INTERNAL AND EXTERNAL INNOVATION:

ANTECEDENTS, MODERATORS, AND CONSEQUENCES

by

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Never, Never, Never Give Up

To Margaret

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by

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This dissertation endeavors to advance our understanding on firms' internal and external innovation. The three essays focus on studying the antecedents, moderators, and performance consequences of firms' innovation via internal (patenting) and external (alliance) modes. By leveraging signaling, dynamic capabilities, diversity, and regulatory focus mechanisms, this dissertation enriches theories in strategic management and behavioral economics.

Essay 1 focuses on consequences of firms' internal innovation as reflected by firms' patenting. Specifically, I investigate the influence that firms' patenting patterns (trajectory and velocity) have on firms' evaluation by investors. By integrating signaling mechanisms, the essay proposes that patenting patterns can signal to investors about firms' intentions and potential. The results encourage future researchers to acknowledge the interplay of patenting behavior and patenting velocity to promote a differentiated approach that maximizes firms' market evaluation.

Essay 2 introduces balanced sourcing portfolios as reflecting firms' efforts to simultaneously rely on both internal (internal R&D) and external (alliances) sourcing. I suggest that using balanced sourcing portfolios allows firms to increase overall performance by separating the development

of sensing and seizing capabilities. Further, the essay conceptualizes and operationalizes stiff slack as the most difficult-to-redeploy absorbed slack category. Given possible conflicting routines introduced by the use of stiff slack, I hypothesize and find that firms should avoid using stiff slack in balanced sourcing portfolios to improve performance.

Essay 3 investigates the individual and joint effects that racial diversity in the upper management group (UMG) and regulatory focus of the CEO have in deciding the composition of firms' alliance portfolios. Using categorization elaboration, social contact, and regulatory focus mechanisms, I find that while matching levels of UMG racial diversity and CEO regulatory focus (congruence) at low levels of racial diversity tilt the composition of firms' alliance portfolios in a more exploratory direction, mismatching levels (incongruence) tilt it in a more exploitative direction. Polynomial regression and response surface analysis show support.

Managerial implications: Understanding what factors affect innovation is both important and relevant for managers of firms in technology-intensive industries. This dissertation encompasses of three essays, each focusing on one distinct category of factors with implications on firm innovation: factors that determine innovation, factors that may interact with innovative efforts, and factors that result from innovating. Overall, this dissertation helps managers better understand the role that innovation plays for firms in technology-intensive industries.

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CHAPTER 1

PATENTING VELOCITY AND PATTERNS IN MARKET SIGNALING

Abstract

How do firms' patenting patterns affect their market value? We enrich signaling theory by suggesting that patterns in patenting behavior and velocity act as signals to investors. We differentiate patenting patterns along exploration and exploitation dimensions and introduce two new boundary mechanisms—pattern fit and expectation fit. Results from a set of U.S. public firms from high technology industries indicate that while patenting at a high velocity makes exploratory behavior more attractive to investors, it makes the exploitative behavior less appealing. Due to a mismatch in firm-investor expectation, these effects are reversed when firms pursue both exploratory and exploitative patenting at high velocities. Ambidextrous high velocity patenting increases investors' prospect for high future returns in the case of exploratory firms but diminishes it in the case of exploitative firms. The results encourage management scholars to acknowledge the interplay of patenting patterns to promote a differentiated approach that maximizes firms' market valuation.

Introduction

As part of a larger academic undertaking trying to explain what factors affect investors' valuation of firms' future returns, this article endeavors to sketch a pattern-based perspective of firms' signaling. Signaling theory (Connelly, Certo, Ireland, & Reutzel, 2011; Spence, 1973, 2002) has been extensively used to address questions about firms' activities (Conti, Thursby, & Thursby, 2013; Ederer & Manso, 2013; Hoenig & Henkel, 2015; Hsu & Ziedonis, 2008; Janney & Folta, 2003; Su, Peng, Tan, & Cheung, 2016). Recently, the signaling role of patents has emerged as a research avenue in the context of knowledge-intensive firms (Conti, Thursby, & Rothaermel, 2013; Haeussler, Harhoff, & Mueller, 2014; Hoenen, Kolympiris, Schoenmakers, & Kalaitzandonakes, 2014; Useche, 2014). Patents serve as an indicator of firms' quality and business viability (Baum & Silverman, 2004; Stuart, Hoang, & Hybels, 1999) and traditionally reflect firms' research and development (R&D) activities (Hall, Jaffe, & Trajtenberg, 2005). However, because the number of patents loses its signaling value over time (Hoenen et al., 2014), we propose that *patterns* of firms' R&D activities reflected by patenting are likely to suggest more about firms' future potential than the mere number of patents could. Complementing existing research, a pattern-based view of firms' patenting activities has the potential to answer two important questions underpinning signaling theory research: (1) How do a firm's patterns in patenting behavior and velocity inform investors about its potential? (2) How do a firm's patenting patterns (patenting behavior and velocity) influence investors' valuation of its future returns?

Signaling theory argues that information asymmetries that exist between firms and their stakeholders determine stakeholders to rely on signals—observable actions with potential to provide information about unobservable attributes and future potential (James, Leiblein, & Lu, 2013; Spence, 2002). In this paper, we investigate two patenting patterns in firms' R&D activities that signal firms' potential to investors. The first pattern is the direction of firms' R&D behavior which is reflected by the degree to which firms' portfolio of patents is either wide or deep. A wide patent portfolio indicates that R&D activities have been exploratory— hence we call this pattern "exploratory patenting." A deep patent portfolio indicates that R&D activities have been geared more towards exploiting already-discovered technology spaces—therefore we call this pattern "exploitative patenting." These two patterns provide information about firms' future potential. Specifically, when firms patent in technology spaces new to them, they signal their aim to learn (explore) new domains. Else, when firms patent in the same domains in which they are already, they signal their intention to leverage (exploit) what they already know (March, 1991; Yayavaram & Chen, 2015).

The second patenting pattern in firms' R&D activities that signal firms' potential to investors is *the change in the rate of growth in firms' patenting breadth/depth. This pattern* reflects the displacement in the intensity of patenting for each R&D behavior. We call this pattern, ***patenting velocity***. While patenting behavior can signal firms' potential to investors, patenting velocity increases signaling effectiveness (Janney & Folta, 2003, 2006; Long, 2002) and indicates firms' commitment to a certain patenting behavior (DiMasi, Hansen, & Grabowski, 2003; Gagnon & Lexchin, 2008; Harryson, Dudkowski, & Stern, 2008). We introduce the concept of expectation fit to explain the effects of various configurations of patterns in patenting behavior and velocity. Additionally, we introduce the mechanism of pattern fit to contour boundaries on patenting velocity. Overall, Figure 1.1 illustrates our model:

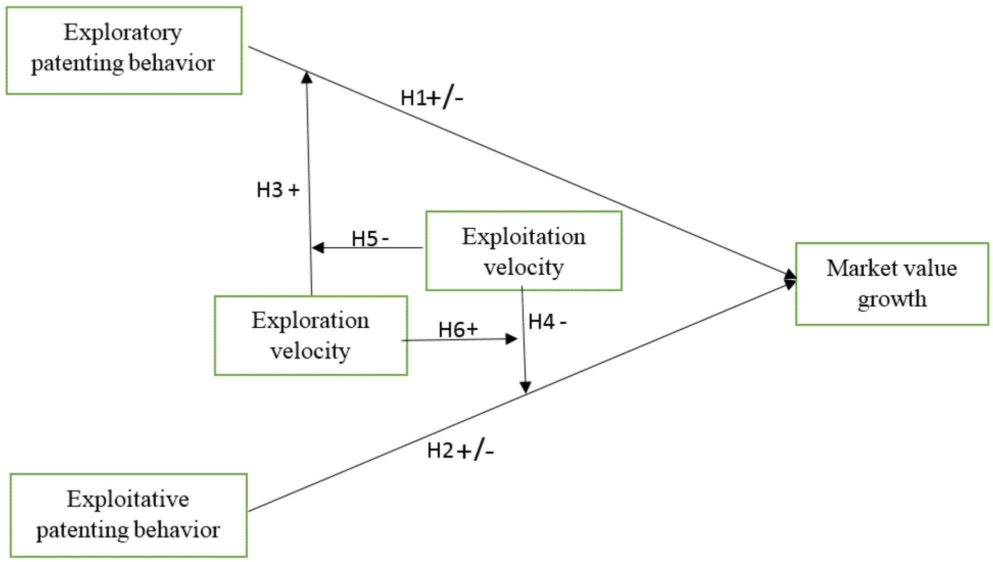

Figure 1.1 Theoretical model.

