Converting technological inventions into new products: The role of CEO human capital

Shukhrat NASIROV

Alliance Manchester Business School, University of Manchester, U.K.

Qian Cher LI

Nottingham University Business School, University of Nottingham, U.K.

Yasemin KOR

Cambridge Judge Business School, University of Cambridge, U.K.

ABSTRACT

Despite technological inventions being a key input to new product development, companies often struggle with commercializing new technologies via the product development route. Drawing on a sample of publicly traded U.S. manufacturing companies that spans the period 1992–2013, our study shows that CEOs play a catalytic role in the technology conversion process, but this role is highly nuanced and depends on the characteristics (generalist vs. specialist) of their human capital. Specifically, generalist CEOs tend to be better at facilitating the conversion process in companies with more diverse and/or higher quality inventions. In contrast, specialist CEOs play a catalytic role in technology conversion when companies have less diverse and/or lower quality inventions. Hence, our article offers a solution to the technology conversion problem that consists in aligning CEO human capital characteristics with the characteristics of the company's inventions portfolio.

KEYWORDS

CEO human capital; technology conversion; new product development; patents; trademarks

CITE AS: Nasirov, S., Li, Q.C., and Kor, Y.Y. (2021) Converting technological inventions into new products: The role of CEO human capital. *Journal of Product Innovation Management*. In press.

INTRODUCTION

As only a fraction of technological inventions reaches the commercialization stage (Brusoni *et al.*, 2001; Danneels, 2007; Pavitt, 1998), the conversion of new technologies into new products has long been a strategic concern for companies. The extant literature on technological innovation and new product development (NPD) has emphasized that corporate leaders play a crucial role in technology conversion (e.g., Cooper, 1999; Ernst, 2002; Evanschitzky *et al.*, 2012; Felekoglu and Moultrie, 2014; Krishnan and Ulrich, 2001). Scholars have particularly argued that top leadership is instrumental in the dedication and allocation of resources needed to support the developmental efforts of NPD teams (Calantone *et al.*, 1995; Zirger and Maidique, 1990). They have also viewed top leadership as vital to creating and maintaining an organizational culture that fosters the product development process by supporting risk-taking, tolerating failures, and enabling individuals to learn from their own experience (Ernst, 2002; Krishnan and Ulrich, 2001; Poolton and Barclay, 1998). However, it is still not clear how the personal characteristics of corporate leaders affect their ability to effectively navigate companies through technology conversion (e.g., Caridi-Zahavi *et al.*, 2016; Felekoglu and Moultrie, 2014), especially in large companies that have rigid management systems, as well as preference for lower risks and immediate reward (O'Connor and McDermott, 2004).

More specifically, a research gap remains in the literature concerning how the knowledge, skills, and professional experiences of CEOs — that is, *human capital* attributes — matter for their ability to facilitate the technology conversion process in companies. Management studies building on human capital and upper echelons theories suggest that the expertise and knowledge repertoire of chief executives, which are largely shaped by and reflected in their professional experiences, have an influence over the strategic choices and performance levels of their companies (e.g., Carpenter *et al.*, 2004; Finkelstein *et al.*, 2009; Gruber *et al.*, 2013; Helfat and Martin, 2015). Recent research on CEO human capital stresses the importance of the generality of this capital, with the chief executive's career diversity (i.e., experience in different industries, firms, and functional areas) being positively associated with firm-level strategic novelty and distinctiveness (Crossland *et al*., 2014). Generalist CEOs are also found to spur innovation due to their broader understanding of various technology domains (Custódio *et al*., 2019). At the same time, specialist expertise in a firm or an industry can nevertheless be highly relevant to a proper matching of the company's competencies with external opportunities (Kor, 2003; Penrose, 1959; Schefczyk and Gerpott, 2001; Shamsie and Mannor, 2013). In light of empirical evidence from human capital and upper echelons literatures on the importance of the CEO's (personal and professional) attributes for strategic decisions, there is merit in studying the role that CEO human capital plays in determining their ability to be meaningfully involved in the commercialization of new technologies. Such an inquiry is also timely, considering that general managerial skills have been increasingly perceived as highly desirable and generalist CEOs receive a premium in their pay (see Custódio *et al*., 2013; Harris and Helfat, 1997).

Recognizing this important gap, we employ human capital and upper echelons theories to examine the role that CEO human capital plays in converting technological inventions into new products. In building our theory, we acknowledge that although new technologies are often seen as a prerequisite for the company's NPD success, they are rarely homogeneous and vary along *diversity* and *quality* dimensions, with each of these dimensions determining the invention's market appeal and commercial potential (Lanjouw and Schankerman, 2004; O'Connor and Veryzer, 2001; Slater *et al.*, 2014). We elaborate on the challenges encountered by the technology conversion process and conceptualize how CEO human capital can be used to mitigate those challenges, taking into account both the diversity and the quality characteristics of the company's portfolio of new technologies. When theorizing, we also distinguish between the *generalist* and the *specialist* aspect of CEO human capital. In line with Becker (1962), we regard CEOs who have knowledge, skills, and experience transferable across various companies and industries as generalists; in turn, CEOs with the human capital valuable only at few companies and industries are regarded as specialists. Hence, we focus on the usefulness of each type of CEO human capital for integrating diverse knowledge domains, as well as on how it can shape the chief executive's attitude toward risk, ability to facilitate cross-functional communication, and stance on the allocation of resources (Betzer *et al.*, 2016; Ferreira and Sah, 2012; Mishra, 2014; Wang and Murnighan, 2013; Xuan, 2009), which are all important factors for the success of the technology conversion process.

We test our hypotheses using a sample of publicly traded U.S. manufacturing companies. As technology conversion holds the key to their ability to stay relevant and survive in the market, such companies tend to be involved in developing new technologies and commercializing them via the NPD route. Our empirical results show that CEO human capital plays a catalytic but differing role in facilitating the conversion of technological inventions into new products, with the role being contingent upon the diversity and quality characteristics of the company's portfolio of inventions. In particular, we discover that generalist CEOs show a superior ability in the conversion of more diverse and higher quality inventions into new products; in contrast, specialist CEOs are found to be more effective in fostering the conversion of the inventions of low to moderate levels of diversity and quality. Our study thus uncovers a new potential solution to the technology conversion problem and adds to the literature highlighting the importance of the CEO's leadership and personality attributes for commercializing new technologies (e.g., Chen *et al*., 2014; Nadkarni and Chen, 2014; Stock *et al*., 2019; Yadav *et al*., 2007). Our findings also highlight the need for achieving a closer alignment between CEO human capital and the characteristics of the company's portfolio of new technologies. Finally, insights from this study suggest that a better utilization of CEO human capital may constitute a source of advantage for companies that rely on NPD to compete in the marketplace.

As such, our study aims to make two principal contributions to NPD and, more generally, innovation management literatures. First, it extends the line of inquiry into the corporate leadership side of NPD in technological companies (e.g., Caridi-Zahavi *et al.*, 2016; Felekoglu and Moultrie, 2014; Stock *et al.*, 2019) by putting forward CEO human capital as a factor that has an impact on the effectiveness of technology conversion. Our inquiry here responds to the call for more research into micro-mechanisms — such as CEO personal characteristics — that explain how companies can achieve and benefit from better knowledge integration (see Brenton and Levin, 2012; Brusoni *et al.*, 2001; Shane and Ulrich, 2004). Second, our study contributes to the literature investigating radical product innovation (e.g., O'Connor and Rice, 2001; Rice *et al.*, 2001; Slater *et al.*, 2014) by noting the need for *a closer alignment* between the attributes of CEO human capital and the characteristics of the company's portfolio of new technologies to achieve better NPD outcomes, especially when product development draws on more diverse and higher quality inventions.

The findings underscore that the one-size-fits-all approach does not work in the technology conversion process: generalist and specialist CEOs have their own advantages that can be uncovered only when one considers the overall diversity and quality of the company's portfolio of inventions. Promoting only generalist (or specialist) CEOs across all companies can have an adverse effect on their success with technology conversion. The discovery of this insight is timely, given an increasing popularity of generalist CEOs (see Crossland *et al.*, 2014; Custódio *et al.*, 2013; 2019; Li and Patel, 2019), which can lead to poorer NPD performance when technological diversity and technological quality are at low to moderate levels. Our findings warn against the institutionalization of generalist CEOs as a superior leadership form for all companies and, instead, suggest a more nuanced approach to tailoring the attributes of CEO human capital to fit in the technological needs of their companies.

THEORETICAL FRAMEWORK

Technological inventions as an input to product development

From an engineering viewpoint, a product is a combination of technologies that underpin its physical attributes, production methods, and performance levels. This implies, *inter alia*, that when designing a new product, the company's choice of product attributes should be in sync with the technologies at their disposal — an approach that ultimately results in a robust new product pipeline (Evanschitzky *et al.*, 2012; Krishnan and Ulrich, 2001). Hence, the NPD performance of the company serves as an indication of its technology conversion, or commercialization, success, given the technological portfolio the company has (Chandy *et al.*, 2006; Danneels, 2007; Iansiti, 1995a; 1995b; 1997). Facing increasingly sophisticated consumer demands, companies have to invest strategically in creating new and updating existing technologies (Poolton and Barclay, 1998) because such investments tend to "influence time to market, quality, innovativeness, and market share […,] thereby enhancing new product sales and future cash flows" (Bond and Houston, 2003: 122). At the same time, there are still notable differences among companies when it comes to their technological portfolios (Brusoni *et al.*, 2001; Leifer *et al.*, 2000; Patel and Pavitt, 1997; Pavitt, 1998). These differences usually occur along diversity and quality dimensions, each of which can have an impact on the company's ability to commercialize its technological inventions via the NPD route (Ernst, 2001; Gao and Hitt, 2012; Iansiti, 1995a).[i]

The diversity of technologies. Technological diversity is the range of technology domains, or classes, covered by the company's technological portfolio (Schmoch, 2008), which has a tendency to expand over time as part of the natural evolution of research activities conducted by the company. The company's research program often starts with a narrow focus, but the discovery and invention processes can subsequently take its technological portfolio into neighboring technology domains (Chang, 1996; Penrose, 1959). As a result, the company may find itself in a situation when it has a much broader technological portfolio consisting of a variety of inventions outside the company's core technology domain (Gambardella and Torrisi, 1998).

A diverse portfolio of technological inventions offers a number of benefits for the company. First, technological diversity can strengthen the company's absorptive capacity, which matters both for acquiring and utilizing external technologies, and for developing new technologies internally (Cohen and Levinthal, 1990). Second, the company can achieve economies of scope in costly R&D activities by re-using — via combination and recombination — technologies from different projects and applications (Kim *et al.*, 2016). For example, all major technologies that the Boeing Company developed during its Sonic Cruiser project were subsequently re-used in the company's 787 project

(Marsh, 2006). Finally, a diverse technological portfolio can also help the company to collaborate more effectively with suppliers that provide technology-based components and with partners that sell complementary products (Adner and Kapoor, 2010).

Companies often know more than what is needed to make a specific product, and this extra knowledge enables them "to cope with imbalances caused by uneven rates of development in the technologies on which they rely and with unpredictable product-level interdependencies" (Brusoni *et al.*, 2001:597). At the organizational level, diverse technologies lay the foundation for designing new products and improving existing ones (Pavitt, 1998). Suzuki and Kodama (2004) note that this can be achieved both by directly using generated technological trends to develop new products, as well as by fostering cross-fertilization across various technology domains. In turn, at the market level, "[the] growing breadth and depth of technological and scientific knowledge [... provides] new options for meeting the needs of an increasingly diverse and demanding market" (Wheelwright and Clark, 1992:29). Thus, companies that can generate inventions across multiple technology domains are likely to have a greater chance of developing novel and commercially viable products compared to companies with a more limited range of new technologies (Gao and Hitt, 2012; Iansiti, 1995a).

The quality of technologies. Another dimension of the company's technological portfolio, technological quality, refers to the utility value of a technological invention (i.e., the invention's ability to solving a technological puzzle) and the spectrum of market opportunities it can provide (Chandy *et al.*, 2006; Ernst, 2001). Previous research indicates that companies with higher quality technologies achieve faster sales growth and better financial performance, including much higher market value because investors perceive the creation of a higher quality invention as a signal of future cash flows from its commercialization (Ernst, 1995; 2001; Lanjouw and Schankerman, 2004). Put differently, technological quality is closely linked to "the maximum potential rent the innovation can generate" (Lanjouw and Schankerman, 2004:445). On the contrary, lower quality technologies provide fewer opportunities for commercial success. They are less likely to lead to new products that can generate repeat purchases and superior returns for the companies in the long run. Lower quality technologies may even face a complete boycott or rejection by buyers when new product solutions utilizing higher quality technologies arrive in the market (Liebeskind and Rumelt, 1989).

As an example of the relative performance of lower-versus-higher quality technological inventions, one can consider the mobile handset industry (see Koski and Kretschmer, 2007): this industry traditionally experiences sharp peaks in NPD activities following the introduction of novel mobile telecommunication technologies, such as when 3G wireless telephony entered the market to replace 2G. Among other things, the new protocol offered access to mobile internet and video calls, which not only revolutionized the telecommunication industry, but also attracted new entrants who chose to innovate around this superior technology. Eventually, the commercial potential of products relying on the previous generation technology started vanishing, and they were dominated by solutions that incorporated the newer and better quality technology.

Hence, we conclude that both the diversity and the quality of new technologies matter for the development of new products. Below we present our baseline hypotheses, which we build on in the next section to elaborate on the role of CEO human capital in technology conversion.

Hypothesis 1(a): The *diversity* of technological inventions has a positive association with NPD performance.

Hypothesis 1(b): The *quality* of technological inventions has a positive association with NPD performance.

Top managers and the technology conversion process

A more diverse and/or higher quality technological portfolio is likely to provide the basis for the success of NPD activities, but simply having such a portfolio is not sufficient, especially in large companies with their rigid management systems, orientation toward low risks, and preference for immediate reward (O'Connor and McDermott, 2004). Prior studies that examined the conversion process in established organizations revealed that, before a technological invention can make it to the marketplace in the form of a new product, companies have to overcome two frequently faced organizational barriers (e.g., Bond and Huston, 2003; O'Connor and DeMartino, 2006; O'Connor and Rice, 2001). First, despite strong inventive productivity, many companies fail to dedicate sufficient financial and human resources to the commercialization effort. Without those resources, as well as clear direction from top leadership, companies struggle to decide which technologies to invest in and which business units should develop or commercialize the selected technologies (De Brentani *et al*., 2010; Salomo *et al*., 2010). They also usually find it challenging to assess the market potential of new technologies and formulate the ways to satisfy consumer needs in a superior fashion than alternative technologies (Unger *et al*., 2012). Second, the conversion of new technologies into new products may be hindered by the organizational culture that fails to encourage risk taking and suffers from communication barriers, including functional silos and divergent opinions on how to manage product development activities (Cooper, 1999; Ernst, 2002; Krishnan and Ulrich, 2001).

The NPD literature emphasizes the importance of top leadership in overcoming these two critical barriers, which is ultimately linked to NPD success (e.g., Ernst, 2002; Evanschitzky *et al.*, 2012; Felekoglu and Moultrie, 2014; Krishnan and Ulrich, 2001). Top managers approve financial and human resources necessary for the development of new products and put an emphasis on the virtue of their programmatic engagement in product development activities (Calantone *et al.*, 1995; Zirger and Maidique, 1990). In companies with successful NPD, top managers are shown to be involved in the high-level screening and coordination of different NPD initiatives (De Brentani *et al*., 2010; Kleinschmidt *et al*., 2007). They decide on which projects to give priority, which ones to keep, and which to kill; they are viewed as instrumental in guaranteeing continued availability of resources for each project (Cooper, 1999; Salomo *et al*., 2010). Other forms of engagement in individual projects include setting goals for project reviews, determining standards for the quality of project execution, and mentoring project teams (Cooper, 1999; O'Connor and DeMartino, 2006).

For the second barrier to technology conversion, top leadership plays an important role by supporting the creation and maintenance of an organizational culture that encourages innovation and entrepreneurial behavior (Poolton and Barclay, 1998; Tsui *et al.*, 2006; Zirger and Maidique, 1990). Such a culture is expected to facilitate the NPD process by supporting risk-taking, tolerating failures, and enabling individuals to learn from their experience (Ernst, 2002; Krishnan and Ulrich, 2001). Top managers can be influential in defining technology and product development elements of the organizational culture (Cooper, 1999), while also ensuring that the culture sustains a continuing interest in the development of new products and fuels the commitment to bridging technological and product development stages (Poolton and Barclay, 1998). CEOs in particular have the power to shape this environment via the provision of necessary resources and the promotion of an atmosphere where NPD failures are perceived as a learning opportunity (Cooper, 1999). They can also promote cross-functional communication and sharing knowledge with colleagues (Thieme *et al*., 2003).

Focusing on CEOs as the most powerful actors in their organizations, past studies have built on the upper echelons theory (Finkelstein *et al.*, 2009; Hambrick, 2007) to show that chief executives' personal attributes and psychological traits help facilitate a better integration between technological and product development processes (e.g., Caridi-Zahavi *et al.*, 2016; Chen *et al.*, 2014; Stock *et al.*, 2019; Yadav *et al.*, 2007). They particularly reveal that visionary innovation leadership promotes relational connectivity in organizations and supports knowledge integration (Caridi-Zahavi *et al*., 2016). The present or future temporal orientation of CEOs, in turn, assists companies with achieving a higher rate of NPD under the dynamic environment condition (Nadkarni and Chen, 2014). Finally, chief executives with a greater external focus facilitate a faster development of initial products based on technological opportunities and a superior deployment of them (Yadav *et al*., 2007).

