.065	-0.473*	-0.560**
	(0.073)	(0.072)	(0.075)	(0.253)	(0.074)	(0.271)	(0.252)
Functional structure	0.383	0.401	0.236	0.384	-3.043**	-2.749**	-0.840
	(0.436)	(0.436)	(0.399)	(0.431)	(1.328)	(1.321)	(1.153)
Firm size	0.387***	0.378***	0.293***	0.377***	0.335***	0.259***	0.003
	(0.100)	(0.099)	(0.092)	(0.099)	(0.097)	(0.091)	(0.085)
Firm age	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.024***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.006)
Financial performance	-0.142	-0.156	-0.164	-0.161	-0.121	-0.145	-0.034
	(0.243)	(0.250)	(0.255)	(0.247)	(0.243)	(0.240)	(0.205)
Financial slack	0.002	0.002	0.002	0.002	0.000	0.002	0.000
	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.005)
R&D intensity	0.001*	0.001*	0.001	0.001*	0.001*	0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D centralization	0.296	0.296	0.270	0.305	0.308	0.284	0.194
	(0.225)	(0.233)	(0.223)	(0.236)	(0.224)	(0.218)	(0.184)
Acquisitions	-0.020	-0.017	-0.014	-0.016	-0.020	-0.018	-0.028
	(0.030)	(0.031)	(0.031)	(0.031)	(0.030)	(0.030)	(0.041)
Diversification	-0.025	-0.025	0.008	-0.028	-0.028	-0.003	-0.051
	(0.089)	(0.091)	(0.092)	(0.092)	(0.089)	(0.092)	(0.088)
Institutional ownership	0.144	0.184	0.051	0.199	0.269	0.144	0.445**
	(0.246)	(0.236)	(0.224)	(0.236)	(0.238)	(0.225)	(0.197)
Board independence	-0.822	-0.816	-1.045*	-0.833*	-0.889*	-1.142**	-1.604***
	(0.509)	(0.502)	(0.561)	(0.493)	(0.510)	(0.540)	(0.510)
CEO research	0.054	0.052	0.033	0.054	0.055	0.038	0.006
	(0.041)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.037)
Founders	-0.008	-0.002	0.008	-0.005	-0.002	0.000	-0.086
	(0.074)	(0.073)	(0.070)	(0.073)	(0.073)	(0.071)	(0.067)
TMT size	0.091***	0.085***	0.079**	0.083**	0.091***	0.078**	0.018
	(0.034)	(0.033)	(0.032)	(0.033)	(0.032)	(0.032)	(0.031)
TMT age	-0.032*	-0.032*	-0.027	-0.032*	-0.032*	-0.026	-0.012
	(0.018)	(0.018)	(0.017)	(0.018)	(0.018)	(0.017)	(0.017)
Gender composition	0.679	0.706	0.820	0.690	0.716	0.801	1.000**
	(0.527)	(0.542)	(0.582)	(0.536)	(0.547)	(0.574)	(0.450)

Functional heterogeneity	-2.185	-2.129	-1.461	-2.048	-2.285	-1.471	-0.513
	(1.925)	(1.893)	(1.877)	(1.932)	(1.855)	(1.878)	(1.313)
Tenure heterogeneity	0.043	0.036	0.039	0.037	0.047	0.051	0.106***
	(0.037)	(0.036)	(0.038)	(0.037)	(0.035)	(0.038)	(0.036)
Proportion PhDs	-0.067	-0.063	0.010	-0.054	-0.224	-0.104	-0.230
	(0.324)	(0.318)	(0.318)	(0.324)	(0.324)	(0.326)	(0.290)
Company tenure	-0.029	-0.027	-0.022	-0.027	-0.030*	-0.028	-0.058**
	(0.019)	(0.018)	(0.017)	(0.018)	(0.018)	(0.017)	(0.024)
Inventors	0.618***	0.426**	0.065	0.450***	0.604***	0.286	0.303
	(0.165)	(0.172)	(0.182)	(0.171)	(0.181)	(0.221)	(0.372)
Classes	0.284***	0.143*	-0.037	0.146*	0.226***	0.049	-0.022
	(0.071)	(0.085)	(0.095)	(0.083)	(0.079)	(0.100)	(0.117)
Granted patents	0.011***	0.011***	0.012***	0.011***	0.012***	0.012***	0.071***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)
Presample patent stock	0.031	0.020	0.001	0.027	0.051	0.045	0.065
	(0.066)	(0.061)	(0.056)	(0.060)	(0.050)	(0.049)	(0.062)
Constant	6.726***	5.555***	4.103**	5.489***	9.106***	7.139***	5.161***
	(1.680)	(1.627)	(1.613)	(1.647)	(2.176)	(2.286)	(1.910)
Observations	862	862	862	862	862	862	772
QIC	7179.95	7178.98	7181.36	7170.48	7179.92	7171.73	7171.61
Wald chi-square	1318.29***	1303.18***	1723.73***	1312.23***	1359.15***	1826.83***	1422.80***