We hope to expand upon existing signaling theory research by offering a pattern-based view of firms' signaling. To do so, we integrate signaling theory with organizational learning (Lavie, Kang, & Rosenkopf, 2011; March, 1991) and coin three new concepts: patenting velocity, pattern fit, and expectation fit. Based on the fact that approximately 97 percent of patents never make any money (Key, 2015), we consider the effects of patenting patterns instead of a simple patent count, allowing a clear distinction between the signaling and economic value residing in firms' R&D activities. Our conceptualization of patenting velocity as signal is the first of its kind, enriching a recent scholarly attention to the concept of speed (Nadkarni, Chen, & Chen, 2015; Pacheco-De-Almeida, Hawk, & Yeung, 2015; Rockart & Dutt, 2015).

Patenting Patterns as Signals

Under the tenets of signaling theory, a signal's cost creates a separating equilibrium that helps receivers differentiate between the "good type" and the "bad type" firms (Connelly et al., 2011; Spence, 2002). We go beyond cost as the main separating criterion and focus on patenting patterns to give a more nuanced view of signaling that can help receivers clarify the "true" potential of firms. Patenting patterns (patenting behavior and patenting velocity), by themselves or in combination, send different signals that may be highly informative of firms' future potential. For investors, to be able to distinguish firms' potential is highly relevant (Hottenrott, Hall, & Czarnitzki, 2016; Kolympiris, Hoenen, & Kalaitzandonakes, 2017) because it lowers the uncertainty surrounding firms' potential.

We start by describing how the two patenting patterns identified (patenting behavior and patenting velocity) would satisfy the requirements of a signal. Following the basic logic of signaling theory (Spence, 1973), a signal must first be observable to the receiver (Janney & Folta, 2006) and then costly to the sender (Cohen & Dean, 2005; Lee, 2001; McGrath & Nerkar, 2004). As the cost of signaling increases, misleading signals do not proliferate and senders communicating dishonest signals are filtered out (Riley, 2001; Srivastava, 2001). With an informational value eroding faster (Davis, Eisenhardt, & Bingham, 2009; Eisenhardt, 1989), dynamic industries pose a serious problem to investors. Patenting patterns have a higher potential than simple patent count to reduce information asymmetries that investors face (Conti, Thursby, & Thursby, 2013). Information asymmetries affects the decision-making process of the investor and the firms' actions (Stiglitz, 2002). As information depreciates faster, firms know more than outside investors and investors may definitely make better decisions if they knew this information (Spence, 2002).

Beyond investigating the signaling potential of patenting behavior and velocity, we identify two trajectories that these signals can take: exploratory and exploitative. Exploratory behavior is reflected by patenting that widens firms' knowledge, and exploitative behavior is reflected by patenting that deepens firms' knowledge (Fleming & Sorenson, 2004; Katila & Ahuja, 2002; Kotha, Zheng, & George, 2011; March, 1991). Exploratory and exploitative patenting patterns carry different meaning and value for investors. Specifically, in highly dynamic industries such as computer software, nursing a fertile milieu for young and small firms (Stettner & Lavie, 2015), the environment contains highly attractive targets for investors and the potential for gain is high (Suarez, Cusumano, & Kahl, 2013; Useche, 2014). Young firms in such industries face increased information asymmetries as their age, success, or years of experience do not clearly separate them from other firms in the eyes of their potential investors (Wen, Ceccagnoli, & Forman, 2015). Separating exploratory from exploitative trajectories in firms' patenting patterns becomes an essential step illuminating the power that signaling theory has to capture firms' potential in dynamic markets.

In line with signaling theory mechanism, patenting patterns may hold a richer informational value about firms' potential (Conti, Thursby, & Thursby, 2013; Graham, Merges, Samuelson, & Sichelman, 2009; Heeley, Matusik, & Jain, 2007; Long, 2002). The signaling literature informs us that there is a high uncertainty among investors regarding the *true* value of firms—value given by firms' intrinsic characteristics and hidden agenda (Harhoff, 2011; Hoenen et al., 2014). Patenting is a more reliable source of information than the reported accounting measures—such as return on investment—that have been shown to be easily manipulated (Lawrence, 2013; Mousa, Ritchie, & Reed, 2014). Additionally, as a dynamic industry changes (Eisenhardt & Brown, 1997), signals are likely to lose their value faster compared to the relatively stable information existent in traditional industries. This makes firms' patenting patterns an important reference point for investors as a more stable signal over time.

We endeavor to suggest a new methodological approach aimed to capture exploratory and exploitative patterns through the types of patents that firms file with patenting offices such as the U.S. Patent and Trademark Office (USPTO). The filing process requires firms (patentees) to specify at least one classification for each patent they file. This classification places the patent within a specific class and subclass of innovations. Each patent, depending on the breadth (number of classes) and depth (average number of subclasses per class) of its classification tree, conveys firms' intentions: whether to widen or deepen organizational knowledge pool. For each firm, we delineate a firm's patenting behavior by looking at the classes and subclasses of its entire pool of patents granted in a certain year. Consistent with the learning literature arguing that exploration and exploitation efforts can independently coexist (Stettner & Lavie, 2015; Zahavi & Lavie, 2013), we compute a measure of exploratory patenting (average degree of classification breadth) and a measure of exploitative patenting (average degree of classification depth). Distinguishing exploratory from exploitative patterns helps investors define a firm's degree of involvement in each trajectory and minimizes the existent informational gaps (Conti, Thursby, & Thursby, 2013; Conti, Thursby, & Rothaermel, 2013; Hagedoorn, Link, & Vonortas, 2000; Heeley et al., 2007).

The Role of *Exploratory* Patenting Pattern in Firms' Market Valuation

An exploratory patenting pattern reflects firms' distant search. Such a pattern may increase firms' potential for commercialization, therefore *positively* affecting firms' market value through two defining mechanisms: wider base of choices and increased credibility. First, when firms patent in new domains they increase the diversity of their knowledge pool and widen their patent portfolio (Larrañeta, Zahra, & Galán González, 2014; Su & Tsang, 2015). This horizontal, unrelated diversification of the patent pool helps firms establish a portfolio of potential ideas that can be transformed into economically-viable products (Belderbos, Cassiman, Faems, Leten, & Van Looy, 2014; Chen, Li, Shapiro, & Zhang, 2014). Investors positively evaluate firms with wider knowledge pools because this diversity opens the door for other innovations. According to organizational learning, a single set of knowledge elements can create a limited number of value-adding products (Katila & Ahuja, 2002). However, a wider knowledge base is comprised of multiple sets of knowledge elements that allow for more possible recombinations (Garcia-Vega, 2006; Katila & Ahuja, 2002). Investors are more appreciative of firms with wider knowledge pools because they see a wider potential for commercialization deriving from these firms' recombinatory power.

Second, an exploratory patenting pattern may positively affect firms' market value by increasing its credibility. Pursuing an exploratory patenting pattern incurs significant costs in terms of R&D dollars and time; hence it is likely that firms would only invest in exploratory patenting if they truly believe in the potential of the new ideas. Due to the costs, an exploratory patenting pattern attracts investors' attention because they seem more valid, being associated with a positive sentiment (Arthurs, Busenitz, Hoskisson, & Johnson, 2009; Cohen & Dean, 2005).

Yet, an exploitation patenting pattern may also yield conflicting interpretations that make the real value of firms' trajectory unclear, ultimately with a *negative* effect on firms' market valuation. When firms engage in an exploratory patenting, they expand their innovations portfolio, making some investors unsure of the value that this expansion may bring. For smaller firms, augmenting patenting portfolio with new domains may be shadowed by investors' skepticism as these firms usually lack the capabilities to leverage the discovered knowledge (Xin & Song, 2015). The fact the 97 percent of patents never make any money (Key, 2015) reflects the bare reality that many investors are afraid of. As a fact, investors do not know for sure the future value of the new knowledge created, whether the firm is capable of leveraging this knowledge, or how long it will take to see results. Thus, different investors may attribute different market values to the same innovation (Perkins & Hendry, 2005; Srivastava, 2001). The confusion increases as investors listen to other investors' opinions (Arthurs et al., 2009; McNamara, Haleblian, & Dykes, 2008; Sliwka, 2007), and may result in a lower valuation of a firm's exploratory patenting behavior.