However, a research gap remains in the literature concerning how the CEO's knowledge, skills, and professional experiences — known as *human capital attributes* — may matter to the chief executive's ability to facilitate technology conversion in their companies. Research that draws on human capital and upper echelons theories demonstrates that the CEO's expertise and knowledge repertoire have a substantial influence on the key strategic choices and performance levels of the company (e.g., Carpenter *et al.*, 2004; Crossland *et al.*, 2014; Finkelstein *et al*., 2009; Helfat and Martin, 2015). It particularly stresses the importance of the generality of CEO human capital that ensures the transferability of the chief executive's expertise to multiple business domains (Becker, 1962; Harris and Helfat, 1997; Kor and Mesko, 2013). The CEO's career variety (i.e., experience in different industries, firms, and functional areas) is found to be positively related to firm-level strategic novelty and distinctiveness (Crossland *et al*., 2014); generalist CEOs also tend to spur innovation because of their understanding of different technology domains (Custódio *et al*., 2019). At the same time, this line of research reveals that specialist experience in a particular company or a particular industry is crucial for a proper matching of the company's competencies with external opportunities (Kor, 2003; Penrose, 1959; Schefczyk and Gerpott, 2001). It is therefore unclear how CEO human capital characteristics in general and the generality of their human capital in particular matter for technology conversion in organizations. Accordingly, we develop this line of inquiry in the next section by considering the theoretical mechanisms that are likely to shape the CEO's ability to be meaningfully involved in the commercialization of new technologies.

The role of CEO human capital in converting new technologies into new products

Human capital includes the skills and knowledge possessed by an individual, with education and professional experience as its principal sources (Becker, 1962; Castanias and Helfat, 2001; Kor and Mesko, 2013). The management literature distinguishes between general and specialist human capital. General human capital refers to managerial skills that can be transferred to multiple settings, while managerial experience in a certain context — such as an industry, a unique firm, or a specific technological regime — yields specialist human capital, which is not easily transferable to another business context (Adner and Helfat, 2003; Harris and Helfat, 1997). Specialist human capital tends to have a diminished value outside the context in which it was developed, though it can still matter for the path-dependent growth of the company that draws on existing competencies (Penrose, 1959).

Recent studies show that modern companies put a greater emphasis on the general human capital and abilities of their CEOs compared to what it was a few decades ago (Custódio *et al.*, 2013; 2019; Li and Patel, 2019; Murphy and Zábojník, 2004). The main reasons for such a trend include a significant increase in the diversity of functions that chief executives are expected to supervise, the growing complexity of business operations, and the intensified nature of problem solving at the corporate level (Betzer *et al.*, 2016; Ferreira and Sah, 2012; Wang and Murnighan, 2013). All these challenges demand the CEO who can utilize a diverse set of professional experiences gained in different organizational and industrial settings (Crossland *et al.*, 2014; Gruber *et al.*, 2013). Since the accumulation of the diverse set of experiences enhances cognitive flexibility (Furr *et al.*, 2012), generalist CEOs may be better suited to resolve the mismatches between the company's strategy and the changing business environment by, for example, designing unorthodox strategic reorientations or developing innovative product solutions (Kor and Mesko, 2013; Miller and Friesen, 1983).

Turning specifically to the role of CEO human capital in converting new technologies into new products, we concentrate on the differences between generalist and specialist CEOs in how well each type can perform the bridging function in the conversion process — the function that has been so emphasized in the product development literature (e.g., Cooper, 1999; Ernst, 2002; Felekoglu and Moultrie, 2014).[ii] We explicate four key mechanisms that help us explain why generalist CEOs may be better suited to perform this function; all these mechanisms are summarized in Table 1. In devising our arguments, we build on Hypotheses 1(a) and 1(b) about the diversity and the quality of the company's technological portfolio to offer more nuanced insights into the moderating role of CEO human capital in shaping technology conversion (see Figure 1 for our conceptual model).

---- Insert Table 1 and Figure 1 here ----

Integrating diverse knowledge domains. When it comes to assessing the market potential of an invention from a wide spectrum of technology domains, we expect generalist CEOs to be at an advantage. As previous research suggests, due to experience in a variety of organizational and industrial settings, generalist executives have access to a richer repertoire of tools, solutions, and business know-how that can be used to evaluate the commercial potential of diverse technologies (Crossland *et al.*, 2014; Kor and Mesko, 2013). The experience gained in multiple business contexts provides generalist CEOs with insights into how entire product value chains can be developed and modified (Byun *et al.*, 2018), which, we argue, enables them to assist NPD teams with the design and execution of NPD projects that cut across many technology domains. Without a vision about how these projects can be integrated in the value chain, CEOs may not encourage the conversion of technological inventions into new products. We also expect that chief executives with general human capital may be more skilled at getting to the essence of various business propositions without getting bogged down with the intricate details of each project. This particular skill can be useful in assessing competing NPD projects across a range of technology domains. The complex knowledge-processing environment of modern corporations demands top leadership to perform a highly diverse range of tasks that often benefit from a simplification skill (Mishra, 2014; Murphy and Zábojník, 2004). While narrow domain experts may struggle to envision how to integrate new technologies with other parts of an NPD project, CEOs with diverse experience can provide high-level guidance based on their diverse technological and product market expertise, as well as facilitate conversations and collaboration among research teams with dissimilar expertise.

Hence, drawing on their diverse knowledge repertoire, generalist CEOs can address one of the key challenges of technology conversion — helping to decide which invention to commercialize, which is a perplexing challenge in organizations with a diverse portfolio of inventions (De Brentani *et al*., 2010; Salomo *et al*., 2010). Generalist CEOs can provide a high-level support to NPD teams in assessing the market potential of new technologies and in formulating commercial solutions that satisfy consumers in superior ways than alternative products (Unger *et al*., 2012).

Specialist executives, in turn, possess firm-specific and industry-specific experience which allows them to better assess the promise of technological inventions in their field of expertise (Kor, 2003; Harris and Helfat, 1997). Their knowledge of firm-specific competencies can be valuable in better matching those competencies with the opportunities that emerge in the external environment (Penrose, 1959). At the same time, specialist CEOs can be less effective in overseeing NPD projects relying on distant or broader technology domains. They are likely to be constrained in their vision of unfamiliar technologies or markets, and this curtailed vision can constrict their ability to advise NPD teams on project choices and to formulate new solutions based on a diverse set of inventions. The accumulation of focused knowledge may even result in cognitive entrenchment as the stability in one's domain knowledge and interrelationships among its elements can lead to a problem-solving fixation limiting radical idea generation and the ability to adapt (Dane, 2010). Such CEOs may thus be less effective in supporting NPD projects that rely on distant or broader technology domains.

Solving the communication problem. As we have explained before, the conversion of new technologies into new products may be significantly hindered by the organizational culture where there are communication barriers, including functional silos and divergent views on how to manage the NPD process (Cooper, 1999; Ernst, 2002; Krishnan and Ulrich, 2001). Considering that product development is often a shared responsibility of multiple functional areas, there is always a risk that technology conversion is negatively affected by deficiencies in cross-functional communication. We envisage that this risk can be even higher in companies operating in a diverse set of technology domains. Previous studies reveal that the provision of leadership and the encouragement from top managers can be one of the most effective ways to ensure that all the elements of the NPD process collectively yield a desired outcome (Calantone *et al.*, 1995; Cooper, 1999; Felekoglu and Moultrie, 2014). The ability of top managers to successfully mitigate the detrimental influence of functional silos on technology conversion depends largely on "the depth of knowledge necessary to understand technical options [... and the] experience of how their discipline base interacts with other knowledge bases and context-specific factors" (Iansiti, 1995b:536). Generalist CEOs are expected to be better at tackling the functional disintegration problem because they can develop — building on the breadth of their expertise and experience — a more inclusive decision-making process that unites various functional competencies of the company to achieve NPD success (Betzer *et al.*, 2016; Ferreira and Sah, 2012). Such chief executives are likely to be more effective in facilitating the pursuit of market opportunities with NPD projects that span a broad range of technology domains and for which cross-functional and cross-divisional communication is necessary (Gruber *et al*., 2013).

Encouraging risk taking. The extant literature on technology conversion suggests that top leadership plays a critical role in the promotion of an organizational culture that facilitates the NPD process by supporting risk-taking, tolerating failures, and enabling individuals to learn from their experience (Ernst, 2002; Krishnan and Ulrich, 2001; Poolton and Barclay, 1998). However, such an impact on the culture in general and risk taking in particular is not automatic and may be linked to the human capital attributes of CEOs. Recent human capital studies underscore a fundamental difference in risk-taking attitude between generalist executives and their specialist counterparts in link with the transferability of their human capital to other company settings (Mishra, 2014). Chief executives with predominantly general human capital tend to have higher job mobility because their knowledge, skills, and expertise are applicable in multiple industry settings (Becker, 1962; Harris and Helfat, 1997). As such, it is argued that generalist CEOs are more apt to pursue new and riskier projects because their human capital will still be useful elsewhere if the failure of an NPD project wields a credible threat of dismissal: their diverse expertise acts as an insurance policy and gives such CEOs career opportunities elsewhere (Custódio *et al.*, 2019).

In turn, we expect that chief executives with weaker job mobility due to the specificity of their expertise and relational networks may be more cautious of encouraging projects that convert technological inventions into new products, especially when inventions come from a wider range of technology domains that they may be less familiar with. Since a risk-taking atmosphere is among the key success factors for technology conversion (O'Connor and McDermott, 2004; Poolton and

Barclay, 1998), specialist CEOs may thus become less effective in this facilitating role, especially if NPD projects require blending diverse technologies or technologies with high market potential.

Achieving efficiency in resource allocation. To bridge the gap between the creation of new technologies and their commercialization via the NPD route, the CEO's programmatic engagement in the conversion process is pivotal. Prior research finds that without a clear leadership direction and the involvement of top managers in the high-level screening of competing product development initiatives, companies may struggle to properly choose which technologies to commercialize (De Brentani *et al*., 2010; Salomo *et al*., 2010). However, we maintain that the quality of the leadership direction can vary among chief executives based on how their human capital attributes are aligned with the company. Resource allocation inefficiencies during the screening process may occur when a diverse portfolio of new technologies is evaluated by the CEO with a narrow domain expertise. This inefficiency is closely linked to the lack of relevant expertise, but upper-echelons scholars also note that an extended experience in specific domains, such as function, firm, or industry, leads to cognitive entrenchment and favoritism toward those domains (Carpenter *et al*., 2004; Hambrick, 2007). Domain expert CEOs may have higher commitment to their area of expertise and be prone to biases in the assessment of alternative investment options (Finkelstein *et al*., 2009). As Xuan (2009) shows, CEOs with specialist human capital provide more resources to the business and functional areas they are most familiar with, which contributes to resource allocation inefficiencies. Building on the agency theory, such area-specific investment promotes the continued vitality of the specialist chief executive's domain, which then reinforces the value of their human capital for the company.

In contrast, due to their low risk of human capital redundancy or domain-based cognitive entrenchment, we expect generalist executives to be less biased in how they choose and distribute resources across NPD projects, as well as how they allocate projects to various divisions for product development activities. Generalist CEOs tend to have access to a diverse set of network ties that are external to the company, which can offer them external connectivity and unbiased information on technological and competitive trends (Ma *et al*., 2020). Such an external attention and connectivity are found to be positively linked to the NPD success (Yadav *et al*., 2007). Therefore, we argue that in providing strategic leadership for the NPD process, CEOs with diverse expertise are more likely to prioritize new technologies that are worth betting on rather than those put forward by an intra-organizational group dynamic. All this may ultimately result in generalist chief executives pushing the inventions of higher quality into the product development pipeline in a more systematic manner compared to their specialist counterparts.

Considering the outlined mechanisms, we thus hypothesize that CEO *general* human capital amplifies the link between the diversity and the quality of new technologies, and NPD performance.

Hypothesis 2(a): The generality of CEO human capital positively moderates the association between the *diversity* of technological inventions and NPD performance.

Hypothesis 2(b): The generality of CEO human capital positively moderates the association between the *quality* of technological inventions and NPD performance.

METHODOLOGY

Data collection and the sample

The hypotheses formulated above were tested with a longitudinal sample of U.S. publicly-traded manufacturing companies spanning the period 1992–2013. We decided to concentrate on the manufacturing sector not only because companies in it often rely on technological development as a means for competition and growth, but also because the commercialization of new technologies via the product development route is a strategy commonly used there. A multistage approach was adopted to construct the sample: in S&P's Compustat North America database, we first identified companies that operated in the manufacturing industry (SIC codes 2000–3999) and then extracted financial data for each of them. For comparability, we adjusted all monetary variables to constant 2009 U.S. dollars using the GDP deflator from the U.S. Bureau of Economic Analysis. Next, we collected information on CEO compensation, demography, and career history from such sources as S&P's ExecuComp database, the BoardEx database, Marquis Who's Who directories, the Bloomberg database, the companies' websites, press releases, SEC filings, university yearbooks, and obituaries. For example, we used each CEO's full name from S&P's ExecuComp database in conjunction with the corresponding company's name to search for and extract the CEO's career history in the BoardEx database. If there were any gaps or incomplete information, we employed other sources (e.g., Marquis Who's Who directories, Bloomberg database, and so on) to add the missing data. It should be noted, however, that for the majority of the CEOs included in our sample, the information containing in both S&P's ExecuComp database and the BoardEx database was complete and did not require an extensive input from other sources. We relied on other sources (e.g., the companies' websites, press releases, SEC filings, university yearbooks, and obituaries) mostly to extract data on the CEO's education history, which we then used in order to conduct robustness checks. Finally, to obtain patent and trademark statistics, we drew on the OECD patent databases[iii] and the USPTO Trademark Case Files dataset, respectively. Due to the absence of a unique identifier enabling us to link this information to the rest of our data, we utilized company names — an approach widely used in studies on intellectual property rights (e.g., Thoma *et al.*, 2010). For each company in our sample, we determined the most unique element in its name and searched for this element in both trademark and patent databases, while also controlling for such factors as country, state, city, and address to minimize false positives.

The resulting dataset contains 3,058 firm-year observations covering 455 CEOs in 139 U.S. manufacturing companies between 1992 and 2013.[iv] The number of firm-year observations used in the empirical analysis below is lower because all explanatory variables are lagged by one period.

Dependent variable

We capture *NPD performance* using the number of trademarks introduced by the company in the given year as evident from the USPTO Trademark Case Files dataset. There are several reasons for why we choose to employ trademark statistics. First of all, relying on trademark data to reveal the outputs of technology conversion in conjunction with patent data to reveal its inputs should yield greater methodological consistency because we effectively draw from the same realm of innovation measures. Such an approach is also in line with the value transference strategy that is adopted by many manufacturing companies. This approach represents shifting a product's technical benefits, originally reserved in patents and copyrights, to trademarks in order to enhance the appropriation of innovation returns (Conley *et al.*, 2013; Mendonça *et al.*, 2004). In addition, the use of trademark statistics helps to resolve the challenge of obtaining systematic information about product lines and product categories, especially when the research involves an analysis of multiple companies observed over a long period of time (Castaldi, 2019; Gao and Hitt, 2012).

In our adoption of trademarks as a proxy of the company's NPD performance, we rely on evidence from the existing literature. In one of the pioneering studies utilizing trademark statistics, Greenhalgh and Longland (2001:677) argued that "the timing of new applications for trademarks can be a good reflection of the bringing to market of new products, so these data provide another indicator of innovation." This idea was corroborated by numerous subsequent studies drawing on empirical trademark analysis (e.g., Castaldi *et al.*, 2020; Flikkema *et al.*, 2014; Gallié and Legros, 2012; Greenhalgh and Rogers, 2012; Jensen and Webster, 2009; Mendonça *et al.*, 2004; Seip *et al.*, 2018). Some firms consider trademark applications as a form of a new product preannouncement and, as such, adopt strategies aimed at preventing an unintentional disclosure of information about NPD initiatives because of trademarking (see Fink *et al.*, 2018; Nasirov, 2020). In a recent study, Flikkema *et al.* (2019) conducted a survey of trademark owners to investigate whether a specific trademark corresponds to a product or a service innovation. They revealed confirming evidence of the trademark-innovation link, which was particularly strong for the trademarks owned by firms in the manufacturing sector. Finally, Gao and Hitt's (2012) interviews of attorneys who specialized in trademark law, trademark officers responsible for managing trademarks for their companies, and officers of the USPTO led to virtually the same conclusion — companies' trademarking activities are integrally and intimately linked to their performance in developing new products.

We acknowledge that the use of trademark data in the context of product development has some limitations. For example, not all products are trademarked, and the same trademark can be put on several products if there is a need to leverage the brand equity embedded in the trademark to promote new or less successful products (Rao *et al.*, 2004). Companies may also differ with respect to their propensity to trademark, thereby creating disparities in their trademarking behavior (Gao and Hitt, 2012). Thus, in utilizing trademark data, we ensured that our trademark-based measure captured product development outcomes, not brand-related activities (for example, rebranding at the corporate level) by excluding corporate marks, certification marks, and collective marks, as well as marks with non-U.S. or individual owners. We further relied on the "first use in U.S. commerce" year to better trace the moment when the new product was released in the marketplace for the first time, which might not necessarily coincide with the year in which the corresponding trademark application was filed or when the trademark registration was issued by the USPTO (Graham *et al.*, 2013). These adjustments allow us to obtain a more fine-grained trademark-based measure of NPD performance (see Online Appendix A for further details). The rest of the above concerns will be addressed by means of econometric modeling and using robustness checks.

Independent variables

To obtain the information about the characteristics of technological inventions generated by companies, we draw on the OECD Patent Quality Indicators database. We determine the company's *diversity of technological inventions* by examining the scope of its patenting activities in different technology fields (Lerner, 1994; Schmoch, 2008). More specifically, we employ Shannon's (1948) entropy measure in order to capture the diversity of technology fields in which the company had patents granted in the given year:

$$TD_{f,t} = \sum_{i,t} \left(P_{i,t} \ \ln \left(\frac{1}{P_{i,t}} \right) \right), \tag{1}$$

where i is a technology field based on the technology classification proposed by Schmoch (2008); $P_{i,t}$ is the ratio of the number of patents registered by Company f in Technology field i in year t to the total number of patents registered by Company f in the same year; and $\ln\left(\frac{1}{P_{i,t}}\right)$ is the weight of Technology field i in year t. Hence, a higher value of the measure corresponds to a greater diversity of the company's technological inventions, while its lower value — to lesser diversity.