Note: Table shows coefficients and robust standard errors (in parentheses) clustered by firms. All models include SIC and time dummies. Significance levels of two-tailed tests: * p <.10 ** p<.05; *** p<.01. [i] This model excludes observations of big pharma firms

Appendix 4.3: IV Poisson GMM estimations

	Model 1	Model 2	Model 3	Model 4	Model 5
Knowledge diversity	0.962*	1.344**	0.962*	3.651	4.018
	(0.522)	(0.593)	(0.521)	(2.963)	(2.951)
Knowledge diversity*Administrative intensity		-2.833***			-3.180***
		(0.713)			(1.040)
Knowledge diversity*Hierarchical structure			0.001		0.160
			(0.132)		(0.209)
Knowledge diversity*Functional structure				-2.713	-2.637
				(2.361)	(2.242)
Administrative intensity	-2.808***	1.550	-2.807***	-2.627***	2.501
	(0.764)	(1.323)	(0.766)	(0.844)	(2.162)
Hierarchical structure	-0.084	-0.074	-0.088	0.046	-0.391
	(0.084)	(0.084)	(0.376)	(0.136)	(0.501)
Functional structure	0.024	-0.093	0.024	8.437	7.951
	(0.383)	(0.365)	(0.335)	(7.345)	(6.847)
Firm size	0.169**	0.099	0.169**	0.293***	0.207**
	(0.071)	(0.076)	(0.077)	(0.105)	(0.088)
Firm age	0.001	0.002	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Financial performance	-0.286	-0.200	-0.286	-0.494	-0.351
	(0.359)	(0.358)	(0.361)	(0.370)	(0.346)
Financial slack	0.018*	0.016*	0.018*	0.019**	0.018**
	(0.010)	(0.010)	(0.010)	(0.007)	(0.008)
R&D intensity	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
R&D centralization	-0.465*	-0.544**	-0.465*	-0.224	-0.370
	(0.252)	(0.241)	(0.263)	(0.350)	(0.299)
Acquisitions	0.012	0.011	0.012	-0.010	-0.012
	(0.021)	(0.022)	(0.021)	(0.029)	(0.028)
Diversification	0.018	0.000	0.018	0.133	0.108
	(0.110)	(0.109)	(0.108)	(0.115)	(0.111)
Institutional ownership	-0.328	-0.387	-0.328	-0.394	-0.477
	(0.343)	(0.339)	(0.344)	(0.353)	(0.372)
Board independence	-0.191	-0.169	-0.192	-0.108	-0.160
	(0.503)	(0.496)	(0.506)	(0.482)	(0.515)
CEO research orientation	0.055	0.044	0.056	0.019	0.019
	(0.053)	(0.051)	(0.055)	(0.052)	(0.054)
Founders	0.031	0.042	0.031	0.069	0.085
	(0.113)	(0.112)	(0.113)	(0.127)	(0.128)
TMT size	0.045*	0.043	0.045*	0.011	0.007
	(0.027)	(0.027)	(0.027)	(0.042)	(0.043)
TMT age	-0.040**	-0.037**	-0.040**	-0.043**	-0.037**
	(0.017)	(0.016)	(0.017)	(0.017)	(0.017)
Gender composition	-0.414	-0.410	-0.414	-0.016	-0.072
	(0.379)	(0.370)	(0.387)	(0.511)	(0.495)
Functional heterogeneity	-0.378	-0.165	-0.376	0.760	1.143
	(1.858)	(1.818)	(1.882)	(2.385)	(2.501)
Tenure heterogeneity	-0.011	-0.009	-0.011	-0.021	-0.023
	(0.025)	(0.025)	(0.025)	(0.028)	(0.028)