Overall, we suggest that an exploratory patenting pattern may increase firms' market value by signaling higher potential for commercialization, but it may also decrease firms' market value by confusing investors about to the potential that these innovations may bring or about firms' ability to leverage them properly and timely. Therefore, we test the following competing hypotheses:

H1a: Firms' exploratory patenting behavior <u>*positively*</u> *affects firms' market value growth.*

H1b. Firms' exploratory patenting behavior <u>*negatively*</u> *affects firms' market value growth.*

The Role of *Exploitative* Patenting Pattern in Firms' Market Valuation

Organizational learning theory informs us that firms engaged in exploitation display an interest in leveraging local knowledge and are short-term focused (March, 1991). We build on the existent literature and suggest firms that maintain a pattern of exploitative patenting behavior may signal either limited learning capability or reliable capability to draw quick returns.

At first glance, exploitative patenting may send a signal with a *negative* connotation to investors because it may suggest the existence of a possible exploitation trap (Piao & Zajac, 2016). Often, firms with a limited learning capacity focus their patenting efforts on exploiting current competences because the outcomes of exploitation are almost immediate and certain (Benner & Tushman, 2015). Such firms may be small, new to the market or may simply lack the capacity to explore newer knowledge domains. Exploitative patenting behavior signals the choice that firms make to leverage existing competencies for immediate returns (Jansen, Van Den Bosch, & Volberda, 2006). However, such local learning may endanger firms' long-term viability by restricting exploratory innovations (He & Wong, 2004). Additionally, an exploitative focus suggests a limited potential because leveraging local knowledge increases the chance that firms become myopic on "what is recorded in [their] organizational memory" (Levitt & March 1988: 327).

The negative effect that such a signal has on the growth in firms' market value is also supported by findings showing that recombining a stable knowledge set yields diminishing returns over time (Dosi, 1988). The mechanism of diminishing returns makes the value-creating potential of a stable knowledge set to be drained at some point. An exploitative patenting pattern brings increasingly lower returns and eventually reaches a limit beyond which no positive returns may exist (Wales, Parida, & Patel, 2013). From investors' perspective, the longer the firm stays on this trajectory, the lower investors' interest. Hence, a negative evaluation is likely.

On the *positive* side, firms focused on exploitation avoid the risks associated with negative learning transfer or lengthy R&D with unsure benefits. Exploitation entails specialization and specialized firms send a consistent signal (Basdeo, Smith, Grimm, Rindova, &

Derfus, 2006), which, according to signaling theory, minimizes information asymmetries. From an investor's perspective, in dynamic industries, the outcomes of exploratory patenting are more uncertain (Wadhwa, Phelps, & Kotha, 2016). Thus, exploitative patenting may be more desirable as it brings more certain outcomes. For firms with an exploitative patenting behavior, an appreciation in market value is possible.

Building on possible exploitation traps and increased likelihood of diminishing returns, we claim that investors may negatively evaluate firms' exploitative patenting behavior. However, based on lower asymmetries signaled by specialization, it is also possible that the same pattern is positively evaluated, leading to an increase in firms' market value. We will therefore test the following competing Hypotheses.

H2a: Firms' exploitative patenting behavior <u>*positively*</u> *affects firms' market value growth.*

H2b: Firms' exploitative patenting behavior <u>*negatively*</u> *affects firms' market value growth.*

Patent Velocity, Pattern Fit, and Expectation Fit

A call has been issued to understand "how signalers efficiently balance the rate at which they signal to effectively reinforce the message they are signaling" (Connelly *et al*., 2011: 57). Even though the call has been issued more than half a decade ago, no research has specifically focused on the issue of *rate* or its reinforcing power. With the purpose to respond this call in mind, our study sheds light on an important patenting pattern affecting the relationship between firms' patenting behavior and their market value—which we call *patenting velocity*. We define patenting velocity as the change in the rate of growth in firms' patenting breadth/depth which reflects the displacement in growth in firms' patenting in their chosen patenting direction (exploratory or exploitative). We view velocity as a direction-aware vector by taking into account the fit between patenting pattern and velocity pattern (i.e. the fit between exploratory patenting and exploration velocity). We further refer to this fit as *pattern fit*. While some recent research has focused on the construct of speed in performing certain business activities (Hoenen et al., 2014; Nadkarni et al., 2015; Pacheco-De-Almeida et al., 2015), scholars did not tackle the issue of velocity. Methodologically, we compute both exploratory and exploitative velocity measures to capture the changes in both breadth and depth in a firm's patenting. Patenting at a higher velocity—sending out an increased number of signals—along the same behavioral pattern chosen by the firm, thus achieving pattern fit, strengthens the signal. It also conceptually identifies our measure as velocity and not speed.

As illustrated in Figure 1.2, pattern fit is the fit achieved when a firm's patenting behavior pattern matches its patenting velocity pattern. In other words, when a firm with an exploratory patenting behavior explores at high velocities, we define it as pattern fit. Similarly, when a firm with an exploitative patenting behavior exploits at high velocities, we define it as pattern fit. Any other configurations would be defined as pattern mismatch.

	Exploratory behavior pattern	Exploitative behavior pattern
High velocity exploratory patenting	**Pattern Fit**	Pattern mismatch
High velocity exploitative patenting	Pattern mismatch	**Pattern Fit**

Figure 1.2 Pattern fit and pattern mismatch configurations.

Further, the effect of velocity pattern in diminishing or augmenting information asymmetries is bounded by investors' expectation. We therefore introduce the construct of *expectation fit* which we define as the fit between the signal sent by the sender and the signal expected by the receiver. The signal sent by a firm is reflected in a certain trajectory of patenting behavior—exploratory patenting or exploitative patenting. The signal expected by the receiver (investor) is based on a firm's recent past pattern in patenting behavior. Firms engaged in exploration are expected to continue exploratory patenting for best long-term results (March, 1991). Firms engaged in exploitation are expected to diminish their patenting and produce immediate outcomes (March, 1991). Figure 1.3 shows that on one side, when the expectation is met, high velocity patenting on the respective trajectory lowers information asymmetries by increasing signals' effectiveness, and on the other side, when the expectation is not met, high velocity patenting increases information asymmetries by weakening signals' effectiveness (Carter, 2006).

On one side, for a firm on an exploratory patenting trajectory, the expectation is to continue exploring new knowledge domains in order to maximize knowledge breadth, increase the number of possible knowledge recombinations, and consequently maximize the chances for commercialization. For such a firm, increasing the velocity of its exploratory patenting activity is viewed as beneficial by investors and an appreciation in market valuation can be expected.

On the other side, for a firm on an exploitative patenting trajectory, the expectation is to slow down its exploitative patenting activity and devote resources to more exploratory patenting endeavors. For such a firm, increasing the velocity of its exploitative patenting activity is viewed as detrimental by investors and a depreciation in market valuation can be expected.

<table>
<tr><td></td><td>Exploratory behavior pattern</td><td>Exploitative behavior pattern</td></tr>
<tr><td>High velocity exploratory patenting</td><td rowspan="2">Expectation fit</td><td rowspan="2">Expectation mismatch</td></tr>
<tr><td>High velocity exploitative patenting</td></tr>
</table>

Figure 1.3 Expectation fit and expectation mismatch configurations.

In the following, we treat exploratory and exploitative velocity patterns independently and aim to study how their fit/misfit with firms' dominant patenting behavior affects how firms are valued on the market.

The Effects of Patenting Velocity When Pattern Fit is Met

Our proposition is that the velocity with which firms have patents granted matters. Not only patenting at a higher velocity sends more signals strengthening the message but also confirms or disconfirms investor's expectation about a firm's trajectory in patenting. There are two conditions for a signal to be positively interpreted: it must be strong enough to be heard and it must meet the expected trajectory. We justify the strengthening effect with the mechanism of signal frequency. According to signaling theory, high frequency signaling improves the effectiveness of the signaling process by making the signal more observable (Janney & Folta, 2003). High velocity patenting, at its core, refers to signaling more frequently. In dynamic environments, patenting at a high velocity is useful because the dynamism of these environments creates noise requiring firms to send stronger signals (Lester, Certo, Dalton, Dalton, & Cannella, 2006). Concurrently, dynamic environments make the information depreciate faster (Davis et al., 2009). With a quickly depreciating informational value transmitted by signals, firms must be more active in their signaling (Park & Mezias, 2005). For firms on an exploration patenting trajectory, issuing exploratory patents (widen the breadth of firms' knowledge) at a higher rate cancels out some of the environmental noise and makes firm's signaling more clear and easier to be perceived by investors. Because in noisy environments it is harder to keep investors informed, we expect that fast rate signaling boosts signals' effectiveness and reduces the information asymmetries between firms and investors.