In turn, the company's *quality of technological inventions* is captured by taking the average of the six-component patent quality index, initially proposed by Lanjouw and Schankerman (2004) and subsequently extended by Squicciarini *et al.* (2013), across all patents granted to the company in the given year. The six components include: the number of forward citations (up to five years after publication); the number of backward citations; the number of claims; the size of the patent family; the patent generality index; and the grant lag index. As explained by Squicciarini *et al.* (2013:59), "[all] components are normalised according to patent cohorts stratified by year and technological field and are given equal importance (no weights)." Accordingly, companies with a higher value of the index are deemed to have higher quality technological inventions; conversely, lower values of the index point to companies with lower quality technological invention.

Finally, to capture *the generality of CEO human capital*, we follow the approach proposed by Custódio *et al.* (2013; 2019). It consists in constructing a general ability index covering "the skills of the CEO that are transferrable across firms and industries, instead of being firm-specific" (Custódio *et al.*, 2013:474). The index has the following elements: the numbers of industries, companies, and positions the chief executive worked in, and whether s/he previously worked as the CEO at another company.[v] The rationale for including the first three elements is that individuals' exposure to and experience of a high number of *distinct* industries, companies, and positions should provide them with opportunities to learn a broad range of skills, tools, and contextual knowledge, thus developing their general human capital that is applicable to a wider set of strategic issues and business settings (Crossland *et al.*, 2014). The fourth element — prior CEO experience — should also contribute to the development of general human capital because serving in the chief executive function offers individuals a training ground for launching and managing business initiatives, often across different industries and geographies. Carrying the responsibility for the entire company further helps individuals boost an overarching leadership perspective, which enhances the generality of their human capital and, hence, expands the range of projects and challenges they can take on.

To construct the index (see Online Appendix B for more details), we determined the number of industries in which the CEO worked up to the given year by counting unique SIC codes (at the 2-digit level) associated with all companies in his/her BoardEx's career history. Similarly, we relied on the BoardEx data to determine the number of companies in which s/he worked, as well as the number of positions s/he held. It should be noted that we harmonized company names beforehand to avoid double counting (for example, when the experience in a company was listed under the company's former or trading name). Finally, to determine the individual's prior CEO experience, we performed a search for such titles as "CEO", "chief executive", and "principal executive". Following Custódio *et al.* (2013), we opted for a dummy variable to capture this experience because the BoardEx database contains missing values in start and end date fields of appointments, so it was difficult to construct a reliable continuous measure reflecting the total number of years of prior CEO experience.

We utilized the principal component analysis to pool these elements into a one-dimensional index (Jolliffe, 2002). This approach allowed us to simultaneously capture multiple sources through which generic human capital can be obtained, while also avoiding the multicollinearity problem due to high correlation among the elements corresponding to these sources. We first extracted principal components, which were mutually orthogonal, and then arranged them according to the proportion of the total variance each could explain. We retained the first component because it accounted for a substantial amount of the overall variation. The resulting index was calculated using the following formula (all variables were mean-centered beforehand; the regression scoring method[vi] was used to derive the weights associated with each element):

$$GAI_{i,t} = 0.320 * Y_{1,i,t} + 0.214 * Y_{2,i,t} + 0.120 * Y_{3,i,t} + 0.343 * Y_{4,i,t}, \quad (2)$$

where $Y_{1,i,t}$ is the number of industries in which CEO *i* worked until year t; $Y_{2,i,t}$ is the number of companies in which CEO *i* worked until year t; $Y_{3,i,t}$ is the number of positions in which CEO *i* worked until year t; and $Y_{4,i,t}$ is a dummy variable that takes the value of one if CEO *i* had prior experience in the CEO function at another company. To improve the interpretability of the index, we normalized it to have zero mean and a standard deviation of one.

For the general ability index, its higher values thus indicate that the CEO has a wider range of professional skills and knowledge, or, in other words, more general human capital. For instance, Margaret Whitman from The Hewlett-Packard Company is a generalist CEO in our sample. In 2011, her professional experience consisted of 13 industries, 19 companies, and 31 positions. Conversely, Richard Gottlieb from Lee Enterprises is an example of a specialist CEO. His professional experience includes a 37-year career with Lee Enterprises, which he joined in 1965 as a management trainee and became the company's CEO in 1991, thus spending his entire career in one company/industry.

Control variables

CEO-level controls. To control for the amount of company-specific knowledge that the CEO has accumulated, as well as the chances that s/he is going to favor established rather than innovative strategies (Carpenter *et al*., 2004; Helfat and Martin, 2015), we include the *company tenure* variable. It is calculated as the number of years since the CEO joined his/her company; we also include its squared value to allow for potential nonlinearity (Finkelstein *et al.*, 2009). Since founders are likely to differ from professional managers in terms of company-specific knowledge, personal objectives, and entrepreneurial behavior (Gedajlovic *et al.*, 2004), we use the *founder CEO* dummy variable that takes the value of one if the CEO is also the company's founder, and zero otherwise, to control for those differences. In turn, the *male CEO* dummy variable is used to control for potential differences between men and women in, for example, their perception of risk (Schubert *et al.*, 1999). Finally, we also control for the latitude to action afforded to chief executives and their ability to influence organizational performance (Wangrow *et al.*, 2015) using two variables: on the one hand, we include the *CEO duality* dummy variable that indicates whether the chief executive doubles as the chair of the board or not (Krause *et al.*, 2014). On the other hand, we include the *CEO ownership* variable, calculated as the percentage of company stock held by the chief executive (Wu *et al.*, 2005).

Company-level controls. To control for differences between larger and smaller companies in the amount of financial resources available to them, as well as the costs that they are likely to incur when generating new technologies or launching new products (Block *et al.*, 2015; Hall and Ziedonis, 2001), we include the *company size* variable, which is calculated as the natural logarithm of the total number of employees. Relatedly, the *company age* variable is included to control for the experience gained by the company in managing its technological and product development activities (Hall and Ziedonis, 2001); it is set to be equal to the number of years since the company's founding. To control for the company's financial performance, we use two measures: first, it is *return on assets* (ROA), calculated as the ratio of income before extraordinary items to total assets (which is winsorized at -1 and +1 to limit the effect of outliers); and second, it is *book leverage*, represented by the ratio of long-term debt plus current liabilities to total assets (Custódio *et al.*, 2019). Finally, we control for the company's *intensity of inventive activities* using the number of patent registrations; we include its quadratic value to control for a potential effect of diminishing returns of patent quantity on NPD performance (Chandy *et al.*, 2006). The *intensity of commercial activities* is, in turn, controlled for using the ratio of selling, general, and administrative expenses to total assets (Knoeber, 1986).

Econometric modeling

Since our dependent variable — the number of trademarks introduced by the company — is a count measure, it can be represented by a discrete probability distribution. So, we follow Allison (2009) and fit the data using this unconditional Poisson model with directly included fixed-effects as our baseline model specification:

$$\begin{aligned} E(y_{i,t}) = exp\big(\mu_t + \beta_1 \times TD_{i,t-1} + \beta_2 \times TQ_{i,t-1} + \beta_3 \times GAI^j_{i,t-1} + \beta_4 \times TD_{i,t-1} \times GAI^j_{i,t-1} \\ + \beta_5 \times TQ_{i,t-1} \times GAI^j_{i,t-1} + \overline{\beta_6} \times \overline{X^j_{i,t-1}} + \overline{\beta_7} \times \overline{M_{i,t-1}} + \zeta_i + \eta_h + \tau_t\big) \end{aligned} \tag{3}$$

where $E(y_{i,t})$ is the number of new products that are expected to be introduced by Company *i* in year *t*; μ_t is the intercept, which varies over time; $TD_{i,t-1}$ is the diversity of technological inventions developed by Company *i* in year *t–1*; $TQ_{i,t-1}$ is the quality of technological inventions developed by Company *i* in year *t–1*; $GAI^{j}_{i,t-1}$ is the generality of the human capital of CEO *j* from Company *i* in year *t–1*; $\overline{\mathrm{X}^{\mathrm{j}}_{\mathrm{i,t-1}}}$ is the vector of controls for CEO *j* from Company *i* in year *t-1*; $\overline{\mathrm{M}_{\mathrm{i,t-1}}}$ is the vector of controls for Company *i* in year *t–1*; ζ_i is unobservable time-invariant company-specific effects; η_h is unobservable time-invariant industry-specific effects; and τ_t is year-specific effects to control for the general economic trend. We lag all independent variables by one year in order to minimize the simultaneity bias and reverse causality.

It should further be noted that instead of using a dummy variable for each company in our sample to control for *unobservable heterogeneity* at the company level, we adopt the mean scaling estimator approach proposed by Blundell *et al.* (1999). More specifically, we first calculate the 5-year average of the total number of trademarks introduced by the company between 1987 and 1991, and then include it directly in out model specification. We have also experimented with longer pre-sample periods, up to nine years, but not found any significant difference in the final results. One of the main advantages of adopting this approach is that it "relaxes the strict exogeneity assumption and provides consistent estimates under the weaker assumption of predetermined [... regressors]" (Galasso and Simcoe, 2011:1476). In our case, it particularly allows us to better capture the (initial) propensity of the company to engage in trademarking activities.

RESULTS

Table 2 reports descriptive statistics and the correlation matrix for the sample.[vii] On average, companies in our sample introduced approximately eight new trademarks per year during the period 1992–2013; in turn, the average number of patents they registered during that period was about 72. Nonetheless, both trademark and patent distributions are highly skewed to the right, indicating that a large share of our companies is infrequently involved in technological and product development activities. As for the chief executive dimension, the average company tenure for the sampled CEOs is about 21 years; about 6 percent of them are founders; and male executives dominate the sample. The situation when the CEO also holds the title of the board chairperson (duality) is fairly common and associated with 70 percent of all observations. Finally, despite correlation coefficients suggest that some variables are significantly correlated (e.g., company size and the diversity of technological inventions), variance inflation factors reveal no evidence of multicollinearity.

---- Insert Table 2 and Table 3 here ----

Models 1–4 in Table 3 provide the results of regression analysis of the association between the diversity/quality of technological inventions and NPD performance, as well as the moderating effect of CEO human capital on this association. Since the interpretation of coefficients in Poisson models is not straightforward (Long and Freese, 2006), all coefficients in our analysis are reported in the form of incidence rate ratios (IRRs), which are derived by exponentiating Poisson regression coefficient: therefore, an IRR above one indicates a *positive association*, while an IRR below one indicates a *negative association*. All else being equal, the value of an IRR can thus be interpreted as the factor change in the company's NPD performance (trademarks) because of a unit change in the associated explanatory variable. Model 1 provides the results of empirical testing of Hypotheses 1(a) and 1(b). In Hypothesis 1(a), we argue for a positive link between the company's diversity of technological inventions and its NPD performance. Model 1 particularly shows that a unit increase in the diversity of technological inventions is associated with a 24% increase in NPD performance (IRR = 1.240; *p*-value = 0.000), thereby supporting Hypothesis 1(a).[viii] Likewise, in Hypothesis 1(b), we argue for a positive link between the company's quality of technological inventions and its NPD performance. According to the results from Model 1, a unit increase in the quality of technological inventions is associated with a 62% increase in NPD performance (IRR = 1.615; *p*-value = 0.049), which supports Hypothesis 1(b).

In Hypotheses 2(a) and 2(b), we argue that CEO general human capital positively moderates the association between: (a) the *diversity* of technological inventions and NPD performance, and (b) the *quality* of technological inventions and NPD performance, respectively. These hypotheses are tested using Models 2–4. More specifically, Model 2 shows that the IRR for the first interaction term is greater than one (IRR = 1.116; *p*-value = 0.000), which indicates that CEO general human capital positively moderates the part of the conversion process drawing on technological diversity. Model 3 similarly shows that the IRR for the second interaction term is greater than one (IRR = 1.816; *p*-value = 0.000) — an indication of a positive moderating effect of CEO general human capital on the technological quality aspect of the conversion process. Thus, our empirical testing lends support to Hypotheses 2(a) and 2(b). It is important to note that both moderating effects are still positive and statistically significant when included in the same model together (see Model 4; the first interaction term: IRR = 1.089; *p*-value = 0.003; the second interaction term: IRR = 1.388; *p*-value = 0.073). Overall, our regression analysis corroborates the proposition that CEO general human capital exerts a catalytic effect on the conversion of technological inventions into new products, with this effect manifesting along the diversity and the quality dimension of the company's technological portfolio.[ix]

In Models 2–4, it can be seen, however, that the main effect of CEO general human capital is negative as evident from its IRRs being below one (*p*-value = 0.000 in all the three models). This suggests that, on average, specialist CEOs are associated with better NPD performance compared to their generalist counterparts. Given the positive moderating effects of CEO general human capital, as well as, more generally, difficulties with interpreting interaction terms in nonlinear models (see Ai and Norton, 2003),[x] we follow Greene (2010) and rely on a graphical representation of our results to better understand the limits of the application of CEO general versus specialist human capital in the context of technology conversion.

---- Insert Figures 2a and 2b here ----

In Figures 2(a) and 2(b), we depict the marginal effects of the diversity and the quality of technological inventions, respectively, on NPD performance for various categories of CEO human capital.[xi] As the general ability index is a continuous variable, we use the value of its: 25th percentile to model the effect of specialist CEOs; and 75th percentile to model the effect of generalist CEOs. Figure 2(a) reveals that chief executives with specialist human capital outperform their generalist counterparts in bolstering the conversion of less diverse technological inventions; at the same time, when technological inventions are more diverse, generalist CEOs are better poised to moderate this process. A very similar pattern is revealed in Figure 2(b) for the quality of technological inventions. Hence, we conclude that the conversion of technological inventions into new products benefits from a specialist CEO when the company has less diverse and/or lower quality technological inventions. In turn, chief executives with general human capital tend to achieve better outcomes of technology conversions in companies with more diverse and/or higher quality technological inventions.

Instrumental variables analysis

To the extent that past NPD performance affects technology conversion and the selection of CEO human capital at present, our results may suffer from endogeneity bias due to *reverse causality*, notwithstanding we have partially addressed it by lagging the attributes of the company's portfolio of inventions (i.e., diversity and quality) and the generality of CEO human capital by one year. In our baseline analysis, we also could not fully rule out the *endogenous matching* in the job market as an alternative explanation: for example, companies may appoint certain types of CEOs in order to implement certain NPD strategies. Finally, our baseline analysis may suffer from *selection bias* arising from CEO candidates being drawn to, and advancing within, the professional environment that better suits their skills, knowledge, and career aspirations.

We address the above sources of endogeneity bias by using an instrumental variables (IV) analysis (see Bascle, 2008; Wooldridge, 2006). We implement this analysis with the help of a control function approach, largely owing to its ability to parsimoniously handle "fairly complicated models that are nonlinear in endogenous explanatory variables" (Wooldridge, 2015:421). It consists of two steps (Lee, 2007): at the first step, we estimate the *reduced-form equation* for the generality of CEO human capital that consists of two sources of exogenous variation (see below) in this supposedly endogenous variable together with all the explanatory and control variables that we identified in the methodology section. At the second step, we estimate the *primary equation* for NPD performance that contains, *inter alia*, the predicted value of the residuals from the reduced-form equation as an additional explanatory variable. In doing so, we are therefore able to condition out the variation in the unobserved variable that is not independent of the endogenous variable.

Human capital theory points to an individual's education, be it formal or on-the-job training, as providing a basis for building his/her human capital (Becker, 1962). Following this insight, we utilize the breadth of the CEO's (prior) higher education as the first source of exogenous variation in CEO human capital because it should ultimately affect his/her ability to acquire a broader set of skills and knowledge (Hitt *et al.*, 2001). According to Frydman (2019), since the 1970s, education has been a principal source of CEO general skills. We capture the breadth of higher education by counting the number of unique degree subjects that the CEO has studied to date. We classify all degree subjects according to seven categories, namely: arts and humanities; natural sciences; life sciences and medicine; engineering and technology; business studies; legal studies; and other social sciences. This classification relies on that designed by Quacquarelli Symonds Limited for its university ranking. Hence, broader higher education indicates that the CEO has mastered more than one subject area, so s/he should possesses — or be able to further acquire — broader human capital.

The second source of exogenous variation in CEO human capital that we use is the CEO's ability to acquire broader set of skills and knowledge through on-the-job training and professional experience. This ability depends significantly on how freely chief executives can move from one job to another, with constraints being usually set by the legal framework in which individuals develop their careers. For example, working in companies that enforce noncompetition contracts may limit the mobility of individuals and, as a result, the generality of their human capital (Garmaise, 2011). So, for each CEO, we compute an index that reflects the average stringency of the noncompetition regimes encountered by him/her at all public companies where s/he has ever worked (Custódio *et al.*, 2019). The index draws on the estimates of state-level noncompetition enforcement in the U.S. that were made by Garmaise (2011). We expect CEOs with higher values of the index to possess less general human capital because "tougher noncompetition enforcement promotes executive stability" (Garmaise, 2011:376). This expectation is in line with the fact that "in state-industry combinations with a higher incidence and enforceability of noncompetes, workers [...] receive relatively fewer job offers, have reduced mobility, and experience lower wages" (Starr *et al.*, 2019:1). In turn, Frydman (2019) suggests that occupational mobility among executives is often promoted by companies to ensure that those executives acquire more general skills during the process of on-the-job training.

---- Insert Table 4 here ----

The results from the reduced-form regression corroborate the conjectures of human capital theory. That is, we find that CEO human capital has a positive association with the breadth of higher education, while its association with the index of the stringency of noncompetition regimes is found to be negative.[xii] Both instrumental variables have the predictive power as indicated by their *p*-values that are below 0.01. The results of the IV regression analysis are reported in Table 4. As Model 5 shows, a unit increase in the diversity of technological inventions is associated with a 22% increase in NPD performance (IRR = 1.217; *p*-value = 0.000), hence supporting Hypothesis 1(a). Model 5 also shows that a unit increase in the quality of technological inventions is associated with a 54% increase in NPD performance (IRR = 1.541; *p*-value = 0.083), which supports Hypothesis 1(b). In turn, Models 6–8 are used to test Hypotheses 2(a) and 2(b). More specifically, Model 6 shows that the IRR for the first interaction term is above one (IRR = 1.099; *p*-value = 0.000), which, given the prediction of Hypothesis 2(a), indicates a positive moderating effect of CEO general human capital on the conversion process when the diversity of technological inventions is studied. Model 7 shows that the IRR for the second interaction term is above one (IRR = 1.726; *p*-value = 0.000); this supports Hypothesis 2(b), predicting a positive moderating effect of CEO general human capital on the conversion process when the quality of technological inventions is considered. Importantly, these moderation effects are still present even if both enter the model simultaneously (see Model 8; the first interaction term: IRR = 1.075; *p*-value = 0.005; the second interaction term: IRR = 1.369; *p*-value = 0.059).