Proportion PhDs	-0.194	-0.158	-0.194	0.378	0.369
	(0.328)	(0.325)	(0.330)	(0.676)	(0.624)
Company tenure	-0.000	-0.001	-0.000	0.009	0.006
	(0.012)	(0.012)	(0.013)	(0.014)	(0.014)
Inventors	-0.000	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Classes	-0.001	-0.007	-0.001	-0.016	-0.021
	(0.007)	(0.008)	(0.007)	(0.020)	(0.021)
Granted patents	0.005***	0.005***	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Presample patent stock	-0.000	-0.000	-0.000	-0.001	-0.001
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Constant	3.110	2.877	3.109	-6.815	-6.818
	(2.012)	(2.013)	(2.013)	(10.476)	(9.926)
Observations	862	862	862	862	862

Note: Table shows coefficients and robust standard errors (in parentheses). All models include SIC and time dummies. Significance levels of two-tailed tests: * p <.10 ** p<.05; *** p<.01.

NEDERLANDSE SAMENVATTING

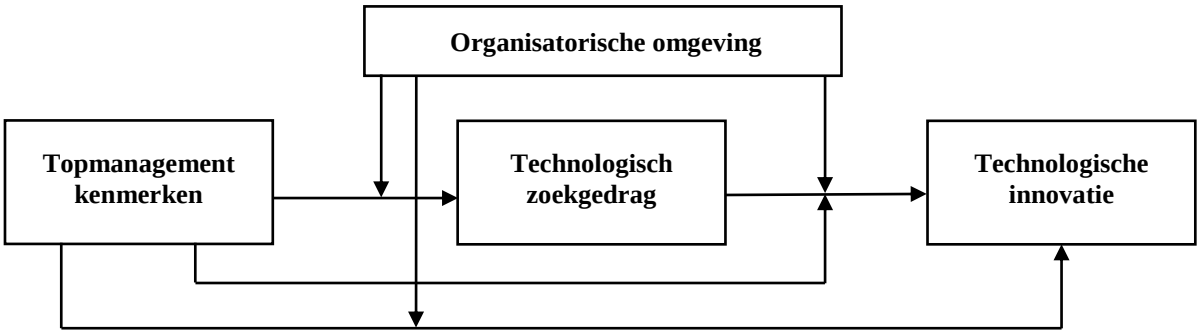
LEIDENDE INNOVATIE:

Hoe Topmanagers Invloed hebben op het Technologische Zoekgedrag en de Innovatieprestaties van Bedrijven

Technologische innovatie, dat gedefinieerd wordt in dit proefschrift als de ontdekking en ontwikkeling van nieuwe technologie, is belangrijk voor bedrijven die concurreren in veranderende omgevingen. Innoverende bedrijven hebben de mogelijkheid te ontsnappen aan concurrentie, kunnen nieuwe markten betreden, nieuwe markten creëren en sneller groeien dan concurrenten. Het is zelfs zo dat ‘s werelds meest innovatieve bedrijven ook de meest waardevolle bedrijven zijn op basis van hun marktwaarde. Het is dan ook geen verrassing dat bijna driekwart van de topmanagers erkent dat innovatie tot hun top drie van strategische prioriteiten hoort en vele geloven dat het de belangrijkste groeimotor is voor hun bedrijf.

Toch verschillen bedrijven enorm in hoe succesvol zij zijn in innovatie. Onderzoek laat zien dat de verschillen tussen bedrijven in innovatieprestaties het resultaat zijn van verschillen in bedrijfskenmerken zoals organisatiecultuur, beloningssysteem, organisatiestructuur en bedrijfsprocessen. Maar er is nog weinig aandacht besteed aan hoe innovatie beïnvloed wordt door het topmanagement van een onderneming. Dit is opmerkelijk, want in de media lees je vaak over het verband tussen bestuurders en innovatie. Dit proefschrift onderzoekt daarom hoe topmanagement de innovatieprestaties van bedrijven beïnvloedt. Dit proefschrift bestaat uit drie onderzoeken. Deze geven waardevolle inzichten in de mate waarin, de manier waarop, en onder welke omstandigheden topmanagement invloed heeft op het technologische zoekgedrag van bedrijven en hoe dit zoekgedrag zich vertaalt in technologische innovatie. Figuur 1.1 illustreert het conceptuele raamwerk van dit proefschrift.