However, stronger signaling is necessary but insufficient to conclude anything about how investors perceive the signal. The mechanism of expectation fit defined earlier helps us explain that. Expectation fit is the fit between the signal sent by the firm and the signal expected by the investor. When the signal fits investors' expectation, an appreciation in firms' value can be expected. When it does not, a depreciation in firms' value is likely.

Investors will expect future patenting behavior based on past behavior. For firms that display recent active exploratory pattern (i.e. IBM, Microsoft), investors expect such firms to be focused on long-term benefits (March, 1991) and therefore they expect to see future exploratory patenting. For firms that display recent active exploitative pattern (i.e. Boomer Inc), investors expect such firms to be focused on short-term outcomes (March, 1991) and thus they expect to see less patenting and more future exploitation that yields immediate outcomes. Given that patenting—either exploratory or exploitative—is a costly activity (Harryson et al., 2008; Stettner & Lavie, 2015; Stiglitz, 2014), from investors' perspective, Boomer Inc should not intensify its patenting activities. Instead, it should reconfigure its resources to actually incorporate its knowledge into producing immediate returns—reflected in low velocity patenting.

To sum up, we first see high velocity as a necessary but insufficient condition imposed on a pattern of patenting behavior to significantly affect a firm's market value. While it boosts the signal and it compensates for the environmental noise, its pattern must further fit investors' expectation in order to significantly lower information asymmetries. For firms perceived as exploratory, patenting at higher velocities should bring an appreciation in a firm's market value. For firms perceived as exploitative, patenting at higher velocities, should be perceived as a discontinuous activity that takes away resources from a firm's exploitative pattern.

H3: The interaction between firms' exploration patterns in velocity and behavior leads to an <u>*appreciation*</u> *in firms' market value.*

H4: The interaction between firms' exploitation patterns in velocity and behavior leads to a <u>*depreciation*</u> *in firms' market value.*

The Effects of Patenting Velocity When Pattern Fit is Not Met

In addition to theorizing about the implications that matching the patterns in patenting behavior and velocity may have on a firm's market value, we also investigate the implications that patenting at a high velocity in the non-dominant direction (i.e. that is *not* the focus of a firm's patenting activity)—thus not achieving pattern fit—may have. Habitually, firms have patents granted in both exploratory and exploitative directions thus displaying both exploration and exploitation velocities simultaneously. The ambidexterity literature studied in detail various ways to separate exploration from exploitation activities, either using units within the same organization (He & Wong, 2004; Sidhu, Commandeur, & Volberda, 2007), using different modes of organization (Lavie et al., 2011; Stettner & Lavie, 2015), or pursuing these activities at different times (Lavie, Stettner, & Tushman, 2010). Regardless of a firm's chosen way to combine these activities, investors "centralize" the information and evaluate firms' potential based on the entire pool of information they have (Alvarez-Garrido & Dushnitsky, 2016). The argument is theoretically relevant because combining patterns of exploratory and exploitative velocities while a firm is focused only on the dominant patenting behavior (either exploratory or exploitative) have a significant impact on investors.

So far, we have argued that patterns of patenting behavior act as signals affecting a firm's market value, and that signaling at a high velocity has different effects depending on a firm's patenting trajectory. Yet, the effectiveness of the signaling process also depends on signal's consistency (Fischer & Reuber, 2007; Zhang & Wiersema, 2009). So, what happens when firms try to simultaneously engage in both exploratory and exploitative patenting at high velocities? We propose that signaling both high velocity exploratory and exploitative patenting behaviors diminishes the effectiveness of the signaling process by making the signal inconsistent. Signal inconsistency refers to the confusion that different signals sent by the same source can create for investors (Gao, Darroch, Mather, & MacGregor, 2008). Inconsistent signals negatively affect the signaling process by diminishing signaling effectiveness (Fischer & Reuber, 2007).

For firms maintaining a dominant exploratory patenting behavior, simultaneously engaging both exploratory and exploitative patenting at high velocities creates confusion and dilutes investors' expectation. With exploration and exploitation activities fighting for the same resources (Lavie et al., 2011) and with exploratory patenting increasingly expensive, we infer that assigning part of resources to exploitative activities signals investors that essential research funds are detracted from exploration. Thus, a negative valuation.

For firms maintaining a dominant exploitative patenting behavior, assigning a part of R&D resources to exploration signals an ability and willingness to overcome exploitation traps and diminishing returns (Dosi, 1988; Levitt & March, 1988). Simultaneously engaging both exploratory and exploitative patenting at high velocities highlights new potential for future value-creation. Even more, the potential of high velocity exploratory patenting may also suggest that the firm is not on a path of diminishing returns anymore. These effects can improve how firms with a dominant exploitative behavior are perceived by investors. Thus, a positive valuation.

Consistent with previous findings of the ambidexterity literature (Stettner & Lavie, 2015), we propose that inconsistent signaling diminishes signaling effectiveness. Regardless of a firm's patenting behavior direction, simultaneously pursuing high velocity exploration and exploitation diminishes the effect of maintaining a consistent pattern fit.

H5: The interaction effect achieved by a fit in firms' exploratory patterns (velocity and behavior) is reversed by firms' exploitative velocity pattern, leading to a depreciation in firms' market value.

H6: The interaction effect achieved by a fit in firms' exploitative patterns (velocity and behavior) is reversed by firms' exploratory velocity pattern, leading to an appreciation in firms' market value.

Methods and Analysis

Sample and Research Context

We set to empirically analyze U.S. publicly traded firms that operate in patenting-intensive industries—the telecommunications industry (SIC 481) and computer programming and data processing industry (SIC 737)—between 2006 and 2013 inclusive, with some data traced back to 2002. Even if biotech and pharma industries have similarly active patenting intensity, we intentionally leave them out because biotech/pharma firms' patenting can be heavily influenced by institutional factors. Firms' patenting patterns may, for example, reflect Federal and Drug Administration's vested interests in promoting a certain drug over another. By comparison, the patenting patterns of telecommunications and software firms are more likely to reflect firms' intrinsic interests in such activities because no strong institutional influences exist. Firms' patenting patterns can thus more accurately signal firms' interests to investors.

We integrate five main data sources. Compustat provides the data necessary for industry concentration measures. Compustat-CRSP database helps us calculate the market value growth using archival data on common shares outstanding and stock prices. We identify patenting patterns using the United States Patents and Trademarks Office (USPTO) publicly available data on granted patents. In the telecom and software industries, focusing on granted patents instead of applications is justified by the lengthy and costly process that firms must go through from application to granting. Patent applications say more about firms' intentions while granted patents say more about firms' potential. While investors may consider patent applications as well, we believe that granted patents are those that ultimately influence investors' opinion considered in firms' market valuation.

To compute the exploratory and exploitative patenting measures, we rely on the USPTO Cooperative Patent Classification system (CPC). The CPC assigns codes to each patent according to five hierarchical levels mandatory for all filed patents: section (level 1), class (level 2), subclass (level 3), group (level 4), and subgroup (level 5). The resulting codes uniquely describe how each patent relates to other patents. We design queries that retrieve the complete classification information for each patent granted between 2002 and 2013 inclusive. We aggregate the data at the class and subclass levels and use these aggregated measures to compute the patenting behavior and velocity variables. USPTO also provides data for all aggregated patent-related and citation-related measures such as patenting experience, top patentees, and innovation fit. We extract prior alliance and acquisitions from the SDC Platinum database and compute firm age based on the incorporation date available in Mergent Online.

Our final data set is a panel of 143 firms analyzed between 2006 and 2013 inclusive with some data traced back to 2002. Multiple observations for each firm over a number of years raises concerns of potential interdependence among observations. We consider a one-year lag for all predictor and control variables relative to the dependent variable. We choose the fixed effects model (Hausman, 1978) and test the interactions using a stepwise moderation approach that minimizes potential multicollinearity (Aiken & West, 1991). We build nine models by sequentially adding variables.