By exploiting these sources of exogenous variation, our IV estimator can effectively deal with the possible endogenous matching or selection bias if the only reason for the CEO's (prior) higher education and state-level noncompetition enforceability is to have an impact on the company's NPD outcome through affecting the generality of its CEO's human capital. To further ensure that our findings are not *solely* driven by matching or selection, we follow Hirshleifer *et al.* (2012) and restrict our analysis to a subsample that excludes observations for newly appointed CEOs. The logic behind this check is that the strength of the effect caused by matching should gradually decline as executive tenure progresses because, unlike human capital qualities that are relatively persistent, company strategies vary over time in response to internal and external pressures. So, for each newly appointed CEO, we drop the first three years of his/her tenure in the CEO position (assuming that in this period, the effect due to matching is likely to be most pronounced) and re-estimate Equation 3 using our IV regressions. We repeat the check with four and five years of CEO tenure as alternative cut-off points (see Online Appendix C, Table C.1). In all these cases, we reveal broad consistency with our baseline results, thus corroborating the causal impact of CEO human capital after taking into account for the job-market matching and self-selection of chief executives.

In the absence of random assignment, our identification strategy (albeit imperfect) therefore consists of several attempts aiming at the isolation of exogenous variation, which, taken together, should provide a fuller consideration of the causal effect that CEO human capital has on the link between technological diversity and/or quality and NPD performance.

Robustness checks

We also conduct a battery of robustness checks to make sure that the results of our baseline analysis are not sensitive to model specification or measurement errors. First, we employ alternative methods to estimate Equation 3, such as *negative binomial* and *ordinary least squares*, and reveal a high level of consistency between the estimates obtained using these methods and our baseline estimates obtained with the help of the Poisson method (see Online Appendix C, Table C.2). Second, we investigate whether our results are sensitive to alterations in the composition of the general ability index. For example, along with the four elements making up the initial index, we further include CEOs' military, academic, and civil service experiences — these experiences are shown to shape managerial perceptions and decision making, as well as, more broadly, can contribute toward the generality of their human capital (Benmelech and Frydman, 2015; Bertrand *et al.*, 2007; Dietz and Bozeman, 2005)[xiii]. The results obtained from this analysis are comparable with our baseline results (see Online Appendix C, Table C.3). Third, instead of relying on the patent quality index to capture the quality of new technologies, we utilize one of its components, namely: the average number of citations received by a patent over a period of five years after the publication date. As Lanjouw and Schankerman (2004:448) point out, having "[c]itations soon after patent application suggests rapid recognition of its importance as well as the presence of others working in a similar area, and thus the expectation of a valuable technological area." We reveal that our results still hold even when the alternative measure of technological quality is used (see Online Appendix C, Table C.4).

To deal with the unobserved confounder problem, we introduce an additional control variable to capture the company's brand strategy that may affect its NPD performance (Agostini *et al.*, 2015; Krasnikov *et al.*, 2009). We draw on the work by Rao *et al.* (2004) which classifies firms into three categories based on the brand strategy they adopt, namely: corporate branders who have a single dominating corporate brand (e.g., Hewlett-Packard); firms with the "house of brands" strategy that involves designing an individual brand for each good or service (e.g., Procter & Gamble); and mixed branders that combine both strategies (e.g., PepsiCo). Corporate branders tend to be associated with a weaker flow of new trademarks than firms with the "house of brands" or mixed brand strategy. Since the firm's brand strategy is not always directly observable, Rao *et al.* (2004) use Tobin's q to approximate the value of the intangible assets owned by the firm, including the value of its brands. They reveal a strong empirical link between brand strategy and Tobin's q values, where the highest values of Tobin's q point to corporate branders, its medium values to the "house of brands" strategy, and the lowest values to the mixed branders. Following this intuition, we verify our results by adding an extra firm-level control for whether the company adopts the corporate brand strategy. We create three more model specifications experimenting with different thresholds of Tobin's q to capture the corporate brand strategy. More specifically, we include a dummy variable that takes the value of one if the firm's Tobin's q in the given year is above the sample median, the 75th percentile, or the 90th percentile, and zero otherwise. The results of this check demonstrate that the effects of all explanatory variables still hold, irrespective of the Tobin's q measure having been included in the model specification or not (see Online Appendix C, Table C.5).

Finally, we analyze the association between NPD performance and such firm performance indicators as total sales and sales growth. The aim of this analysis is twofold: first and foremost, to check whether there is a positive link between the firm's development of new products (captured by trademarks) and its subsequent sales; and also to verify our conclusions regarding the firm-wide effect of technology conversion. Its results a positive association between NPD performance and both firm total sales and sales growth, even after controlling for such firm-specific characteristics as size, age, financial performance, and commercial spending (see Online Appendix C, Table C.6). These results effectively suggest that the trademark-based NPD performance measure we have used behaves in the same way as more "traditional" NPD measures, such as firm total sales. Furthermore, they reveal that technology conversion eventually leads to better firm performance. For performanceoriented firms, this implies that bolstering the conversion of new technologies into new products — by, *inter alia*, leveraging CEO human capital — may lead to greater value for their stakeholders.

DISCUSSION AND CONCLUSION

In this article, we focus on CEO human capital as a mechanism that can have a notable impact on how well companies can convert their new technologies into new products. This is particularly relevant for large companies because of coordination and integration problems they tend to have that may lead to the "chronic" under-utilization of their invention portfolios in the product market. Recognizing that invention portfolios differ along diversity and quality dimensions, we reveal that, on the one hand, CEOs with general human capital amplify the positive effect that a more diverse and higher quality invention portfolio has on the company's NPD performance. Chief executives with specialist human capital, on the other hand, play a catalytic role in technology conversion when the company's invention portfolio is of low to moderate levels of diversity and quality.

The results of our research confirm the insight from the literature that new technologies are a key input to the NPD process. Our article particularly shows that the *diversity* and the *quality* of inventions matter to achieve better NPD performance. However, even though a greater diversity and a higher quality of technological portfolios can boost NPD performance, our article also reveals that simply having such portfolios is not sufficient for commercial success. It is common for established organizations to struggle with converting new technologies into new products because this process necessitates the orchestration of multiple organizational resources, functions, and businesses. That is why input from corporate leaders, and especially CEOs as occupying the most powerful position in organizations, is critical. Our article demonstrates that the direct involvement of top leadership is beneficial for the technology conversion process when the generality/specificity of CEO *human capital* is aligned with the characteristics of the company's portfolio of new technologies because such an alignment, in and of itself, can greatly improve the outcomes of this process.

With these findings, we make two novel contributions to NPD and innovation management literatures. First, we extend the existing body of research on the top leadership aspects of NPD in technological companies (e.g., Caridi-Zahavi *et al.*, 2016; Felekoglu and Moultrie, 2014; Stock *et al.*, 2019): in addition to its current focus on senior managers' attention, as well as personality and psychological attributes, we suggest focusing on CEO human capital as a critical factor influencing the conversion of new technologies into new products. Our results confirm that the characteristics of CEO human capital — particularly, generality versus specificity — have an impact on the link between the diversity/quality of the company's portfolio of inventions and its NPD performance. Second, we add to the body of research that examines radical product innovation and the need for intra-organizational support mechanisms to facilitate technology conversion (e.g., O'Connor and Rice, 2001; Rice *et al.*, 2001; Slater *et al.*, 2014). By recognizing CEOs as such facilitators, our article points to a closer alignment between the attributes of CEO human capital and the attributes of the company's portfolio of new technologies as a source of additional value for the commercialization process. Without this insight about the alignment, there is a potential danger of the universalistic prescription and promotion of generalist CEOs who are not the right facilitators of the technology conversion process across the board. Our article reveals that it is specialist CEOs who deliver better NPD performance in companies with less divers and/or lower quality invention portfolios.

Implications for theory and practice

We have argued that with access to a richer repertoire of tools, solutions, and business know-how, generalist CEOs are expected to be better at fostering the integration of different knowledge domains. In providing a high-level guidance to NPD teams, such executives are likely to draw on their diverse technological and product market expertise. Their knowledge of multiple technology domains and "professional" languages can help the companies they run tackle the functional silos problem by fostering cross-functional communication and cross-divisional collaboration. Generalist CEOs also tend to be less domain entrenched, which should lead to greater efficiency in resource allocation within the NPD process. In contrast, specialist CEOs may have an advantage in guiding technology conversion for a more focused range of technology domains, where the depth of their expertise and a broader intra-domain network should lead to a superior matching of the company's technological competencies with market opportunities. Our findings are in line with this reasoning.

The principal implication of our findings for management theory is that the added value of CEO human capital characteristics is intimately linked to the intra-organizational strategic context. Therefore, it would be misleading and, perhaps, even perilous to deem either a generalist CEO or a specialist CEO as being highly effective across the board inasmuch as their effectiveness clearly differs from one company to another. For a better matching of CEOs to companies, one therefore should pay close attention to the characteristics of the company's resource base that include, *inter alia*, new technologies. In companies with more diverse and/or higher quality invention portfolios, it is important that CEOs have *general* human capital enabling them to aptly evaluate a broader set of technological inventions; to better coordinate NPD activities across various functions, divisions, and businesses; and to be less biased in allocating resources among competing NPD projects. Since those companies have an opportunity to create more value by combining and recombining diverse and/or higher quality technological inventions, their technological profile calls for corporate leaders who can provide an overarching perspective and astute evaluation skills to pick the inventions that offer differentiating and enduring solutions. However, generalist chief executives do not necessarily deliver the strongest NPD performance in companies with invention portfolios that are of low to moderate levels of diversity and quality — such companies would instead benefit from appointing *specialist* CEOs, who are domain experts and can be better at facilitating NPD initiatives that build more closely on (past) internal competencies. Those companies may possess fewer inventions with a blockbuster potential and, thus, may be better off with a less selective approach to the technology conversion process. The catalytic role of specialist executives in this case is to make the most out of the portfolio of inventions that their companies have by introducing new products more frequently within the core business domain.

In turn, the key implication of our findings for practice is that, when grooming or recruiting CEOs, companies should think about their existing and future strategic requirements in conjunction with the resource bundles they intend to deploy. It is usually advisable for chief executives to have a depth of expertise in the businesses and technologies that are central to the company; yet, our article reveals that the breadth of knowledge, skills, and experience is a *sine qua non* for corporate leaders whose companies are involved in inventive activities across various technology domains. Likewise, although many CEOs would benefit from *some* level of generality in their human capital, our article suggests that this is likely to play only a minor, supporting role if there is a high degree of specificity in the company's portfolio of technological inventions. In such a setting, the CEO who has devoted most of his/her career to that company or industry seems to be a preferable choice. Our findings thus underscore that the one-size-fits-all approach does not work for the technology conversion process. The discovery of this insight is timely, given the increasing popularity of generalist CEOs, which could lead to poorer NPD performance in the contexts of low to moderate levels of technological diversity and/or quality. Overall, we caution against the institutionalization of generalist executives as a superior form of leadership for all companies and advocate a more nuanced approach, which is to match CEO human capital attributes to the technological needs and attributes of the company.

Finally, we should also note that because of labor market imperfections, companies are not always able to find or groom their ideal chief executive. Our study reveals one important alignment opportunity for CEO human capital to foster the conversion of new technologies into new products, but we have to acknowledge that there are other contingencies, too. Thus, reducing the choice of a chief executive to only one dimension of value creation may *not* be *universally* advisable, unless the technology conversion process is of principal importance to the company's competitiveness and future viability — in this case, a strong emphasis on this alignment is likely to be most rewarding.

Limitations and future research

Our study is not without limitations, which provide avenues for future research. First, we focus on NPD as a key channel for technology commercialization. However, companies may prefer a contractual model consisting in licensing technologies to other companies (Teece, 1986). Future research can evaluate the role that CEOs and their human capital characteristics play in choosing the licensing model over the NPD model, as well as in searching for potential licensees. Second, we rely on patent data to capture technological inventions and to evaluate the ability of companies to convert them into new products. At the same time, products incorporate a variety of technologies developed both within and outside the company, and also at different time periods (Tatikonda and Stock, 2003). Therefore, another potentially fruitful research avenue is to explore the effect of CEO human capital on the company's involvement in technology sourcing. Third, the radical innovation literature has highlighted the need for special mechanisms that enable radical innovation to occur repeatedly in large organizations (e.g., O'Connor and DeMartino, 2006; Slater *et al.*, 2014). Given the bolstering effect of the generality of CEO human capital on the conversion of higher quality technologies that we have uncovered, future research may draw on this finding to further examine the role of CEO *general* human capital in establishing and sustaining those mechanisms. Fourth, previous research has stressed the effect of other organizational factors, such as company type and location (Sasaki and Yoshikawa, 2014), approaches to innovation and failure (Madsen and Desai, 2018), and approaches to exploration and exploitation (Lin *et al.*, 2013) on technology conversion. Future research can study these factors together with CEO human capital to uncover any synergistic or substitutive effects. Subsequent work can also investigate how these relationships — especially the role of generalist versus specialist CEOs — may vary under different institutional and country contexts. Finally, drawing from upper echelons studies, we reveal certain biases of specialist chief executives, but generalist CEOs may suffer from biases, too. For example, previous research has found that in competitive companies, there is bias against internal knowledge, which gets a closer scrutiny than external knowledge (Menon and Pfeffer, 2003). Generalist CEOs, who tend to have stronger external networks, may discount the advice received from internal managers, which can be problematic for the technology conversion process. An externally sourced advice is usually more objective, but it lacks firm-specific insight (Ma *et al*., 2020). Future research can examine the biases of both generalist and specialist CEOs in shaping their involvement in technology conversion.

In closing, our study revealed the key role of CEO human capital generality/specificity in technology conversion. Generalist and specialist chief executives have differential advantages that are uncovered only when one considers the diversity and the quality of the company's portfolio of technological inventions. CEOs with general human capital exhibit a superior ability in fostering the conversion of diverse and higher quality inventions into new products; on the contrary, CEOs with specialist human capital are more effective in the conversion of new technologies that are of low to moderate levels of diversity and quality. We encourage future research to further examine how such corporate leaders' attributes as demography, psychology, and human capital shape their ability to support the management of inventions for better NPD performance.

References

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

Adner, R., and Kapoor, R. 2010. Value creation in innovation ecosystems: How the structure of technological interdependence affects firm performance in new technology generations. *Strategic Management Journal* 31(3): 306–333.

Agostini, L., Filippini, R., and Nosella, A. 2015. Brand-building efforts and their association with SME sales performance. *Journal of Small Business Management* 53(S1): 161–173.

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

Allison, P.D. 2009. *Fixed effects regression models*. Vol. 160. Thousand Oaks, CA: SAGE Publications.

Bascle, G. 2008. Controlling for endogeneity with instrumental variables in strategic management research. *Strategic Organization* 6(3): 285–327.

Becker, G.S. 1962. Investment in human capital: A theoretical analysis. *Journal of Political Economy* 70(5): 9–49.

Benmelech, E., and Frydman, C. 2015. Military CEOs. *Journal of Financial Economics* 117(1): 43–59.

Bertrand, M., Kramarz, F., Schoar, A., and Thesmar, D. 2007. *Politicians, firms and the political business cycle: Evidence from France*. Mimeo, University of Chicago.

Betzer, A., Ibel, M., Lee, H.S., Limbach, P., and Salas, J.M. 2016. *Are generalists beneficial to corporate shareholders? Evidence from sudden deaths*. CFR Working Paper Series no. 16–12. Cologne: CFR.

Block, J.H., Fisch, C.O., Hahn, A., and Sandner, P.G. 2015. Why do SMEs file trademarks? Insights from firms in innovative industries. *Research Policy* 44(10): 1915–1930.

Blundell, R., Griffith, R., and Van Reenen, J. 1999. Market share, market value and innovation in a panel of British manufacturing firms. *Review of Economic Studies* 66(3): 529–554.

Bond, E.U., and Houston, M.B. 2003. Barriers to matching new technologies and market opportunities in established firms. *Journal of Product Innovation Management* 20(2): 120–135.

Brenton, B., and Levin, D. 2012. The softer side of innovation: The people. *Journal of Product Innovation Management* 29(3): 364–366.

Brusoni, S., Prencipe, A., and Pavitt, K. 2001. Knowledge specialization, organizational coupling, and the boundaries of the firm: Why do firms know more than they make? *Administrative Science Quarterly* 46(4): 597–621.

Buis, M.L. 2010. Stata tip 87: Interpretation of interactions in nonlinear models. *Stata Journal* 10(2): 305–308.

Byun, H., Frake, J., and Agarwal, R. 2018. Leveraging who you know by what you know: Specialization and returns to relational capital. *Strategic Management Journal* 39(7): 1803–1833.

Calantone, R.J., Vickery, S.K., and Dröge, C. 1995. Business performance and strategic new product development activities: An empirical investigation. *Journal of Product Innovation Management* 12(3): 214–223.

Caridi-Zahavi, O., Carmeli, A., and Arazy, O. 2016. The influence of CEOs' visionary innovation leadership on the performance of high-technology ventures: The mediating roles of connectivity and knowledge integration. *Journal of Product Innovation Management* 33(3): 356–376.

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

Castaldi, C. 2019. All the great things you can do with trademark data: Taking stock and looking ahead. *Strategic Organization* 18(3): 472–484.

Castaldi, C., Block, J., and Flikkema, M.J. 2020. Why and when do firms trademark? Bridging perspectives from industrial organisation, innovation and entrepreneurship. *Industry and Innovation* 27(1–2): 1–10.

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

Chandy, R., Hopstaken, B., Narasimhan, O., and Prabhu, J. 2006. From invention to innovation: Conversion ability in product development. *Journal of Marketing Research* 43(3): 494–508.