Figuur 1.1: Het conceptuele raamwerk van dit proefschrift



Er wordt gebruik gemaakt gedetailleerde data over farmaceutische bedrijven en hun dochterondernemingen, topmanagers en uitvinders. Om zo te onderzoeken hoe het menselijke kapitaal, dat bestaat uit de vaardigheden, kennis en ervaringen, van topmanagement van invloed zijn op bedrijfsinvesteringen in onderzoek en ontwikkeling en op de octrooien die een bedrijf ontwikkelt. De eerste studie onderzoekt welke kenmerken van CEOs, of in gewoon Nederlands algemene directeuren, een positieve invloed hebben op de innovatieprestaties van bedrijven, en wanneer en hoe ze dat hebben. De tweede studie onderzoekt hoe het menselijke kapitaal van topmanagement dat beschikbaar is voor een bedrijf van invloed in hoeverre een bedrijf experimenteert met nieuwe en onbekende technologieën. De derde en laatste studie onderzoekt hoe de formele organisatiestructuur invloed heeft op het vermogen van het management om de kennisdiversiteit tussen uitvinders te coördineren voor innovatiesucces.

Dit proefschrift draagt bij aan de academische literatuur door de literatuur over strategie en innovatie te combineren. Deze combinatie maakt het mogelijk om de complexe relatie te ontrafelen tussen de kenmerken, strategische beslissingen en acties van het hoger management van een bedrijf aan de ene kant, en de vertaling daarvan in concrete innovatieactiviteiten en -resultaten aan de andere kant. Dit resulteert in een beter begrip van de rol van het topmanagement bij het verklaren van verschillen tussen bedrijven in innovatieprestaties.

De bevindingen in dit proefschrift hebben belangrijke gevolgen voor het managen van bedrijven. Het tweede hoofdstuk toont aan dat grote R&D-investeringen een belangrijke, maar niet de enige, manier waarop CEO's en mogelijk andere topmanagers de innovatieprestaties van hun bedrijf kunnen beïnvloeden. Bovendien is de positieve invloed van CEO's met een onderzoeksoriëntatie—degenen met aanleg en motivatie voor wetenschap en technologie—op innovatie sterker wanneer hij of zij ook voorzitter is van de raad van commissarissen en wanneer er middelen beschikbaar zijn binnen de organisatie anders dan wat nodig is voor de werkzaamheden op korte termijn. Deze inzichten helpen om de kenmerken en omgevingen van CEO's te identificeren die de innovatieprestaties van een bedrijf verhogen. Dit kan de raad van commissarissen en bedrijfseigenaren helpen om de strategie en het toekomstige traject van een bedrijf te beïnvloeden door een CEO met specifieke karakteristieken in dienst te nemen of te ontslaan. Men moet echter behoedzaam blijven over de mogelijkheid dat CEO's streven naar technologisch succes ten koste van commercieel succes.

De bevindingen van het derde hoofdstuk benadrukken dat het menselijke kapitaal van topmanagement een belangrijke maar niet voldoende voorwaarde is voor bedrijven om een concurrentievoordeel te behalen. Dit soort kapitaal bestaat uit de generieke, sectorspecifieke

en bedrijfsspecifieke vaardigheden, kennis en ervaring van topmanagers. Naast het vergaren van dergelijk menselijk kapitaal, is het op de juiste manier inzetten van menselijk kapitaal een belangrijk aspect van organiseren voor innovatie. Wanneer er teveel gevraagd wordt van een managementteam, raken bestuurders verstrikt in het dagelijkse bestuur en sluipen er vooroordelen in hun besluitvorming. Dit leidt ertoe dat bestuurders te weinig tijd en moeite besteden aan innovatie. Wanneer er minder gevraagd wordt van een managementteam dan waartoe het team in staat is, dan zijn bestuurders meer ontvankelijk voor technologische veranderingen en meer geneigd om strategische vernieuwing te beginnen, en stimuleren daarom innovatie binnen het bedrijf. Deze onderzoeksresultaten laten zien dat bedrijven haar menselijke kapitaal van topmanagers moeten vrijmaken als ze nieuwe wegen willen inslaan door zichzelf af te vragen: Waar zullen we mee stoppen om zo tijd, geld en middelen vrij te maken die nodig zijn voor onze innovatieplannen? Het vrijmaken van middelen op deze manier is een alternatief voor het aannemen van nieuwe topmanagers om de vaardigheden en kennis van het managementteam af te stemmen op de strategische agenda van het bedrijf. Dit inzicht benadrukt het strategische belang van het beheren en toewijzen van menselijk kapitaal als een belangrijke aanjager van het innovatief vermogen van bedrijven.