Dependent Variable

Our dependent variable is firms' growth in market value between two consecutive time periods and is operationalized for each firm *i* for each year *t* as follows:

$$Market\ Value\ Growth_{\ i,t+1} = \frac{Market\ Value_{\ i,t+1} - Market\ Value_{\ i,t}}{Market\ Value_{\ i,t}} \tag{1}$$

For this formulation, we calculate market value as the product between firms' stock price and their number of common shares outstanding. We compensate for the volatility of this measure by averaging the 12 end-of-month values. This measure is in line with prior research (Lavie et al., 2011; Stettner & Lavie, 2015; Uotila, Maula, Keil, & Zahra, 2009) showing that firms' market value effectively predicts the effects of internal organization on performance. To theoretically justify the direction of association between our dependent and independent variables we use the signaling mechanism that a firm's patenting reduces the information asymmetries for investors. Moreover, market value is more appropriate for our model and thus preferable to traditional accounting measures such as ROA or ROI for two reasons. It captures the *ex-ante* expectation about a firm's future performance as viewed by investors as opposed to slowly-adjusting accounting-based performance measures that capture *ex-post* performance. Also, if we consider that different firms use different accounting standards, using accounting measures would be inappropriate to capture investors' performance expectation.

Independent Variables

Exploration/Exploitation Patenting. Traditionally, a firm's patenting behavior is captured by technological diversification that reflects firms' breadth in patenting (Kaplan & Vakili, 2015; Yayavaram & Chen, 2015) or citations (Sterzi, 2013). Yet, to capture a firm's potential behind its exploratory or exploitative behaviors, we assume that patent classifications are representative for a firm's intended patenting direction. We use these classifications to measure each firm's engagement in exploratory and exploitative behaviors (Cao, Gedajlovic, & Zhang, 2009; He & Wong, 2004; Jansen et al., 2006). We measure exploratory behavior with a Herfindahl index of a firm's CPC class-level classifications (level 2 classification) in a firm's entire patent pool for that year. This measure reflects a firm's focus on exploring new classes (breadth) as opposed to exploiting by patenting in the same classes (depth). We correct for the downward bias and adjust the measure for firms with patents filed in few classes (Hall et al., 2005).

$$Exploration\ patenting_{j,t} = \frac{CL_{j,t}}{CL_{j,t}-1} \times \left(1 - \sum_{j}^{n_i} p_{ij,t}^2\right) \quad (2)$$

where $CL_{i,t}$ represents the number of classes for all patents of firm *j* in year *t* and $p_{ij,t}$ denotes the percentage of class iterations in total number of classes for patent *i* that belong to firm *j* in year *t*.

Exploitative patenting measures within-class knowledge coverage and reflects a firm's focus on exploiting its familiarity with that knowledge class. We use a Herfindahl index of a firm's number of subclasses per class (count of level 3 classifications for each level 2 classification) pooled by firm and by year. The higher the percentage of patents filed in the same class but in different subclasses, the higher the likelihood that the firm's orientation is exploitative. We use the Hall-adjusted measure:

$$Exploitation\ patenting_{j,t} = \frac{SUB_{j,t}}{SUB_{j,t-1}} \times \left(1 - \sum_{j}^{n_i} s_{wij,t}^{2}\right) \tag{3}$$

where $SUB_{i,t}$ represents the number of subclasses for all patents of firm *j* in year *t* and $s_{wij,t}$ denotes the percentage of subclass per class iterations in total number of subclasses filed for each class *w* of patent *i* that belongs to firm *j* in year *t*.

Patenting Velocity. We operationalize patenting velocity with the difference in the growth rate in patenting frequency between two consecutive years. We first calculate the patenting frequency for each year, then compute the frequencies rates of growth first, between the current and the previous year and second, between the two previous years. Last, we measure the difference in these two rates of growth, with a positive value reflecting an increase in the frequency of signaling. To differentiate between years with zero growth and years with no patenting, we add controls for class and subclass per class. Exploratory velocity reflects a firm's consistency in exploratory patenting. An increase in the rate of growth in the number of classes signals that a firm is increasing its commitment to exploration by augmenting its knowledge breadth. Exploitative velocity reflects a firm's consistency in exploitative patenting. An increase in the coverage at class-level signals a firm's increasing commitment with an exploitation trajectory and their interest in leveraging an increased number of recombinations.

$$Exploration\ velocity_{j,t} = \frac{CL_{ij,t} - CL_{ij,t-1}}{CL_{ij,t-1}} - \frac{CL_{ij,t-1} - CL_{ij,t-2}}{CL_{ij,t-2}} \tag{4}$$

where $CL_{ij,t}$ is the number of classes all patents *i* of firm *j* granted in year *t* are filed in.

$$Exploitation\ velocity_{j,t} = \frac{SUB_{wij,t} - SUB_{wij,t-1}}{SUB_{wij,t-1}} - \frac{SUB_{wij,t-1} - SUB_{wij,t-2}}{SUB_{wij,t-2}} \tag{5}$$

where $SUB_{wij,t}$ is the number of subclasses per class *w* all patents *i* of firm *j* granted in year *t* are filed in.

Control Variables

We control for a number of characteristics of the firm. *Firm size* can affect a firm's performance output and efficiency (Ahuja, Lampert, & Tandon, 2008). We measure it with a natural logarithmic function of the firm's total assets (in thousands) (Deeds & Decarolis, 1999). We do not consider the number of employees given that the telecommunications and software are not labor-intensive industries. *Firm age* is a crude proxy for firm-specific flexibility with mature firms having more experience but also more rigidities to overcome. We measure it with a natural logarithmic function of the number of years that elapsed since the incorporation event. We control for the previous year ROA as *past performance* may affect investors' attention (McDonald, Khanna, & Westphal, 2008).

We also consider various patent-level and industry-level controls to minimize possible confounding effects. We expect that *patenting experience* could bias investors' opinion about firms' easiness in patenting. According to Mowery, Sampat, and Ziedonis (2002), firms become more efficient in patenting as they learn how to innovate more efficiently. We control for the cumulative number of patents granted to the firm over the last three years (Yayavaram & Chen, 2015).

Top patentee controls for the possibility that investors may confound firms' capability to patent high quality innovations with firms' ranking in the industry (which reflects firms' ability to patent many inventions not necessarily high-quality inventions). We code this variable 1 if the firm is ranked top 5% of firms with most patents and 0 otherwise.

Citations help us correct for patents that are highly cited because those are more likely to be novelty-producing innovations (Kaplan & Vakili, 2015).

We control for *alliance experience* and *acquisition experience*. Firms may externally explore through alliances as a way to overcome resource constraints or they may use acquisitions as a means to innovate (Leiponen & Helfat, 2010). We include the count of alliances and acquisitions reported for each firm.

Industry concentration—measured with the four-firm concentration ratio—reflects whether the industry creates barriers that impede competitiveness allowing dominant firms to clearly signal investors (high concentration) or not (low concentration).

Exploration fit and *exploitation fit* are dummy variables coded 1 when a firm's exploratory/ exploitative growth is higher than an industry's exploratory/exploitative growth and 0 otherwise. Yamakawa, Yang, and Lin (2011) highlighted the importance of achieving a good fit between firms' learning choices and environment's technological trajectory. When industries grow, firms that explore benefit from a variety of opportunities and rewards (March & Shapira, 1987) but when industries slow down, firms can reap more predictable returns from leveraging mutual interdependencies and complementarities (Spanos, Zaralis, & Lioukas, 2004). The growth variables on which a firm's fit and industry's fit are based are computed as a percentage increase in the firm's and industry's technological diversity respectively. We control for time effect with *year dummies* and any remaining heterogeneity inside firms with fixed effects regression.

Findings

Table 1.1 presents descriptive statistics and correlations for the variables used in this study. Over the eight years studied, the average firm has a market value growth of 22 percent which is negatively correlated with previous performance and firm size. Investors, in other words, increase their performance expectations as firms either perform well or grow in size. The exploratory and exploitative patenting behaviors are correlated suggesting that most firms are ambidextrous and patent both for exploratory and exploitative purposes at once. The velocity measures are positively correlated, showing that firms are more likely to explore incrementally rather than radically.

Table 1.2 shows the results of hierarchical panel fixed effects regression. We start with the baseline model with control variables only. Model 1 tests Hypothesis 1 discussing whether a firm focused on exploratory patenting sends a positive or negative signal to investors. The exploratory patenting coefficient is significant (model 1: β = -0.139, p <0.05). The exploratory patenting pattern lowers investors' appreciation of firms' future potential. Hypothesis 1b is supported.