Chang, S.J. 1996. An evolutionary perspective on diversification and corporate restructuring: Entry, exit, and economic performance during 1981–89. *Strategic Management Journal* 17(8): 587–611.

Chen, Y., Tang, G., Jin, J., Xie, Q., and Li, J. 2014. CEOs' transformational leadership and product innovation performance: The roles of corporate entrepreneurship and technology orientation. *Journal of Product Innovation Management* 31(S1): 2–17.

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

Conley, J.G., Bican, P.M., and Ernst, H. 2013. Value articulation: A framework for the strategic management of intellectual property. *California Management Review* 55(4): 102–120.

Cooper, R.G. 1999. The invisible success factors in product innovation. *Journal of Product Innovation Management* 16(2): 115–133.

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

Custódio, C., Ferreira, M.A., and Matos, P. 2013. Generalists versus specialists: Lifetime work experience and chief executive officer pay. *Journal of Financial Economics* 108(2): 471–492.

Custódio, C., Ferreira, M.A., and Matos, P. 2019. Do general managerial skills spur innovation? *Management Science* 65(2): 459–476.

Dane, E. 2010. Reconsidering the trade-off between expertise and flexibility: A cognitive entrenchment perspective. *Academy of Management Review*, 35(4): 579–603.

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

De Brentani, U., Kleinschmidt, E.J., and Salomo, S. 2010. Success in global new product development: Impact of strategy and the behavioral environment of the firm. *Journal of Product Innovation Management* 27(2): 143–160.

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

Egghe, L., and Leydesdorff, L. 2009. The relation between Pearson's correlation coefficient r and Salton's cosine measure. *Journal of the American Society for Information Science and Technology* 60(5): 1027–1036.

Ernst, H. 1995. Patenting strategies in the German mechanical engineering industry and their relationship to company performance. *Technovation* 15(4): 225–240.

Ernst, H. 2001. Patent applications and subsequent changes of performance: Evidence from time-series cross-section analyses on the firm level. *Research Policy* 30(1): 143–157.

Ernst, H. 2002. Success factors of new product development: A review of the empirical literature. *International Journal of Management Reviews* 4(1): 1–40.

Evanschitzky, H., Eisend, M., Calantone, R.J., and Jiang, Y. 2012. Success factors of product innovation: An updated meta-analysis. *Journal of Product Innovation Management* 29(S1): 21–37.

Fama, E.F., and French, K.R. 1997. Industry costs of equity. *Journal of Financial Economics* 43(2): 153–193.

Felekoglu, B., and Moultrie, J. 2014. Top management involvement in new product development: A review and synthesis. *Journal of Product Innovation Management* 31(1): 159–175.

Ferreira, D., and Sah, R.K. 2012. Who gets to the top? Generalists versus specialists in managerial organizations. *RAND Journal of Economics* 43(4): 577–601.

Fink, C., Helmers, C., and Ponce, C.J. 2018. Trademark squatters: Theory and evidence from Chile. *International Journal of Industrial Organization* 59: 340–371.

Finkelstein, S., Hambrick, D.C., and Cannella, A.A. 2009. *Strategic leadership: Theory and research on executives, top management teams, and boards*. New York, NY: Oxford University Press.

Flikkema, M., Castaldi, C., De Man, A.P., and Seip, M. 2019. Trademarks' relatedness to product and service innovation: A branding strategy approach. *Research Policy* 48(6): 1340–1353.

Flikkema, M., De Man, A.P., and Castaldi, C. 2014. Are trademark counts a valid indicator of innovation? Results of an in-depth study of new Benelux trademarks filed by SMEs. *Industry and Innovation* 21(4): 310–331.

Frydman, C. 2019. Rising through the ranks: The evolution of the market for corporate executives, 1936–2003. *Management Science* 65(11): 4951–4979.

Furr, N.R., Cavarretta, F., and Garg, S. 2012. Who changes course? The role of domain knowledge and novel framing in making technology changes. *Strategic Entrepreneurship Journal* 6(3): 236–256.

Galasso, A., and Simcoe, T.S. 2011. CEO overconfidence and innovation. *Management Science* 57(8): 1469–1484.

Gallié, E.P., and Legros, D. 2012. French firms' strategies for protecting their intellectual property. *Research Policy* 41(4): 780–794.

Gambardella, A., and Torrisi, S. 1998. Does technological convergence imply convergence in markets? Evidence from the electronics industry. *Research Policy* 27(5): 445–463.

Gao, G., and Hitt, L.M. 2012. Information technology and trademarks: Implications for product variety. *Management Science* 58(6): 1211–1226.

Garmaise, M.J. 2011. Ties that truly bind: Noncompetition agreements, executive compensation, and firm investment. *Journal of Law, Economics, and Organization* 27(2): 376–425.

Gedajlovic, E., Lubatkin, M. H., and Schulze, W.S. 2004. Crossing the threshold from founder management to professional management: A governance perspective. *Journal of Management Studies* 41(5): 899–912.

Graham, S., Hancock, G., Marco, A., and Myers, A.F. 2013. *The USPTO trademark case files dataset: Descriptions, lessons, and insights*. Alexandria, VA: USPTO.

Greene, W. 2008. *Econometric analysis*. 6th ed. Upper Saddle River, NJ: Pearson Prentice Hall.

Greene, W. 2010. Testing hypotheses about interaction terms in nonlinear models. *Economics Letters* 107(2): 291–296.

Greenhalgh, C., and Longland, M. 2001. Intellectual property in UK firms: Creating intangible assets and distributing the benefits via wages and jobs. *Oxford Bulletin of Economics and Statistics* 63(S1): 671–696.

Greenhalgh, C., and Rogers, M. 2012. Trade marks and performance in services and manufacturing firms: Evidence of Schumpeterian competition through innovation. *Australian Economic Review* 45(1): 50–76.

Gruber, M., MacMillan, I.C., and Thompson, J.D. 2013. Escaping the prior knowledge corridor: What shapes the number and variety of market opportunities identified before market entry of technology start-ups? *Organization Science* 24(1): 280–300.

Hall, B.H., and Ziedonis, R.H. 2001. The patent paradox revisited: An empirical study of patenting in the US semiconductor industry, 1979-1995. *RAND Journal of Economics* 32(1): 101–128.

Hall, B.H., Jaffe, A.B., and Trajtenberg, M. 2001. *The NBER patent citation data file: Lessons, insights and methodological tools*. NBER Working Paper Series no. 8498. Cambridge, MA: NBER.
Hambrick, D.C. 2007. Upper echelons theory: An update. *Academy of Management Review* 32(2): 334–343.
Harris, D., and Helfat, C.E. 1997. Specificity of CEO human capital and compensation. *Strategic Management Journal* 18(11): 895–920.
Helfat, C.E., and Martin, J.A. 2015. Dynamic managerial capabilities: Review and assessment of managerial impact on strategic change. *Journal of Management* 41(5): 1281–1312.
Hirshleifer, D., Low, A., and Teoh, S.H. 2012. Are overconfident CEOs better innovators? *Journal of Finance* 67(4): 1457–1498.
Hitt, M.A., Bierman, L., Shimizu, K., and 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.
Iansiti, M. 1995a. Technology development and integration: An empirical study of the interaction between applied science and product development. *IEEE Transactions on Engineering Management* 42(3): 259–269.
Iansiti, M. 1995b. Technology integration: Managing technological evolution in a complex environment. *Research Policy* 24(4): 521–542.
Iansiti, M. 1997. From technological potential to product performance: An empirical analysis. *Research Policy* 26(3): 345–365.
Jensen, P.H., and Webster, E. 2009. Another look at the relationship between innovation proxies. *Australian Economic Review* 48(3): 252–269.
Jolliffe, I.T. 2002. *Principal component analysis*. 2nd ed. New York, NY: Springer-Verlag.
Jones, W.P., and Furnas, G.W. 1987. Pictures of relevance: A geometric analysis of similarity measures. *Journal of the American Society for Information Science* 36: 420–442.
Kim, J., Lee, C.Y., and Cho, Y. 2016. Technological diversification, core-technology competence, and firm growth. *Research Policy* 45(1): 113–124.
Kleinschmidt, E.J., De Brentani, U., and Salomo, S. 2007. Performance of global new product development programs: A resource-based view. *Journal of Product Innovation Management* 24(5): 419–441.
Knoeber, C.R. 1986. Golden parachutes, shark repellents, and hostile tender offers. *American Economic Review* 76(1): 155–167.
Kor, Y. Y. 2003. Experience-based top management team competence and sustained growth. *Organization Science* 14(6): 707–719.
Kor, Y.Y., and Mesko, A. 2013. Dynamic managerial capabilities: Configuration and orchestration of top executives' capabilities and the firm's dominant logic. *Strategic Management Journal* 34(2): 233–244.
Koski, H., and Kretschmer, T. 2007. Innovation and dominant design in mobile telephony. *Industry and Innovation* 14(3): 305–324.
Krasnikov, A., Mishra, S., and Orozco, D. 2009. Evaluating the financial impact of branding using trademarks: A framework and empirical evidence. *Journal of Marketing* 73(6): 154–166.
Krause, R., Semadeni, M., and Cannella Jr., A.A. 2014. CEO duality: A review and research agenda. *Journal of Management* 40(1): 256–286.
Krishnan, V., and Ulrich, K.T. 2001. Product development decisions: A review of the literature. *Management Science* 47(1): 1–21.
Lanjouw, J.O., and Schankerman, M. 2004. Patent quality and research productivity: Measuring innovation with multiple indicators. *Economic Journal* 114(495): 441–465.
Lee, S. 2007. Endogeneity in quantile regression models: A control function approach. *Journal of Econometrics* 141(2): 1131–1158.

Leifer, R., McDermott, C.M., O'Connor, G.C., Peters, L.S., Rice, M.P., and Veryzer Jr., R.W. 2000. *Radical innovation: How mature companies can outsmart upstarts*. Boston, MA: Harvard Business Press.

Lerner, J. 1994. The importance of patent scope: An empirical analysis. *RAND Journal of Economics* 25(2): 319–333.

Li, M., and Patel, P.C. 2019. Jack of all, master of all? CEO generalist experience and firm performance. *Leadership Quarterly* 30(3): 320–334.

Liebeskind, J., and Rumelt, R.P. 1989. Markets for experience goods with performance uncertainty. *RAND Journal of Economics* 20(4): 601–621.

Lin, H.E., McDonough, E.F., Lin, S.J., and Lin, C.Y.Y. 2013. Managing the exploitation/ exploration paradox: The role of a learning capability and innovation ambidexterity. *Journal of Product Innovation Management* 30(2): 262–278.

Long, J.S., and Freese, J. 2006. Regression models for categorical dependent variables using Stata. 2nd ed. College Station: TX: Stata Press.

Ma, S., Kor, Y.Y., and Seidl, D. 2020. CEO advice seeking: An integrative framework and research agenda. *Journal of Management* 46(6): 771–805.

Madsen, P.M., and Desai, V. 2018. No firm is an island: The role of population-level actors in organizational learning from failure. *Organization Science* 29(4): 739–753.

Marsh, G. 2006. Duelling with composites. *Reinforced Plastics* 50(6): 18–23.

Mendonça, S., Pereira, T.S., and Godinho, M.M. 2004. Trademarks as an indicator of innovation and industrial change. *Research Policy* 33(9): 1385–1404.

Menon, T., and Pfeffer, J. 2003. Valuing internal vs. external knowledge: Explaining the preference for outsiders. *Management Science* 49(4): 497–513.

Miller, D., and Friesen, P.H. 1983. Strategy-making and environment: The third link. *Strategic Management Journal* 4(3): 221–235.

Mishra, D.R. 2014. The dark side of CEO ability: CEO general managerial skills and cost of equity capital. *Journal of Corporate Finance* 29: 390–409.

Murphy, K.J., and Zábojník, J. 2004. CEO pay and appointments: A market-based explanation for recent trends. *American Economic Review: Papers and Proceedings* 94(2): 192–196.

Nadkarni, S., and 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.

Nasirov, S. 2020. Trademark value indicators: Evidence from the trademark protection lifecycle in the U.S. pharmaceutical industry. *Research Policy* 49(4). In press.

O'Connor, G.C., and DeMartino, R. 2006. Organizing for radical innovation: An exploratory study of the structural aspects of RI management systems in large established firms. *Journal of Product Innovation Management* 23(6): 475–497.

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

O'Connor, G.C., and Rice, M.P. 2001. Opportunity recognition and breakthrough innovation in large established firms. *California Management Review* 43(2): 95–116.

O'Connor, G.C., and Veryzer, R. 2001. The nature of market visioning for technology-based radical innovation. *Journal of Product Innovation Management* 18(4): 231–246.

Patel, P., and Pavitt, K. 1997. The technological competencies of the world's largest firms: Complex and path-dependent, but not much variety. *Research Policy* 26(2): 141–156.

Pavitt, K. 1998. Technologies, products and organization in the innovating firm: What Adam Smith tells us and Joseph Schumpeter doesn't. *Industrial and Corporate Change* 7(3): 433–452.

Penrose, E. 1959. *The theory of the growth of the firm*. Oxford: Blackwell.

Poolton, J., and Barclay, I. 1998. New product development from past research to future applications. *Industrial Marketing Management* 27(3): 197–212.

Rao, V.R., Agarwal, M.K., and Dahlhoff, D. 2004. How is manifest branding strategy related to the intangible value of a corporation? *Journal of Marketing* 68(4): 126–141.

Rice, M., Kelley, D., Peters, L., and O'Connor, G.C. 2001. Radical innovation: Triggering initiation of opportunity recognition and evaluation. *R&D Management* 31(4): 409–420.

Salomo, S., Kleinschmidt, E.J., and De Brentani, U. 2010. Managing new product development teams in a globally dispersed NPD program. *Journal of Product Innovation Management* 27(7): 955–971.

Sasaki, I., and Yoshikawa, K. 2014. Going beyond national cultures – Dynamic interaction between intra-national, regional, and organizational realities. *Journal of World Business* 49(3): 455–464.

Schefczyk, M., and Gerpott, T.J. 2001. Qualifications and turnover of managers and venture capital-financed firm performance: An empirical study of German venture capital-investments. *Journal of Business Venturing* 16(2): 145–163.

Schmoch, U. 2008. *Concept of a technology classification for country comparisons*. WIPO Report no. IPC/CE/41/5. Geneva: WIPO.

Schubert, R., Brown, M., Gysler, M., and Brachinger, H.W. 1999. Financial decision-making: Are women really more risk-averse? *American Economic Review* 89(2): 381–385.

Seip, M., Castaldi, C., Flikkema, M., and De Man, A.P. 2018. The timing of trademark application in innovation processes. *Technovation* 72–73: 34–45.

Shamsie, J., and Mannor, M.J. 2013. Looking inside the dream team: Probing into the contributions of tacit knowledge as an organizational resource. *Organization Science* 24(2): 513–529.

Shane, S.A., and Ulrich, K.T. 2004. 50th anniversary article: Technological innovation, product development, and entrepreneurship in Management Science. *Management Science* 50(2): 133–144.

Shannon, C.E. 1948. A mathematical theory of communication. *Bell System Technical Journal* 27(3): 379–423.

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

Squicciarini, M., Dernis, H., and Criscuolo, C. 2013. *Measuring patent quality: Indicators of technological and economic value*. STI Working Paper Series no. 2013/03. Paris: OECD.

Starr, E., Frake, J., and Agarwal, R. 2019. Mobility constraint externalities. *Organization Science* 30(5): 961–980.

Stock, R., Groß, M., and Xin, K.R. 2019. Will self-love take a fall? Effects of top executives' positive self-regard on firm innovativeness. *Journal of Product Innovation Management* 36(1): 41–65.

Suzuki, J., and Kodama, F. 2004. Technological diversity of persistent innovators in Japan: Two case studies of large Japanese firms. *Research Policy* 33(3): 531–549.

Tatikonda, M.V., and Stock, G.N. 2003. Product technology transfer in the upstream supply chain. *Journal of Product Innovation Management* 20(6): 444–467.

Teece, D.J. 1986. Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research Policy* 15(6): 285–305.

Thieme, R. J., Song, X.M., and Shin, G.C. 2003. Project management characteristics and new product survival. *Journal of Product Innovation Management* 20(2): 104–119.

Thoma, G., Torrisi, S., Gambardella, A., Guellec, D., Hall, B.H., and Harhoff, D. 2010. *Harmonizing and combining large datasets — An application to firm-level patent and accounting data*. NBER Working Paper Series no. 15851. Cambridge, MA: NBER.

Tsui, A.S., Zhang, Z.X., Wang, H., Xin, K.R., and Wu, J.B. 2006. Unpacking the relationship between CEO leadership behavior and organizational culture. *Leadership Quarterly* 17(2): 113–137.

Unger, B.N., Kock, A., Gemünden, H.G., and Jonas, D. 2012. Enforcing strategic fit of project portfolios by project termination: An empirical study on senior management involvement. *International Journal of Project Management* 30(6): 675–685.

Wang, L., and Murnighan, J.K. 2013. The generalist bias. *Organizational Behavior and Human Decision Processes* 120(1): 47–61.

Wangrow, D.B., Schepker, D.J., and Barker, V.L. 2015. Managerial discretion: An empirical review and focus on future research directions. *Journal of Management* 41(1): 99–135.

Wheelwright, S.C., and Clark, K.B. 1992. Competing through development capability in a manufacturing-based organization. *Business Horizons* 35(4): 29–43.

Wooldridge, J. M. 2006. Introductory econometrics: A modern approach. 3rd ed. Mason, OH: Thomson-South Western.

Wooldridge, J.M. 2015. Control function methods in applied econometrics. *Journal of Human Resources* 50(2): 420–445.

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

Xuan, Y. 2009. Empire-building or bridge-building? Evidence from new CEOs' internal capital allocation decisions. *Review of Financial Studies* 22(12): 4919–4948.

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

Zirger, B.J., and Maidique, M.A. 1990. A model of new product development: An empirical test. *Management Science* 36(7): 867–883.