Het vierde hoofdstuk laat zien hoe managementstructuren zich verhouden tot de innovatieprestaties van een bedrijf. De bevindingen suggereren dat de formele structuur van een bedrijf de effectiviteit van topmanagement haar betrokkenheid in het innovatieproces bepaalt. Het vermogen van het management om kennisdiversiteit te managen voor innovatie neemt toe wanneer een managementteam bestaat uit van functionele posities in plaats van algemene managementposities. Dit vermogen wordt echter beperkt door intensieve administratieve structuren, welke meer controle van het management over uitvinders mogelijk maken. Dit laatste wijst erop dat bureaucratie, micromanagement en andere vormen van overmatig controle door het hoger management de innovatieprestaties van een bedrijf verminderen. Topmanagers moeten zich er daarom van bewust zijn dat hun rol varieert naargelang de organisatiestructuur, omdat deze structuur hun speelveld verandert en hoe ze daarin moeten werken.

Tot slot zijn er twee belangrijke inzichten gerelateerd aan dit proefschrift die informeren hoe bedrijven en haar topmanagers hun activiteiten in het algemeen kunnen benaderen. De eerste is dat de strategische keuzes en acties van bestuurders belangrijke langetermijngevolgen hebben voor organisaties. Topmanagers hebben namelijk een invloed op een bedrijf haar succes in technologische innovatie. Dat innovatie belangrijk is op de lange termijn wordt

wellicht het beste onthuld door het feit dat de gemiddelde levensduur van een beursgenoteerd bedrijf slechts tien jaar is. Onderzoekers voorspellen zelfs dat ongeveer de helft van de huidige beursgenoteerde bedrijven in de komende tien jaar zal worden vervangen door nieuwkomers. Deze inzichten benadrukken dat de geglobaliseerde, gedigitaliseerde en snel veranderende wereld van vandaag vereist dat organisaties en hun managers voortdurend naar nieuwe kansen zoeken, nieuwe technologieën ontwikkelen en nieuwe markten betreden. Leiders moeten daarom afstand doen van het idee van een langdurig concurrentievoordeel en toegeven dat elk voordeel tijdelijk is. Zodra ze dit idee accepteren, zullen ze snel beseffen dat de enige winnende bedrijfsstrategie er een is die draait om innovatie. Alleen dan zal hun organisatie overleven en uitblinken in de toekomst.

Een tweede belangrijk inzicht van dit proefschrift is dat bedrijven zich effectief kunnen organiseren voor innovatie. Menselijk kapitaal is een vaak over het hoofd gezien maar belangrijk element van innovatieve organisaties. Hoewel de toewijzing van financieel kapitaal al lang wordt erkend als een onmisbare brandstof voor innovatieprestaties, wordt de waarde van het toewijzen van menselijk kapitaal minder algemeen erkend. Toch is het belang van dit laatste al lang erkend door ‘s werelds meest toonaangevende innovators, zoals de volgende opmerking van Steve Jobs (1998) van twee decennia geleden aangeeft: “Innovatie heeft niets te maken met hoeveel R&D-dollars je hebt. Toen Apple met de Mac kwam, besteedde IBM minstens 100 keer meer aan R&D. Het gaat niet om geld. Het gaat over de mensen die je hebt, hoe je wordt geleid en hoe goed je het begrijpt.” Een van de belangrijkste inzichten van dit proefschrift is daarom dat het verhogen van de innovatieprestaties van het bedrijf niet alleen het resultaat is van hoge en voortdurende investeringen in R&D. Het bewust vormgeven van het managementteam en de ondersteunende organisatorische context zodat innovatie kan plaatsvinden, is minstens zo belangrijk om de volledige voordelen van R&D-investeringen te benutten, innovatieprestaties te verhogen en het toekomstige concurrentievoordeel van een bedrijf te verbeteren.