Table 1.1 Descriptive statistics and Pearson correlations.

Variables	Mean	*s.d.*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1 Market value growth $_{t+1}$	0.22	2.55																	
2 Exploratory patenting $_t$	0.27	0.36	-0.04																
3 Exploitative patenting $_t$	0.19	0.31	-0.03	**0.71**															
4 Exploration velocity $_t$	-0.16	4.90	0.00	-0.01	-0.02														
5 Exploitation velocity $_t$	-0.11	3.70	0.00	-0.03	-0.02	**0.22**													
6 Firm size $_t$ (ln)	6.20	2.53	**-0.19**	**0.15**	-0.01	-0.01	0.01												
7 Return on assets $_t$ (ln)	-2.91	1.06	-0.07	**0.08**	0.03	0.02	0.00	**-0.14**											
8 Firm age $_t$	2.67	0.82	-0.01	**0.17**	**0.08**	0.01	0.01	**0.27**	-0.02										
9 Alliances $_t$	0.33	1.32	-0.02	**0.11**	0.03	-0.01	0.00	**0.26**	0.06	**0.10**									
10 Patenting experience $_t$	120.89	927.49	-0.01	**0.10**	0.01	-0.03	0.04	**0.26**	**0.11**	**0.22**	**0.31**								
11 Citations $_t$	431.93	2487.30	-0.02	**0.06**	-0.03	-0.02	0.00	**0.29**	**0.16**	**0.21**	**0.61**	**0.70**							
12 Acquisitions $_t$	0.33	0.92	-0.01	0.01	-0.02	-0.04	-0.01	**0.17**	0.04	**0.05**	**0.09**	-0.01	-0.01						
13 Top patentee $_t$	0.01	0.09	-0.01	**0.07**	0.01	**-0.09**	-0.02	**0.22**	0.04	**0.16**	**0.14**	**0.68**	**0.47**	-0.03					
14 Exploitation fit $_t$	0.78	0.41	0.02	**-0.29**	**-0.09**	0.00	0.01	**-0.16**	**-0.07**	**-0.20**	**-0.07**	**-0.11**	**-0.06**	-0.01	**-0.06**				
15 Exploration fit $_t$	0.80	0.39	0.03	**-0.26**	**-0.14**	0.01	-0.01	**-0.16**	**-0.07**	**-0.17**	**-0.06**	**-0.11**	-0.04	-0.02	**-0.05**	**0.67**			
16 Industry concentration $_t$	0.47	0.10	-0.01	0.00	-0.01	-0.02	-0.01	**0.26**	**-0.14**	**0.06**	-0.03	-0.03	-0.04	**0.09**	**0.10**	0.02	0.01		
17 Subclass per class control $_t$	3.65	2.38	0.05	**-0.08**	**-0.08**	-0.01	-0.03	-0.03	0.01	-0.03	0.01	-0.02	-0.02	0.00	0.00	-0.01	0.04	0.08	
18 Class control $_t$	228.17	1460.63	-0.01	0.04	-0.04	-0.05	0.05	**0.27**	**0.11**	**0.24**	**0.24**	**0.83**	**0.63**	-0.01	**0.61**	-0.04	-0.02	-0.03	-0.01

N: 489 observations

$p < 0.05$ for correlations in bold; two-tailed test

Table 1.2 Regression of patenting behavior and patenting velocity on market value growth.

DV: Market value growth $_{t+1}$		Base model	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept		3.194 **	2.702 *	2.908 *	2.465 *	2.467 *	1.525	1.619
		(1.24)	*(1.25)*	*(1.25)*	*(1.25)*	*(1.21)*	*(1.18)*	*(1.19)*
Predictor variables								
Exploratory patenting	**H1** (+/-)		**-0.139** *		-0.120 †		-0.087	
			(0.06)		*(0.06)*		*(0.06)*	
Exploitative patenting	**H2** (+/-)			**-0.112** †		-0.143 *		-0.152 *
				(0.06)		*(0.06)*		*(0.06)*
Moderator variables								
Exploration velocity					-0.031 ***		-0.030 **	0.010
					(0.01)		*(0.01)*	*(0.00)*
Exploitation velocity						0.029 ***	0.033 **	0.019 *
						(0.01)	*(0.01)*	*(0.01)*
Interactions								
Exploratory patenting × Exploration velocity	**H3** (+)				**0.048** ***		0.041 **	
					(0.01)		*(0.01)*	
Exploitative patenting × Exploitation velocity	**H4** (-)					**-0.097** ***		-0.049 *
						(0.02)		*(0.02)*
[Exploratory patenting × Exploration velocity] × Exploitation velocity	**H5** (-)						**-0.015** ***	
							(0.00)	
[Exploitative patenting × Exploitation velocity] × Exploration velocity	**H6** (+)							**0.008** ***
								(0.00)
Firm-level controls								
Return on assets (ln)		-0.022	-0.021	-0.024	-0.025	-0.022	-0.025	-0.013
		(0.02)	*(0.02)*	*(0.02)*	*(0.02)*	*(0.02)*	*(0.02)*	*(0.02)*
Firm size (ln)		-0.290 ***	-0.268 ***	-0.278 ***	-0.268 ***	-0.280 ***	-0.243 ***	-0.243 ***
		(0.06)	*(0.06)*	*(0.06)*	*(0.06)*	*(0.06)*	*(0.06)*	*(0.06)*
Firm age (ln)		0.036	0.051	0.050	0.030	0.072	0.019	0.059
		(0.13)	*(0.13)*	*(0.13)*	*(0.13)*	*(0.13)*	*(0.13)*	*(0.13)*
Alliances		0.003	0.003	0.004	0.004	0.003	0.002	0.003
		(0.01)	*(0.01)*	*(0.01)*	*(0.01)*	*(0.01)*	*(0.01)*	*(0.01)*
Acquisitions		0.022	0.014	0.018	0.015	0.015	0.010	0.012
		(0.02)	*(0.02)*	*(0.02)*	*(0.02)*	*(0.02)*	*(0.02)*	*(0.02)*
Patent-related controls								
Citations		-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
		(0.00)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*
Top patentee		-0.088	-0.096	-0.091	-0.146	-0.098	-0.192	-0.146
		(0.22)	*(0.22)*	*(0.22)*	*(0.22)*	*(0.22)*	*(0.22)*	*(0.22)*
Patenting experience		-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
		(0.00)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*
Class control		0.000	0.000		0.000		-0.000	-0.000
		(0.00)	*(0.00)*		*(0.00)*		*(0.00)*	*(0.00)*
Subclass per class control		-0.003		-0.005		-0.008	0.000	-0.001
		(0.01)		*(0.01)*		*(0.01)*	*(0.01)*	*(0.01)*
Industry-level controls								
Exploration fit		-0.050	-0.025	-0.048	-0.021	-0.076 †	-0.021	-0.055
		(0.04)	*(0.04)*	*(0.04)*	*(0.04)*	*(0.04)*	*(0.04)*	*(0.04)*
Exploitation fit		0.089 *	0.091 *	0.106 **	0.084 *	0.120 **	0.077 *	0.111 **
		(0.03)	*(0.03)*	*(0.03)*	*(0.03)*	*(0.03)*	*(0.03)*	*(0.03)*
Industry concentration		-2.466	-1.719	-1.994	-1.140	-1.053	0.625	-0.310
		(2.45)	*(2.45)*	*(2.45)*	*(2.43)*	*(2.38)*	*(2.31)*	*(2.35)*
Year fixed effects		Included	Included	Included	Included	Included	Included	Included
Firm-year observations		489	489	489	489	489	489	489
Number of firms		143	143	143	143	143	143	143
F		9.14 ***	9.51 ***	9.34 ***	9.51 ***	10.18 ***	10.48 ***	9.71 ***
Increase in R-square			0.92%	0.49%	2.96%	4.94%	11.09%	9.17%

Fixed effects panel regression (standard error reported in parentheses)

Significance levels: † $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Hypotheses in **bold** are supported

Hypothesis 2 claims that an exploitative patenting behavior may affect investors' evaluation in both positive and negative manners. The exploitative patenting behavior coefficient is marginally significant (model 2: $\beta = -0.112$, $p < 0.1$). The exploitative patenting pattern lowers investors' appreciation of firms' potential. Hypothesis 2b is marginally supported.

Hypothesis 3 argues that for firms with an exploratory patenting behavior, high velocity exploration leads to an appreciation in firms' market value. The interaction term is positive and significant (model 3: $\beta = 0.048$, $p < 0.001$). Hypothesis 3 is supported.