Table 1. CEO human capital: A comparison between specialist and generalist chief executives

Theoretical mechanisms	**Specialist CEOs**	**Generalist CEOs**
The applicability of human capital (Becker, 1962)	More valuable in the specialized domain	Transferable across companies and industries
Knowledge domains (Wang and Murnighan, 2013)	Strong, narrowly focused expertise in few domains	Expert knowledge in multiple domains
Cross-functional communication (Betzer *et al.*, 2016; Ferreira and Sah, 2012)	Less capable of overcoming functional silos	More capable of overcoming functional silos
Risk-taking behavior (Mishra, 2014; Custódio *et al.*, 2019)	Likely to be risk averse	Likely to be risk taking
Resource allocation (Xuan, 2009)	Bias to favor projects in the area of their expertise	Less susceptible to bias in resource allocation

Figure 1. The role of CEO human capital in converting new technologies into new products

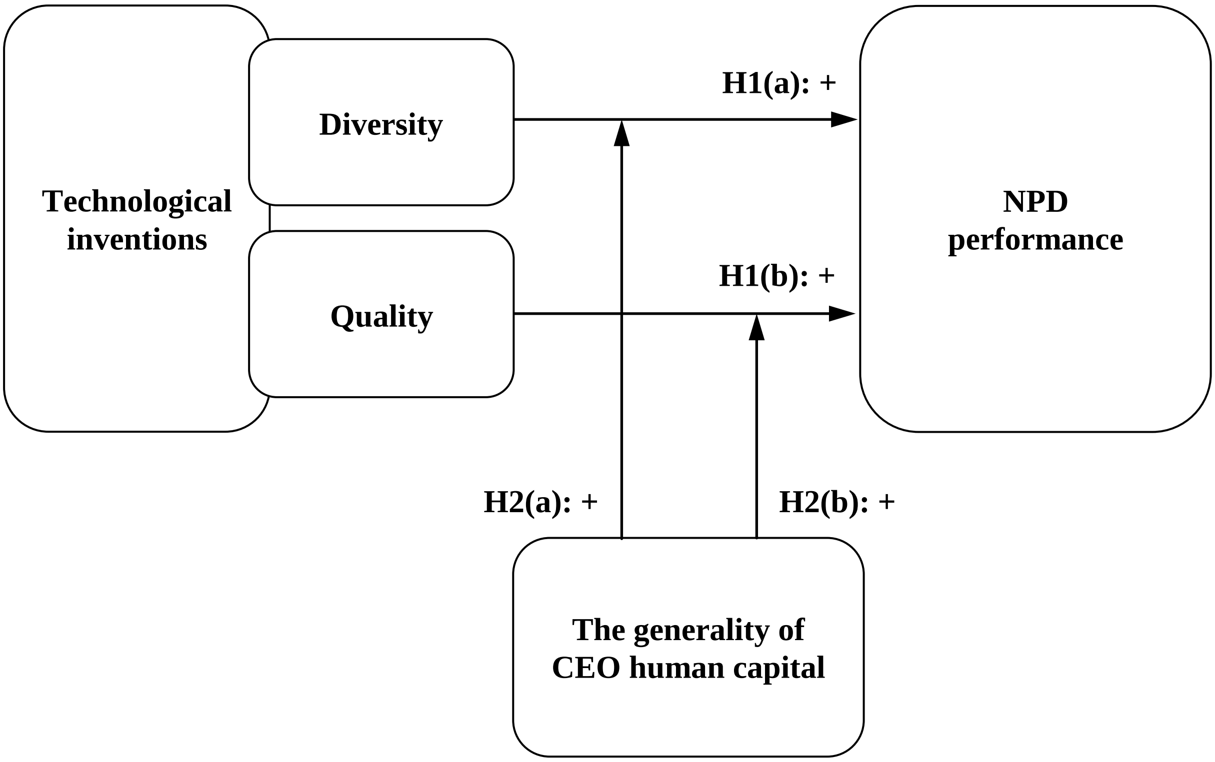


Table 2. Summary statistics and the correlation matrix

No.	Variable	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	NPD performance	8.24	15.15	0.00	218.00	1.00														
2	Technological inventions' diversity	0.97	0.87	0.00	2.95	0.30	1.00													
3	Technological inventions' quality	0.26	0.16	0.00	0.71	0.21	0.63	1.00												
4	CEO general human capital	0.00	1.00	-1.65	5.62	0.15	0.15	0.10	1.00											
5	Company tenure	21.43	11.70	0.25	50.87	0.14	0.12	0.01	-0.14	1.00										
6	Founder CEO	0.06	0.24	0.00	1.00	-0.08	-0.13	-0.13	-0.17	0.07	1.00									
7	Male CEO	0.98	0.14	0.00	1.00	-0.03	0.01	0.07	-0.16	0.10	0.04	1.00								
8	CEO duality	0.69	0.46	0.00	1.00	0.13	0.18	0.11	0.14	0.19	0.08	-0.01	1.00							
9	CEO ownership	0.02	0.05	0.00	0.44	-0.09	-0.24	-0.23	-0.12	0.13	0.22	0.04	0.11	1.00						
10	Company size	31.32	50.02	0.14	486.00	0.43	0.43	0.19	0.23	0.15	-0.12	-0.12	0.17	-0.15	1.00					
11	Company age	84.88	38.39	7.00	211.00	0.21	0.18	0.14	0.23	0.11	-0.40	-0.08	0.11	-0.18	0.15	1.00				
12	Return on assets	0.06	0.07	-0.85	0.95	0.11	0.02	0.07	-0.10	0.07	0.05	0.06	0.01	0.04	-0.02	-0.07	1.00			
13	Book leverage	0.23	0.15	0.00	1.39	0.02	0.03	0.02	0.09	0.01	-0.16	-0.10	0.08	-0.13	0.13	0.31	-0.24	1.00		
14	Intensity of inventive activities	71.65	199.18	0.00	2,051.00	0.23	0.42	0.16	0.11	0.01	-0.06	-0.08	0.06	-0.10	0.45	-0.03	-0.03	-0.04	1.00	
15	Intensity of commercial activities	0.19	0.12	-0.03	0.80	0.13	-0.10	0.02	0.01	-0.08	0.01	-0.00	-0.05	0.08	-0.13	-0.08	0.19	-0.15	-0.11	1.00

The table presents descriptive statistics and Pearson's pairwise correlation coefficients for the study variables. Company size is included before taking the natural logarithm (in thousands workers).

Table 3. Technological inventions and NPD performance: Poisson models (baseline)

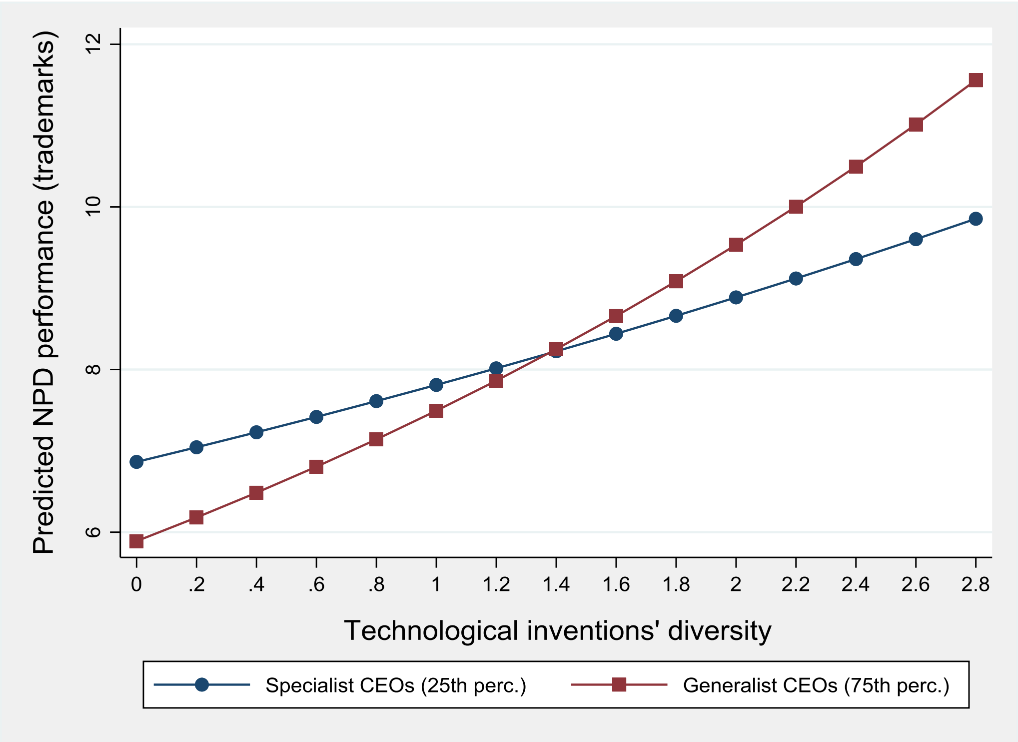
Dependent variable: NPD performance $_{i, t}$	**MODEL 1**	**MODEL 2**	**MODEL 3**	**MODEL 4**
Technological inventions' diversity $_{i, j, t-1}$	1.240 (0.055) [0.000]	1.207 (0.053) [0.000]	1.241 (0.055) [0.000]	1.213 (0.053) [0.000]
Technological inventions' quality $_{i, j, t-1}$	1.615 (0.394) [0.049]	1.699 (0.421) [0.033]	1.584 (0.395) [0.065]	1.699 (0.428) [0.035]
CEO general human capital $_{i, j, t-1}$	0.988 (0.024) [0.630]	0.857 (0.032) [0.000]	0.831 (0.041) [0.000]	0.804 (0.042) [0.000]
Technological inventions' diversity $_{i, j, t-1}$ × CEO general human capital $_{i, j, t-1}$		1.116 (0.027) [0.000]		1.089 (0.031) [0.003]
Technological inventions' quality $_{i, j, t-1}$ × CEO general human capital $_{i, j, t-1}$			1.816 (0.279) [0.000]	1.388 (0.254) [0.073]
Company tenure $_{i, j, t-1}$	1.025 (0.009) [0.004]	1.025 (0.009) [0.003]	1.025 (0.009) [0.004]	1.025 (0.009) [0.003]
Company tenure^2 $_{i, j, t-1}$	0.9995 (0.000) [0.011]	0.9995 (0.000) [0.009]	0.9995 (0.000) [0.012]	0.9995 (0.000) [0.010]
Founder CEO $_{i, j, t-1}$	1.000 (0.103) [1.000]	0.962 (0.097) [0.703]	0.970 (0.098) [0.765]	0.955 (0.096) [0.645]
Male CEO $_{i, j, t-1}$	1.770 (0.272) [0.000]	1.716 (0.250) [0.000]	1.688 (0.260) [0.001]	1.686 (0.250) [0.000]
CEO duality $_{i, j, t-1}$	1.177 (0.071) [0.007]	1.182 (0.071) [0.005]	1.160 (0.070) [0.014]	1.171 (0.071) [0.009]
CEO ownership $_{i, j, t-1}$	1.213 (0.737) [0.750]	0.909 (0.524) [0.868]	0.880 (0.508) [0.824]	0.817 (0.461) [0.720]
Company size $_{i, t-1}$	1.238 (0.036) [0.000]	1.249 (0.036) [0.000]	1.248 (0.037) [0.000]	1.252 (0.037) [0.000]
Company age $_{i, t-1}$	1.001 (0.001) [0.101]	1.001 (0.001) [0.234]	1.001 (0.001) [0.135]	1.001 (0.001) [0.223]
Return on assets $_{i, t-1}$	2.169 (0.674) [0.013]	2.053 (0.641) [0.021]	2.109 (0.657) [0.017]	2.042 (0.639) [0.022]
Book leverage $_{i, t-1}$	0.563 (0.100) [0.001]	0.582 (0.103) [0.002]	0.582 (0.103) [0.002]	0.587 (0.104) [0.003]
Intensity of inventive activities $_{i, j, t-1}$	1.0012 (0.000) [0.000]	1.0012 (0.000) [0.000]	1.0011 (0.000) [0.000]	1.0011 (0.000) [0.000]
Intensity of inventive activities^2 $_{i, j, t-1}$	0.9999 (0.000) [0.000]	0.9999 (0.000) [0.000]	0.9999 (0.000) [0.000]	0.9999 (0.000) [0.000]
Intensity of commercial activities $_{i, t-1}$	2.748 (0.630) [0.000]	2.755 (0.633) [0.000]	2.847 (0.652) [0.000]	2.815 (0.648) [0.000]
Firm fixed effects	BGV	BGV	BGV	BGV
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Log likelihood	-12,534.7	-12,444.2	-12,470.6	-12,430.7
Pseudo R^2	0.525	0.528	0.527	0.528
Number of observations	2,919	2,919	2,919	2,919

Robust standard errors adjusted for overdispersion are in parentheses; *p*-values are in brackets.

Coefficients are reported as incidence rate ratios (IRRs): an IRR greater than one suggests a positive effect, while an IRR below one — a negative effect. Firm fixed effects (BGV) are based on the company's 5-year pre-sample mean of the dependent variable (Blundell *et al.*, 1999). Industry fixed effects are based on the Fama and French (1997) industry classification.

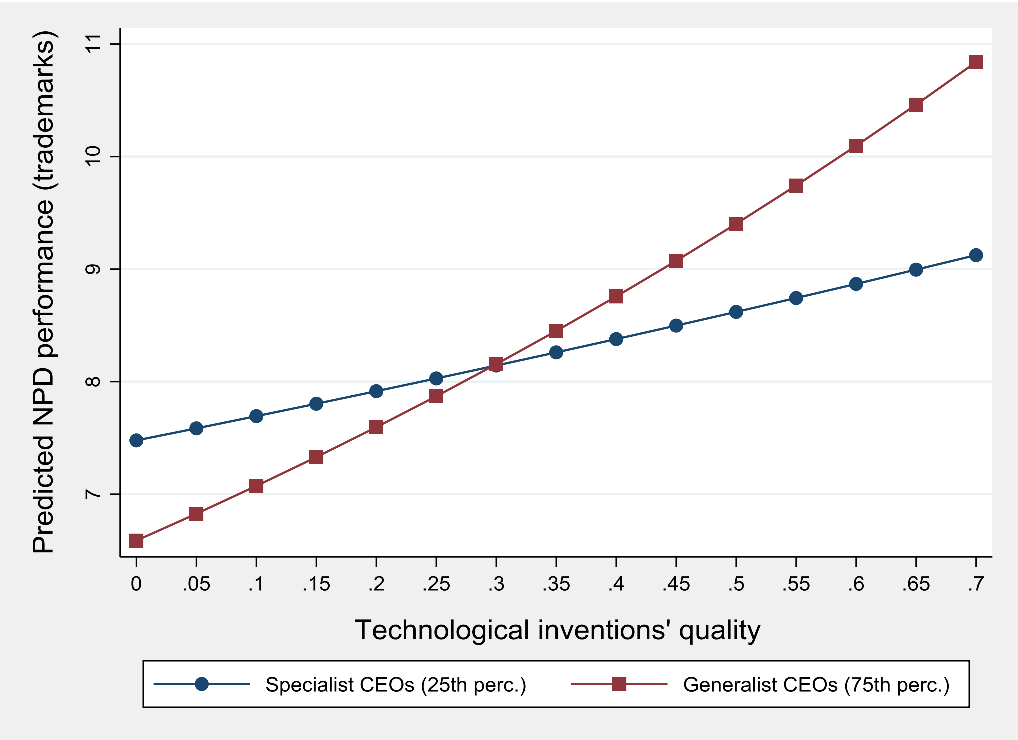
Figure 2. Interaction effects

(a) The interaction effect of the *diversity* of technological inventions and CEO human capital on NPD performance (based on Model 4 in Table 3)



All marginal effects are significant at the p < 0.001 level.

(b) The interaction effect of the *quality* of technological inventions and CEO human capital on NPD performance (based on Model 4 in Table 3)



All marginal effects are significant at the p < 0.001 level.

Table 4. Technological inventions and NPD performance: Poisson models with instrumental variables (a control function approach)

Dependent variable: NPD performance $_{i, t}$	**MODEL 5**	**MODEL 6**	**MODEL 7**	**MODEL 8**
Technological inventions' diversity $_{i, j, t-1}$	1.217 (0.059) [0.000]	1.185 (0.057) [0.000]	1.217 (0.059) [0.000]	1.193 (0.057) [0.000]
Technological inventions' quality $_{i, j, t-1}$	1.541 (0.384) [0.083]	1.590 (0.405) [0.069]	1.509 (0.384) [0.106]	1.593 (0.410) [0.070]
CEO general human capital $_{i, j, t-1}$	0.752 (0.087) [0.014]	0.631 (0.070) [0.000]	0.639 (0.075) [0.000]	0.610 (0.071) [0.000]
Technological inventions' diversity $_{i, j, t-1}$ × CEO general human capital $_{i, j, t-1}$		1.099 (0.026) [0.000]		1.075 (0.028) [0.005]
Technological inventions' quality $_{i, j, t-1}$ × CEO general human capital $_{i, j, t-1}$			1.726 (0.271) [0.000]	1.369 (0.228) [0.059]
Company tenure $_{i, j, t-1}$	1.013 (0.009) [0.123]	1.010 (0.009) [0.272]	1.012 (0.009) [0.156]	1.011 (0.009) [0.194]
Company tenure^2 $_{i, j, t-1}$	0.9997 (0.000) [0.080]	0.9997 (0.000) [0.151]	0.9997 (0.000) [0.105]	0.9997 (0.000) [0.114]
Founder CEO $_{i, j, t-1}$	0.893 (0.112) [0.364]	0.857 (0.106) [0.211]	0.876 (0.106) [0.275]	0.862 (0.104) [0.219]
Male CEO $_{i, j, t-1}$	1.493 (0.295) [0.042]	1.419 (0.271) [0.067]	1.420 (0.281) [0.077]	1.408 (0.271) [0.076]
CEO duality $_{i, j, t-1}$	1.294 (0.091) [0.000]	1.323 (0.091) [0.000]	1.279 (0.089) [0.000]	1.298 (0.090) [0.000]
CEO ownership $_{i, j, t-1}$	1.126 (0.767) [0.861]	0.851 (0.555) [0.805]	0.824 (0.536) [0.766]	0.767 (0.492) [0.679]
Company size $_{i, t-1}$	1.288 (0.045) [0.000]	1.309 (0.046) [0.000]	1.298 (0.045) [0.000]	1.306 (0.046) [0.000]
Company age $_{i, t-1}$	1.002 (0.001) [0.029]	1.001 (0.001) [0.071]	1.002 (0.001) [0.044]	1.001 (0.001) [0.071]
Return on assets $_{i, t-1}$	1.625 (0.595) [0.185]	1.479 (0.537) [0.282]	1.576 (0.574) [0.211]	1.518 (0.552) [0.251]
Book leverage $_{i, t-1}$	0.525 (0.097) [0.000]	0.533 (0.098) [0.001]	0.543 (0.101) [0.001]	0.543 (0.100) [0.001]
Intensity of inventive activities $_{i, j, t-1}$	1.0016 (0.000) [0.000]	1.0015 (0.000) [0.000]	1.0014 (0.000) [0.000]	1.0015 (0.000) [0.000]
Intensity of inventive activities^2 $_{i, j, t-1}$	0.9999 (0.000) [0.000]	0.9999 (0.000) [0.000]	0.9999 (0.000) [0.000]	0.9999 (0.000) [0.000]
Intensity of commercial activities $_{i, t-1}$	2.969 (0.721) [0.000]	3.053 (0.749) [0.000]	3.091 (0.751) [0.000]	3.097 (0.759) [0.000]
Residuals	1.348 (0.162) [0.013]	1.435 (0.169) [0.002]	1.359 (0.160) [0.009]	1.390 (0.162) [0.005]
Firm fixed effects	BGV	BGV	BGV	BGV
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Log likelihood	-12,480.4	-12,364.6	-12,412.6	-12,363.8
Pseudo R^2	0.527	0.531	0.529	0.531
Number of observations	2,919	2,919	2,919	2,919

Bootstrapped standard errors (calculated using 100 repetitions) are in parentheses; *p*-values are in brackets.