Hypothesis 4 suggests that firms focusing their innovation efforts on exploiting known knowledge domains worsen investors' opinion by speeding up such patenting. The negative and significant coefficient (model 4: $\beta = -0.097$, $p < 0.001$) supports Hypothesis 4.

Hypothesis 5 claims that for exploratory firms with high velocity exploratory patenting, simultaneous engagement in high velocity exploitation counteracts the positive effect of exploratory pattern fit. The three-way coefficient (model 5: $\beta = -0.015$, $p < 0.001$) shows support.

Hypothesis 6 claims that for exploitative firms with high velocity exploitative patenting, simultaneous engagement in high velocity exploration mitigates the negative effect of exploitative pattern fit. The three-way coefficient (model 6: $\beta = 0.008$, p < 0.001) shows support.

To better evaluate the results obtained and to better interpret the interaction effects, we graphically represent firms' market value growth and its covariates. The results of the two-way and three-way interactions tested by the regression Models 4 – 5 and 7 – 8 are graphically represented in Figure 1.4. The graphical representations endorse our conclusions.

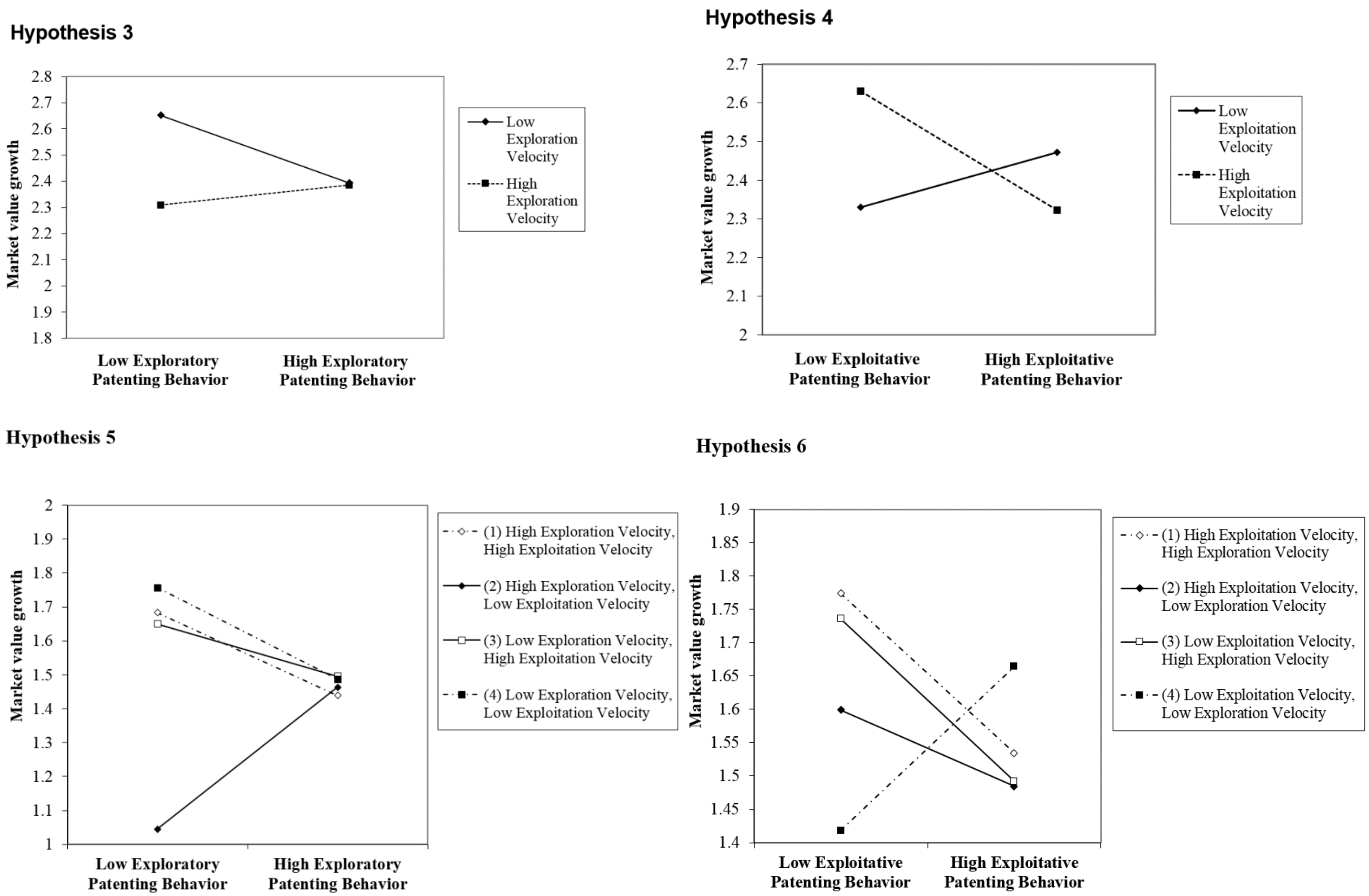

Figure 1.4 Interaction plots.

Robustness Checks and Post-hoc Tests

We test the robustness of our analyses by running three additional tests. First, since fixed panel data models cannot very well estimate time invariant effects, which we have in our dataset in form of exploratory patenting, we use the feasible generalized least square (FGLS) regression to test the robustness of our results. This regression model is more efficient for data sets with potential serial correlation which we may have in our panel in the form of slowly changing (time invariant) effects (Baltagi, 2008; Greene, 2003). The results for FGLS regression are consistent with the results obtained from the fixed panel data model.

Second, we consider a different time period. According to Connelly et al. (2011) the signaling timeline is very short so that from the moment a signal is sent and the moment that the signal is received is a very short time period. Testing our model on a shorter time frame should reassure us whether patenting patterns function as signals for investors. The pattern of significance and the direction of the hypothesized interactions remained robust over a five-year window (2008-2013), which is three years shorter than our initial window.

Third, we replace our velocity measures with alternative measures. Specifically, we weight the difference in the rates of growth with the difference from the starting point so that for firms that started with zero patents, the first year when they patent does not have an abnormally huge velocity. Results remain robust though they have slightly lower significance levels.

Lastly, we conduct a post-hoc analysis to test whether there is any interaction between exploratory and exploitative patenting behaviors or between exploring and exploiting at high velocities. We find that there is no significant interaction in the first case but there is a significant interaction in the second case. The insignificant interaction justifies our choice to consider exploration and exploitation patenting behaviors as patterns that send separate signals. The significant interaction justifies our last two hypotheses claiming that the pattern mismatch has a significant effect on investors.

Discussion

In this study, we embark in a challenging quest to distinguish patents intrinsic productive contribution (Heeley et al., 2007; Levitas & Chi, 2010; Teece, 2000) from their signaling function. The purpose of the article is to emphasize the role that firms' patenting patterns have in firms' signaling. We focus on knowledge-intensive industries whose dynamism creates noise (Davis et al., 2009; Eisenhardt, 1989) that diminishes the effect of firm's signaling. In such industries, a firm's patenting patterns have a high potential to inform external parties about firm's potential. Specifically, we focus on two patterns in patenting: patenting behavior and patenting velocity. The interactions between these two patterns reveal interesting effects and allow for a better contouring of a pattern-based view of signaling.

An interesting effect that we observe is that patterns of patenting behavior, both exploratory and exploitative, have a negative effect on how firms are valued on the market. While in theory, exploratory patenting may reflect a higher potential for commercialization with a positive effect on firms' market value, our results show that for dynamic industries, exploratory patenting is viewed with skepticism by investors. In an industry where everyone patents, persistent exploratory behavior may be problematic as investors cannot be reassured that these patents will ever be used or commercialized. The observation is interesting because it tells us that investors most probably weigh a firm's estimated potential heavier than firm's intentions. This means that signal's content matters. While the main point of this work is that patenting patterns act as signals to investors, we hypothesize and find support for the idea that the direction of these patterns—which reflects signals' content—matters as well. Whether patterns are exploratory or exploitative is important and their interaction, fit or misfit, is what guides the investor and ultimately decides firms' market value.