Coefficients are reported as incidence rate ratios (IRRs): an IRR greater than one suggests a positive effect, while an IRR below one — a negative effect. Firm fixed effects (BGV) are based on the company's 5-year pre-sample mean of the dependent variable (Blundell *et al.*, 1999). Industry fixed effects are based on the Fama and French (1997) industry classification.

[i] Licensing represents yet another channel for technology commercialization, along with NPD (see Teece, 1986). However, in this article, we focus on NPD as the main mechanism for technology conversion.

[ii] Although we conceptualize that generalist CEOs and specialist CEOs reside at the opposite ends of the spectrum, the empirical operationalization of the human capital construct that we use (see the methodology section) allows for a continuum of in-between options. So, CEOs can have different levels of general/specialist human capital.

[iii] The OECD HAN database (September 2016 edition) was first used to derive assignee names. We then employed the application identifier to link individual entries to the OECD Patent Quality Indicators database (March 2017 edition). Only applications submitted to the U.S. Patent and Trademark Office (USPTO) were considered.

[iv] The lower bound of the observation period is determined by the availability of data on executive compensation in S&P's ExecuComp database. The upper bound is set to minimize selection bias caused by the completeness of patent and trademark statistics, as well as by the discrepancies in time to issuance across different intellectual property rights (see Graham *et al.*, 2013; Hall *et al.*, 2001).

[v] Due to data availability, we could not include the fifth element of the original index, which is the chief executive's conglomerate experience. Nevertheless, we feel confident about our measure's ability to capture CEO general human capital, given that the missing element was assigned the lowest weight in Custódio *et al.*'s (2013) original research. This confidence is further supported by the results of correlation analysis: despite the methodological difference, the two indices show a high degree of similarity, with a correlation coefficient being 0.72.

[vi] In STATA, the regression scoring method can be implemented in the following way: first, the "*pca*" command should be used to extract principal components. The "*predict*" command should then be used to derive the index based on the retained component. Finally, the index calculated at the previous stage should be regressed on its four elements using the "*regress*" command to extract the weight (that is, the β coefficient) of each element.

[vii] In this section, if the results are not reported, they are available from the authors upon request.

[viii] It needs to be pointed out that *p*-value = 0.000 means that the *p*-value is less than 0.001. Several of the *p*-values in our regression analysis are found to be less than 0.001.

[ix] We follow previous research (e.g., Buis, 2010; Greene, 2008; Greene, 2010) to model the moderation effect of CEO human capital by interacting it with the diversity/quality of the firm's technological inventions. Another approach to capturing the alignment between the firm's managerial and technological resources could be with the use of a cosine measure (see Egghe and Leydesdorff, 2009; Jones and Furnas, 1987).

[x] As they note, "[the] magnitude of the interaction effect in nonlinear models does not equal the marginal effect of the interaction term, can be of opposite sign, and its statistical significance is not calculated by standard software" (Ai and Norton, 2003:123).

[xi] We should emphasize here that the significance of the marginal effects for both interaction terms has statistical support (that is, all *p*-values are below 0.001).

[xii] For the index of noncompetition enforcement, the results still hold if we use alternative specifications that focus either on the CEO's most recent position or his/her first position, namely: (i) the average level of stringency of the noncompetition regimes across all public companies in which the CEO held a position *in the previous year*, or (ii) where the CEO held his/her *first position*.

[xiii] We have also experimented with excluding the number positions that the CEO has held because this element may be prone to the recordation problem (e.g., if the name of a position changes without a change in the underlying functionality or when several positions are reported as one using the "various position" label).

ONLINE APPENDIX A. MEASURING NEW PRODUCT DEVELOPMENT WITH TRADEMARK DATA

A trademark is a symbol, word, drawing, or other permitted device that can be used to identify and distinguish the offering of one party from that of another. The idea that trademarks can serve as a proxy of NPD is not novel and has been discussed in the academic literature for almost two decades (e.g., Castaldi, 2019; Castaldi *et al.*, 2020; Gallié and Legros, 2012; Gao and Hitt, 2012; Greenhalgh and Rogers, 2012; Jensen and Webster, 2009; Mendonça *et al.*, 2004), with several recent studies directly testing and confirming this idea (see Flikkema *et al.*, 2014; Flikkema *et al.*, 2019; Seip *et al.*, 2018). There are two main reasons to expect that trademarks can reflect NPD activities at the firm level: first of all, the timing argument suggests that firms tend to apply for trademark protection when they introduce a new product in the marketplace (Greenhalgh and Longland, 2001; Seip *et al.*, 2018). This has even resulted in casting trademark applications as a form of a new product preannouncement (Nasirov, 2020), so the firms that are willing to avoid disclosing their NPD activities because of trademarking have started adopting so-called submarine trademark filing strategies (Fink *et al.*, 2018). Another argument to justify the use of trademarks as an NPD measure emphasizes the crucial role they play in appropriating innovation returns. According to Mendonça *et al.* (2004:1392), "[n]ew trademarks are a critical instrument in helping to position new products in the market. When compared to patents, they are closer to commercialization and cover a broader range of activities from manufacturing product classes to service classes."

In this study, we rely on trademark statistics extracted from the USPTO Trademark Case Files dataset (see Graham *et al.*, 2013) to capture the NPD performance of the companies in our sample. As with other innovation indicators, such as R&D expenditure and patents, trademark data need to be cleaned before being used in empirical analysis. Unlike other sources of data, the USPTO Trademark Case Files dataset contains information on when a trademark was first used in commerce. Having this information is important because there can be a noticeable gap between the start of the trademark's actual use and filing a trademark application, especially in common law countries (e.g., the U.S., the U.K., Canada) where applying for federal protection is not mandatory to enjoy some degree of legal protection. For example, one of the companies included in our sample is *Hewlett-Packard*. In 2010, the company launched "HP Slate" – a line of consumer tablets and all-in-one desktops; however, the corresponding trademark was filed with the USPTO only in 2013. Hence, 2010 should be used to better capture the moment when the product was actually introduced in the marketplace.

Interestingly, the opposite is true as well: with the introduction of the Trademark Law Revision Act of 1988, companies have been given an opportunity to apply for federal protection before the commercial use of a mark – on the intent-to-use basis. In this case, the mark owner has to demonstrate their bona fide intent to use the mark in commerce. To continue with *Hewlett-Packard*, in 2010, the company launched "ColorPro" – a line of continuous roll printing paper, although the trademark for this product was filed with the USPTO in 2008. So, using the filing year would lead to mis-timing the product introduction moment by two years.

STATUS | DOCUMENTS | MAINTENANCE | ? | Download | Print Preview

Generated on: This page was generated by TSDR on 2021-04-14 04:16:37 EDT

Mark: HP SLATE

HP SLATE

US Serial Number:	85855414	**Application Filing Date:**	Feb. 20, 2013
US Registration Number:	4556890	**Registration Date:**	Jun. 24, 2014

Register: Principal

Mark Type: Trademark

TM5 Common Status Descriptor: DEAD/REGISTRATION/Cancelled/Invalidated

The trademark application was registered, but subsequently it was cancelled or invalidated and removed from the registry.

Status: Registration cancelled because registrant did not file an acceptable declaration under Section 8. To view all documents in this file, click on the Trademark Document Retrieval link at the top of this page.

Status Date: Jan. 29, 2021

Publication Date:	Sep. 03, 2013	**Notice of Allowance Date:**	Mar. 04, 2014

Date Cancelled: Jan. 29, 2021

Mark Information

Expand All

Goods and Services

Note:
The following symbols indicate that the registrant/owner has amended the goods/services:

- Brackets [..] indicate deleted goods/services;
- Double parenthesis ((..)) identify any goods/services not claimed in a Section 15 affidavit of incontestability; and
- Asterisks *..* identify additional (new) wording in the goods/services.

For: Computers, personal computers, tablet computers, handheld computers; computer hardware

International Class(es):	009 - Primary Class	**U.S Class(es):**	021, 023, 026, 036, 038

Class Status: SECTION 8 - CANCELLED

Basis: 1(a)

First Use:	Dec. 01, 2010	**Use in Commerce:**	Dec. 01, 2010

STATUS | DOCUMENTS | MAINTENANCE | ? | Download | Print Preview

Generated on: This page was generated by TSDR on 2021-04-14 04:28:52 EDT

Mark: COLORPRO

COLORPRO

US Serial Number:	77473478	**Application Filing Date:**	May 13, 2008
US Registration Number:	3931421	**Registration Date:**	Mar. 15, 2011

Register: Principal

Mark Type: Trademark

TM5 Common Status Descriptor: LIVE/REGISTRATION/Issued and Active

The trademark application has been registered with the Office.

Status: A Sections 8 and 15 combined declaration has been accepted and acknowledged.

Status Date: Apr. 20, 2017

Publication Date:	Oct. 28, 2008	**Notice of Allowance Date:**	Jan. 20, 2009

Mark Information

Expand All

Goods and Services

Note:
The following symbols indicate that the registrant/owner has amended the goods/services:

- Brackets [..] indicate deleted goods/services;
- Double parenthesis ((..)) identify any goods/services not claimed in a Section 15 affidavit of incontestability; and
- Asterisks *..* identify additional (new) wording in the goods/services.

For: Continuous roll coated printing paper; continuous roll kaolinite-coated printing paper; continuous roll plastic-coated printing paper

International Class(es):	016 - Primary Class	**U.S Class(es):**	002, 005, 022, 023, 029, 037, 038, 050

Class Status: ACTIVE

Basis: 1(a)

First Use:	May 14, 2010	**Use in Commerce:**	May 14, 2010

Finally, there is a degree of heterogeneity among trademark types, which also needs to be taken into account before using trademark data in empirical analysis. For example, companies can apply for *certification marks*: according to the USPTO web-site,[1] "a certification mark is any word, name, symbol, device, or any combination, used, or intended to be used, in commerce by someone other than its owner, to certify regional or other origin, material, mode of manufacture, quality, accuracy, or other characteristics of such person's goods or services, or that the work or labor on the goods or services was performed by members of a union or other organization." For example, in 2010, *Lockheed Martin Corporation* applied for and subsequently registered the "C-130 D-H Approved Repair Center Hologram Products Lockheed Martin" certification mark with the intent to use it in order to certify that the company has inspected and approved the quality system of a repair and/or overhaul facility. Cleary, such marks, as well as corporate marks and collective marks, should be excluded from the analysis because they are not related to companies' NPD activities.

STATUS | DOCUMENTS | MAINTENANCE | ? | Download | Print Preview

Generated on:	This page was generated by TSDR on 2021-04-14 05:48:14 EDT		
Mark:	C-130 B-H APPROVED REPAIR CENTER HOLOGRAM PRODUCTS LOCKHEED MARTIN		
US Serial Number:	85060185	Application Filing Date:	Jun. 10, 2010
US Registration Number:	4046330	Registration Date:	Oct. 25, 2011
Register:	Principal		
Mark Type:	Certification Mark		
TM5 Common Status Descriptor:	LIVE/REGISTRATION/Issued and Active The trademark application has been registered with the Office.		
Status:	A Sections 8 and 15 combined declaration has been accepted and acknowledged.		
Status Date:	Oct. 28, 2019		
Publication Date:	Dec. 07, 2010	Notice of Allowance Date:	Feb. 01, 2011

Mark Information Expand All

Mark Literal Elements:	C-130 B-H APPROVED REPAIR CENTER HOLOGRAM PRODUCTS LOCKHEED MARTIN
Standard Character Claim:	No
Mark Drawing Type:	3 - AN ILLUSTRATION DRAWING WHICH INCLUDES WORD(S)/ LETTER(S)/NUMBER(S)
Description of Mark:	The mark consists of a circle containing the words "C-130 B-H APPROVED REPAIR CENTER" surrounding two overlapping arrow shapes located above the words "HOLOGRAM PRODUCTS LOCKHEED MARTIN".
Color(s) Claimed:	Color is not claimed as a feature of the mark.
Disclaimer:	"PRODUCTS" AND "APPROVED REPAIR CENTER"
Design Search Code(s):	24.15.10 - More than one arrow; Arrows, more than one 24.15.25 - Other arrows 26.01.17 - Concentric circles, two; Two concentric circles; Circles, two concentric
Certification Statement:	The certification mark, as intended to be used by authorized persons, is intended to certify that the services have been provided pursuant to quality control standards for safety and reliability in connection with parts for aircraft initially manufactured by the certifier, as determined and specified by the certifier, and which supplement the standards established by federal regulations.

[1] See https://www.uspto.gov/learning-and-resources/glossary.

References

Castaldi, C. 2019. All the great things you can do with trademark data: Taking stock and looking ahead. *Strategic Organization* 18(3): 472–484.

Castaldi, C., Block, J., and Flikkema, M.J. 2020. Why and when do firms trademark? Bridging perspectives from industrial organisation, innovation and entrepreneurship. *Industry and Innovation* 27(1–2): 1–10.

Fink, C., Helmers, C., and Ponce, C.J. 2018. Trademark squatters: Theory and evidence from Chile. *International Journal of Industrial Organization* 59: 340–371.

Flikkema, M., Castaldi, C., De Man, A.P., and Seip, M. 2019. Trademarks' relatedness to product and service innovation: A branding strategy approach. *Research Policy* 48(6): 1340–1353.

Flikkema, M., De Man, A.P., and Castaldi, C. 2014. Are trademark counts a valid indicator of innovation? Results of an in-depth study of new Benelux trademarks filed by SMEs. *Industry and Innovation* 21(4): 310–331.

Gallié, E.P., and Legros, D. 2012. French firms' strategies for protecting their intellectual property. *Research Policy* 41(4): 780–794.

Gao, G., and Hitt, L.M. 2012. Information technology and trademarks: Implications for product variety. *Management Science* 58(6): 1211–1226.

Graham, S., Hancock, G., Marco, A., and Myers, A.F. 2013. *The USPTO trademark case files dataset: Descriptions, lessons, and insights*. Alexandria, VA: USPTO.

Greenhalgh, C., and Longland, M. 2001. Intellectual property in UK firms: Creating intangible assets and distributing the benefits via wages and jobs. *Oxford Bulletin of Economics and Statistics* 63(S1): 671–696.

Greenhalgh, C., and Rogers, M. 2012. Trade marks and performance in services and manufacturing firms: Evidence of Schumpeterian competition through innovation. *Australian Economic Review* 45(1): 50–76.

Jensen, P.H., and Webster, E. 2009. Another look at the relationship between innovation proxies. *Australian Economic Review* 48(3): 252–269.

Mendonça, S., Pereira, T.S., and Godinho, M.M. 2004. Trademarks as an indicator of innovation and industrial change. *Research Policy* 33(9): 1385–1404.

Nasirov, S. 2020. Trademark value indicators: Evidence from the trademark protection lifecycle in the U.S. pharmaceutical industry. *Research Policy* 49(4). In press.

Seip, M., Castaldi, C., Flikkema, M., and De Man, A.P., 2018. The timing of trademark application in innovation processes. *Technovation* 72: 34–45.

ONLINE APPENDIX B. THE CONSTRUCTION OF THE GENERAL ABILITY INDEX

To evaluate the generic human capital acquired by chief executives over their professional careers, we decided to follow the approach set out by Custódio *et al.* (2013), and compiled the general ability index. In doing so, we started by examining the career progression statistics from the BoardEx database and other sources to extract information on the number of (1) industries, (2) companies, and (3) positions in which the chief executive worked, as well as on (4) the chief executive's previous experience in the CEO function.[2] Due to data availability, we could not include the fifth element of the original index, which is the chief executive's conglomerate experience. However, we are confident that our measure still captures a great deal of generic human capital, given that the missing element was actually assigned the lowest weight in Custódio *et al.*'s (2013) original study. This confidence is supported by the results of the correlation analysis: despite the methodological difference, the two indices show a high degree of similarity (Pearson's correlation coefficient is 0.72).[3]

Turning back to the index used in the present study, the *number of industries* was derived by counting unique SIC codes aggregated at the 2-digit level. As the BoardEx database contains no industry affiliation, we first extracted the historical list of companies across all executives and then hand-collected industry codes by looking up each company's name in the Compustat database; the company's official web-site; SEC filings; and organizational profiles compiled by Nasdaq, Morningstar, siccode.com, and manta.com. Maximum effort was given to avoiding mismatches: for example, when searching for the industry data, we took account of location, legal form, and name similarity. Whenever there was a doubt about the validity the obtained result, the matching was rejected. Overall, we were able to identify an industry affiliation for 89.3 percent of the companies in the historical list. Next, we counted the *number of companies* in which the chief executive worked. Before proceeding with this step, we harmonized company names to exclude various artificial parts that could inflate the resulting variable (e.g., former name, trading name, or the date when the company was de-listed). We relied on position names to count the *number of previous positions* held by the chief executive. This variable was constructed without any further adjustment, although having "Various positions" as a post name might lead to underestimating the overall effect (in total, 308 CEOs had at least one position denoted in this way). Finally, we looked at firm names, post names, and role descriptions to create a dummy variable for *previous experience in the CEO position*. To reveal this experience, we searched for such patterns as "CEO", "chief executive", and "principal executive." The dummy takes the value of unity if the chief executive previously had worked as the CEO, and zero otherwise.

We used the principal component analysis to pool these variables into a one-dimensional index (Jolliffe, 2002). This approach allowed us to capture the multiplicity of sources through which generic human capital could be obtained, while avoiding the

[2] Since we were unable to find 21 CEOs from our sample in the BoardEx database, the missing information was then manually collected by searching: the LexisNexis news database; Marquis *Who's Who* biographical data; SEC filings; obituaries; and other similar data sources.

[3] Custódio *et al.* (2013) made their index freely available at http://jfe.rochester.edu/data.htm. Although we were unable to utilize it because of the differences in the period of coverage, we still used it for robustness checks.

multicollinearity problem due to high correlation among the components. We first extracted principal components, which are mutually orthogonal, and then arranged them according to the proportion of the total variance each can explain (see Tables A.1 and A.2).

Table A.1. Eigenvalues of the correlation matrix

Component	Eigenvalue	Difference	Proportion	Cumulative
Component 1	2.417	1.415	0.604	0.604
Component 2	1.002	0.578	0.251	0.855
Component 3	0.425	0.269	0.106	0.961
Component 4	0.156	.	0.039	1.000

Table A.2. Principal components (eigenvectors)

Variable	Component 1	Component 2	Component 3	Component 4
Number of industries	0.589	-0.040	-0.467	0.659
Number of companies	0.603	-0.029	-0.287	-0.744
Number of positions	0.538	0.050	0.834	0.113
Previous experience as the CEO	0.014	0.998	-0.069	-0.001

Our decision regarding the factors that should be retained for further examination is based on the results of Horn's (1965) parallel analysis. This analysis starts with extracting principal components from a randomly generated dataset that contains the same number of variables and observations as the original sample, and then proceeds to calculate the corresponding eigenvalues. The same procedure is repeated N times (we set N = 100 iterations), after which it returns the average eigenvalue for each of the components. The rule for choosing the factors to retain from the principal component analysis is that their eigenvalues must be greater than the average eigenvalues obtained from the parallel analysis. As Table A.3 indicates, only the first factor satisfies the described rule and, hence, will be used to finalize the index construction.

Table A.3. Parallel analysis

Component	Principal component analysis	Parallel analysis	Difference
Component 1	2.417	1.039	1.378
Component 2	1.002	1.013	-0.010
Component 3	0.425	0.988	-0.563
Component 4	0.156	0.960	-0.804

As expected, the first component has positive loadings on all four variables, ranging from 0.014 for the prior CEO experience to 0.603 for the number of companies in which the chief executive has worked (see Table A.2). It also captures 60.4 percent of the total variation in the characteristics. We thus interpret it as being a measure of the generic human capital of the chief executive, with its higher values indicating a wider set of general knowledge and skills.[4]

We completed the analysis by calculating the general ability index for each CEO in our sample. The regression scoring method was used to derive the weights that were linked to each demographic factor according to the following formula (all variables were mean-centered beforehand):

$$GAI_{i,t} = 0.320 * Y_{1,i,t} + 0.214 * Y_{2,i,t} + 0.120 * Y_{3,i,t} + 0.343 * Y_{4,i,t},$$

where $Y_{1,i,t}$ is the number of industries CEO_i had worked in until year t; $Y_{2,i,t}$ is the number of companies CEO_i had worked for until year t; $Y_{3,i,t}$ is the number of positions CEO_i had worked in until year t; and $Y_{4,i,t}$ is a dummy variable that takes the value of one for the chief executive with previous professional experience in the CEO function at another company, and zero otherwise. In order to improve the index's interpretability, it was normalized to have zero mean and a standard deviation of unity.

REFERENCES

Cronbach, L.J. 1951. Coefficient alpha and the internal structure of tests. *Psychometrika* 16(3): 297–334.

Custódio, C., and Metzger, D. 2013. How do CEOs matter? The effect of industry expertise on acquisition returns. *Review of Financial Studies* 26(8): 2008–2047.

Horn, J.L. 1965. A rationale and test for the number of factors in factor analysis. *Psychometrika* 30(2): 179–185.

Jolliffe, I.T. 2002. *Principal component analysis*. 2nd ed. New York, NY: Springer-Verlag.

Nunnally, J.C., and Bernstein, I.H. 1994. *Psychometric theory*. 3rd ed. New York, NY: McGraw-Hill.

[4] We also assessed the internal consistency of the items in the general ability index by deriving Cronbach's alpha (Cronbach, 1951). This analysis shows that our set of career-based indicators is internally consistent because the alpha coefficient is 0.692, and a coefficient of 0.70 or higher is considered to indicate sufficient reliability (see Nunnally and Bernstein, 1994).

ONLINE APPENDIX C. RESULTS OF ROBUSTNESS CHECKS

Table C.1. Technological inventions and NPD performance: Poisson regression results in the subsamples that exclude the new CEO effect

Dependent variable: NPD performance $_{i, t}$	**Poisson models** (based on Model 8)						
	FY_BASE	**CEO tenure > 3 years**			**CEO tenure > 4 years**		
		Diversity only	**Quality only**	**Both**	**Diversity only**	**Quality only**	**Both**
Technological inventions' diversity $_{i, j, t-1}$	1.193 (0.057) [0.000]	1.182 (0.073) [0.007]	1.224 (0.074) [0.001]	1.190 (0.072) [0.004]	1.179 (0.075) [0.009]	1.225 (0.079) [0.002]	1.188 (0.075) [0.006]
Technological inventions' quality $_{i, j, t-1}$	1.593 (0.410) [0.070]	1.503 (0.458) [0.182]	1.384 (0.417) [0.281]	1.498 (0.452) [0.181]	1.432 (0.463) [0.267]	1.298 (0.407) [0.405]	1.414 (0.453) [0.279]
CEO generic human capital $_{i, j, t-1}$	0.610 (0.071) [0.000]	0.599 (0.093) [0.001]	0.619 (0.100) [0.003]	0.600 (0.096) [0.001]	0.618 (0.096) [0.002]	0.642 (0.106) [0.007]	0.620 (0.100) [0.003]
Technological inventions' diversity $_{i, j, t-1}$ × CEO general human capital $_{i, j, t-1}$	1.075 (0.028) [0.005]	1.124 (0.035) [0.000]		1.103 (0.042) [0.009]	1.118 (0.039) [0.001]		1.097 (0.046) [0.026]
Technological inventions' quality $_{i, j, t-1}$ × CEO general human capital $_{i, j, t-1}$	1.369 (0.228) [0.059]		1.725 (0.292) [0.001]	1.257 (0.256) [0.261]		1.678 (0.299) [0.004]	1.249 (0.276) [0.315]
CEO controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	BGV	BGV	BGV	BGV	BGV	BGV	BGV
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log (pseudo)likelihood	-12,363.8	-9,077.7	-9.126.6	-9,087.6	-7,844.7	-7,884.6	-7,853.3
Pseudo R^2	0.531	0.529	0.526	0.528	0.531	0.529	0.531
Number of observations	2,919	2,166	2,166	2,166	1,903	1,903	1,903

Robust standard errors adjusted for overdispersion are in parentheses; *p*-values are in brackets.

Coefficients are reported as incidence rate ratios (IRRs): an IRR greater than one suggests a positive effect, while an IRR below one — a negative effect. Firm fixed effects (BGV) are based on including the firm's 5-year pre-sample mean of the dependent variable (Blundell *et al.*, 1999). Industry fixed effects are based on the Fama and French (1997) industry classification. FT_BASE is the baseline model. CEO tenure > 3 year is the subsample where the CEOs with three or fewer years of tenure in the CEO position are excluded. CEO tenure > 4 year is the subsample where the CEOs with four or fewer years of tenure in the CEO position are excluded.

Table C.2. A comparison of different estimation methods

Dependent variable: NPD performance $_{i, t}$	**Different estimation methods** (based on Model 8)		
	EM_BASE	**EM_NBIN**	**EM_OLS**
Technological inventions' diversity $_{i, j, t-1}$	1.193 (0.057) [0.000]	1.211 (0.052) [0.000]	1.284 (0.202) [0.000]
Technological inventions' quality $_{i, j, t-1}$	1.593 (0.410) [0.070]	1.583 (0.347) [0.036]	4.552 (0.919) [0.000]
CEO generic human capital $_{i, j, t-1}$	0.610 (0.071) [0.000]	0.521 (0.053) [0.000]	-2.235 (0.453) [0.000]
Technological inventions' diversity $_{i, j, t-1}$ × CEO generic human capital $_{i, j, t-1}$	1.075 (0.028) [0.005]	1.083 (0.026) [0.001]	0.115 (0.129) [0.373]
Technological inventions' quality $_{i, j, t-1}$ × CEO generic human capital $_{i, j, t-1}$	1.369 (0.228) [0.059]	1.786 (0.312) [0.001]	3.211 (0.871) [0.000]
CEO controls	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes
Firm fixed effects	BGV	BGV	BGV
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Log (pseudo)likelihood	-12,363.8	-7,734.7	-
(Pseudo) R^2	0.531	0.130	0.337
Number of observations	2,919	2,919	2,919

Robust standard errors adjusted for overdispersion are in parentheses; *p*-values are in brackets.

Coefficients (apart from EM_OLS) are reported as incidence rate ratios (IRRs): an IRR greater than one suggests a positive effect, while an IRR below one — a negative effect. Firm fixed effects (BGV) are based on including the firm's 5-year pre-sample mean of the dependent variable (Blundell *et al.*, 1999). Industry fixed effects are based on the Fama and French (1997) industry classification. EM_BASE is the baseline (Poisson) model. EM_NBIN is the negative binomial model. EM_OLS is the ordinary least squares model with the log-transformed dependent variable.

Table C.3. The general ability index: Alternative measures

Dependent variable: NPD performance $_{i, t}$	**Poisson models** (based on Model 8)		
	GA_BASE	**GA_EXT**	**GA_SHR**
Technological inventions' diversity $_{i, j, t-1}$	1.193 (0.057) [0.000]	1.180 (0.057) [0.001]	1.203 (0.059) [0.000]
Technological inventions' quality $_{i, j, t-1}$	1.593 (0.410) [0.070]	1.563 (0.397) [0.079]	1.568 (0.403) [0.080]
CEO general human capital $_{i, j, t-1}$	0.610 (0.071) [0.000]	0.537 (0.060) [0.000]	0.723 (0.085) [0.006]
Technological inventions' diversity $_{i, j, t-1}$ × CEO general human capital $_{i, j, t-1}$	1.075 (0.028) [0.005]	1.081 (0.027) [0.002]	1.075 (0.027) [0.004]
Technological inventions' quality $_{i, j, t-1}$ × CEO general human capital $_{i, j, t-1}$	1.369 (0.228) [0.059]	1.324 (0.218) [0.088]	1.225 (0.192) [0.197]
CEO controls	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes
Firm fixed effects	BGV	BGV	BGV
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Log (pseudo)likelihood	-12,363.8	-12,261.2	-12,436.4
Pseudo R^2	0.531	0.535	0.528
Number of observations	2,919	2,919	2,919

Robust standard errors adjusted for overdispersion are in parentheses; *p*-values are in brackets.

Coefficients are reported as incidence rate ratios (IRRs): an IRR greater than one suggests a positive effect, while an IRR below one — a negative effect. Firm fixed effects (BGV) are based on including the firm's 5-year pre-sample mean of the dependent variable (Blundell *et al.*, 1999). Industry fixed effects are based on the Fama and French (1997) industry classification. GA_BASE is the baseline model. GA_EXT is the model where the general ability index also accounts for the CEO's military, academic, and civil service experiences. GA_SHR is the model where the general ability index is calculated without accounting for the number of positions that the CEO has held.

Table C.4. The patent quality index: An alternative measure

Dependent variable: NPD performance $_{i, t}$	**Poisson models** (based on Model 8)	
	PQ_BASE	**PQ_FW5**
Technological inventions' diversity $_{i, j, t-1}$	1.193 (0.057) [0.000]	1.179 (0.060) [0.001]
Technological inventions' quality $_{i, j, t-1}$	1.593 (0.410) [0.070]	1.014 (0.007) [0.064]
CEO general human capital $_{i, j, t-1}$	0.610 (0.071) [0.000]	0.681 (0.076) [0.001]
Technological inventions' diversity $_{i, j, t-1}$ × CEO general human capital $_{i, j, t-1}$	1.075 (0.028) [0.005]	1.065 (0.031) [0.030]
Technological inventions' quality $_{i, j, t-1}$ × CEO general human capital $_{i, j, t-1}$	1.369 (0.228) [0.059]	1.008 (0.004) [0.055]
CEO controls	Yes	Yes
Firm controls	Yes	Yes
Firm fixed effects	BGV	BGV
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Log (pseudo)likelihood	-12,363.8	-12,369.8
Pseudo R^2	0.531	0.531
Number of observations	2,919	2,919

Robust standard errors adjusted for overdispersion are in parentheses; *p*-values are in brackets.

Coefficients are reported as incidence rate ratios (IRRs): an IRR greater than one suggests a positive effect, while an IRR below one — a negative effect. Firm fixed effects (BGV) are based on including the firm's 5-year pre-sample mean of the dependent variable (Blundell *et al.*, 1999). Industry fixed effects are based on the Fama and French (1997) industry classification. PQ_BASE is the baseline model. PQ_FW5 is the model where technological inventions' quality is captured by the average number of patent 5-year forward citations.

Table B.5. The effect of the corporate brand strategy on NPD performance

Dependent variable: NPD performance $_{i,\ t}$	**Poisson models** (based on Model 8)			
	TQ_BASE	**TQ_MED**	**TQ_75**	**TQ_90**
Technological inventions' diversity $_{i,\ j,\ t\text{-}1}$	1.193 (0.057) [0.000]	1.194 (0.057) [0.000]	1.193 (0.058) [0.000]	1.195 (0.057) [0.000]
Technological inventions' quality $_{i,\ j,\ t\text{-}1}$	1.593 (0.410) [0.070]	1.566 (0.406) [0.084]	1.593 (0.428) [0.083]	1.598 (0.415) [0.071]
CEO general human capital $_{i,\ j,\ t\text{-}1}$	0.610 (0.071) [0.000]	0.611 (0.072) [0.000]	0.610 (0.071) [0.000]	0.610 (0.071) [0.000]
Technological inventions' diversity $_{i,\ j,\ t\text{-}1}$ × CEO general human capital $_{i,\ j,\ t\text{-}1}$	1.075 (0.028) [0.005]	1.074 (0.028) [0.006]	1.075 (0.028) [0.005]	1.074 (0.028) [0.006]
Technological inventions' quality $_{i,\ j,\ t\text{-}1}$ × CEO general human capital $_{i,\ j,\ t\text{-}1}$	1.369 (0.228) [0.059]	1.375 (0.225) [0.051]	1.367 (0.228) [0.061]	1.367 (0.228) [0.061]
High Tobin's q $_{i,\ t}$		1.038 (0.059) [0.512]	1.001 (0.081) [0.988]	0.934 (0.076) [0.407]
CEO controls	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Firm fixed effects	BGV	BGV	BGV	BGV
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Log (pseudo)likelihood	-12,363.8	-12,360.7	-12,363.4	-12,359.4
Pseudo R^2	0.531	0.531	0.531	0.531
Number of observations	2,919	2,919	2,919	2,919

Robust standard errors adjusted for overdispersion are in parentheses; *p*-values are in brackets.

Coefficients are reported as incidence rate ratios (IRRs): an IRR greater than one suggests a positive effect, while an IRR below one — a negative effect. Firm fixed effects (BGV) are based on including the firm's 5-year pre-sample mean of the dependent variable (Blundell *et al.*, 1999). Industry fixed effects are based on the Fama and French (1997) industry classification. TQ_BASE is the baseline model. TQ_MED is the model where Tobin's q is included as a dummy variable that takes the value of one if a firm's Tobin's q in a given year is above the sample median, and zero otherwise. TQ_75 is the model where Tobin's q is included as a dummy variable that takes the value of one if a firm's Tobin's q in a given year is within the sample's top 75 percent, and zero otherwise. TQ_90 is the model where Tobin's q is included as a dummy variable that takes the value of one if a firm's Tobin's q in a given year is within the sample's top 90 percent, and zero otherwise.

Table C.6. The effect of NPD performance on firm total sales and sales growth

	OLS models	
	Dependent variable: ln(Sales $_{i,t+1}$)	**Dependent variable:** Sales growth $_{i,t+1}$
NPD performance $_{i, t}$	0.0090 (0.0008) [0.000]	0.0006 (0.0002) [0.001]
Company size $_{i, t}$	0.894 (0.007) [0.000]	-0.015 (0.003) [0.000]
Company age $_{i, t}$	-0.0001 (0.0003) [0.629]	-0.0004 (0.0001) [0.000]
Return on assets $_{i, t}$	1.166 (0.148) [0.000]	0.095 (0.066) [0.148]
Book leverage $_{i, t}$	0.235 (0.069) [0.001]	0.054 (0.029) [0.061]
Intensity of commercial expenditures $_{i, t-1}$	-0.893 (0.094) [0.000]	-0.183 (0.032) [0.000]
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
R^2	0.929	0.159
Number of observations	2,919	2,919

Robust standard errors corrected for heteroskedasticity are in parentheses; *p*-values are in brackets.

Industry fixed effects are based on the Fama and French (1997) industry classification. *Sales growth* is calculated as the ratio of total sales at T+1 to total sales at T.