While a previous call for research has been issued for researchers to investigate the effect of firms' signaling at increased rates (Connelly *et al*., 2011), no study truly dealt with the issue. We introduce the concept of *patenting velocity* which reflects how much more patents are granted while active on a certain patenting trajectory. Measuring velocity by the means of displacement in firms' patenting in their chosen patenting direction (exploratory or exploitative), we compute it as a direction-aware vector and consider it different than speed which is a direction-less scalar. The post-hoc analysis performed brings additional support to our theorizing by revealing that the simple interaction between two different velocities has a positive effect while not considering firms' patenting pattern. However, while considering patenting patterns—which involve direction-aware vectors—as hypothesized in Hypotheses 4a and 4b, the interaction of the same two velocities has a negative effect. This difference can be justified by a misfit in patenting patterns that appears when a firm displaying an exploratory patenting behavior has both exploratory and exploitative patents granted at an increased velocity.

The concept of patenting velocity reveals interesting effects when investors' expectation comes into play. The literature informs us that investors form their own expectations about each firm in their portfolio (Wadhwa et al., 2016). These expectations refer to the behavior firms should display under certain circumstances. From investors' perspective, in dynamic industries, because of the uncertainty that governs business affairs, firms are expected to perform better if they maintain the behavior they excel at. While firms that traditionally explore are expected to explore at higher rates, those that traditionally do not explore are expected to maintain their ideology and extract results the same way they ever did it—by exploitation. We theorize and find support that if firms change direction in a way that investors do not expect it then their market value will diminish. This fit/misfit between investors' expectation and the velocity of patenting activity reveals an interesting interplay that has not been investigated in the literature before opening new avenues for research and a better understanding of the science of management.

Contributions and Future Research

This study has a number of contributions to theory. First, we conceptualize, operationalize, and substantiate patenting velocity as a new construct to help scholars understand what draws the positive and negative evaluation of firms by investors. Prior research informs us that in knowledge-intensive industries opportunities emerge faster and knowledge becomes obsolete at a higher speed than in stable industries (Davis et al., 2009). It is therefore expected that firms' innovation velocity may be important because it affects the way investors perceive firms' degree of involvement in patenting activities. Yet, only very recently have researchers tackled the issue of speed of firms' activities (Nadkarni et al., 2015; Pacheco-De-Almeida et al., 2015; Rockart & Dutt, 2015) but none of these studies focus on velocity and its signaling function. Our conceptualization of patenting velocity as signal is the first of its kind, opening new avenues for research and extending signaling theory while offering a plausible explanation of the mechanism behind firms' market valuation.

Second, we enrich signaling theory by introducing the concepts of pattern fit and expectation fit. They help us investigate the boundaries on the role of velocity patterns through a two-step process. First, when the patterns in firms' patenting behavior and velocity match, the signal is strengthened. Second, the way this signal affects firms' market valuation depends on whether the patterns fit investors' expectation. When they do, we can expect an increase in firms' value and when they don't we expect a decrease in firms' value. The findings are in line with previous signaling theory research claiming that firms may confuse their investors by sending signals with contradictory meanings (Fischer & Reuber, 2007; Gao et al., 2008; Zhang & Wiersema, 2009). This fit or misfit between investors' expectation and patterns of patenting activity exposes a new and interesting relationship that may initiate a new era of research allowing for a better understanding of firms' strategies in dynamic industries.

Third, we distinguish patents' signaling value from patents' economic contribution. We operationalize patents' signaling value by capturing patterns in patenting behavior and velocity. We look into the information that is transparently conveyed by patents (e.g. the classifications under which patents are listed) and using a content-capture procedure we identify exploratory or exploitative patterns. While a significant number of researchers studied how signals' characteristics—such as cost, intensity, clarity, or visibility—matter (Arthurs et al., 2009; Zhang & Wiersema, 2009), no clear statement has been made about the role of signals' content. This is because in most cases it is difficult to conceptually differentiate how much content or characteristics such as visibility matter for investors (Conti, Thursby, & Rothaermel, 2013). Building on previous theorizing that signals can be positive or negative (Fischer & Reuber, 2007; Perkins & Hendry, 2005), we find that exploratory and exploitative patterns of patenting behavior, though equally visible to investors, have distinct effects. This study therefore deepens our understanding of how signals' content matters in investors' decisions.

While this research contributes with new insights into the mechanisms that affect firms' market valuation, it also opens the way for new avenues for management research. In this study, we launch the term of *patenting velocity* and two related concepts: pattern fit and expectation fit. We believe that they deserve further consideration and scholars should consider the portfolio of effects and interactions that these may have. Additionally, there are a number of factors such as governmental regulations, culture or norms that have not been considered. Also, firms' patenting activity is usually related to various modes of organization such as alliances or acquisitions or to firms' entrepreneurial strategy. Future research should consider these alternative configurations, factors, and strategies with potential to affect investors' evaluation of firms' potential.

Conclusion

How do firms' patenting patterns affect firms' market valuation by investors? We integrate signaling and organizational learning mechanisms and propose that in dynamic industries patenting patterns act as signals for investors. We differentiate patenting patterns along exploration and exploitation dimensions and identify velocity as a crucial boundary for patent signaling. We also unveil two vital mechanisms with potential to bound the effects of patenting velocity: pattern fit and expectation fit. While patenting at a high velocity makes exploratory behavior more attractive to investors, the effect is inverted for firms displaying an exploitative behavior. Due to an expectation misfit, these effects are reversed when firms pursue both exploratory and exploitative patenting at high velocities. The results encourage future researchers to acknowledge the interplay of patenting behavior and velocity to promote a differentiated approach that maximizes firms' market evaluation.

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CHAPTER 2

BALANCED SOURCING PORTFOLIOS, STIFF SLACK, AND DYNAMIC CAPABILITIES

Abstract

Balanced sourcing portfolios refer to firms' efforts to simultaneously rely on both internal and external sourcing as a way to separate the development of sensing and seizing capabilities. Adopting a dynamic capabilities perspective, we investigate why and when balanced sourcing portfolios improve firm performance. In addition, we conceptualize stiff slack as the most difficult-to-redeploy resource bundle. We find that stiff slack has a direct positive effect on firm performance but, when used in balanced sourcing portfolios, it has a negative moderating effect on firm performance. Using a panel of 216 U.S. software firms, this study advances the dynamic capabilities perspective while articulating the mechanisms linking research on sourcing and slack.

Introduction

Dynamic capabilities are "skills, procedures, organizational structures, and decision rules that firms utilize to create and capture value" (Teece, 2010: 680). They focus on sensing opportunities, seizing chances, and reconfiguring the organization to help it renew and thrive over time (Augier & Teece, 2009; Teece, 2007). These capabilities—sensing, seizing, and reconfiguring—are likely to be especially valuable when generated in technology sourcing portfolios, which are configurations of "make, buy, or ally" modes to source technology (Capron & Mitchell, 2013).

Leveraging previous dynamic capabilities research (Capron & Mitchell, 2009, 2013; Helfat et al., 2006; Teece, 2007, 2010, 2012), we conceptualize both internal sourcing and external sourcing vehicles as platforms for the development of both sensing and seizing capabilities. The internal sourcing vehicle—reflected by firms' internal research and development (R&D)—develops capabilities by creating (sensing) and leveraging (seizing) proprietary knowledge (Leiponen & Helfat, 2010). The external sourcing vehicle—reflected by firms' alliances—develops capabilities by creating (sensing) and leveraging (seizing) knowledge with partners (Ahuja, 2000; Rothaermel & Deeds, 2004; Rothaermel & Hess, 2007). Because sensing and seizing entail different sets of activities, developing one set within a single sourcing vehicle comes at the expense of developing the other set within the same sourcing vehicle (Teece, 2007, 2012). Teece (2007) claims that developing both sensing and seizing capabilities is essential. Extending these insights, we argue that a strategy of balancing both sensing and seizing across different sourcing vehicles may avoid potential tradeoffs and lead to better performance. A simultaneous engagement with both vehicles for different purposes (one to sense and the other one to seize)—a *balanced* sourcing portfolio—stimulates "firms to achieve new resource configurations as markets emerge" (Eisenhardt and Martin, 2000: 1110). We posit that balanced sourcing portfolios allow for the simultaneous development of sensing and seizing capabilities, circumventing potential tradeoffs of developing both within a single sourcing vehicle.

Alongside sensing and seizing, reconfiguration is essential in firms' dynamic adaptation (Teece, 1986, 2007, 2014b). Instrumental in firms' reconfiguration is the organizational context, especially readily available resources under firms' control such as slack (Augier & Teece, 2009; Capron & Mitchell, 2009; Jansen, Tempelaar, Van den Bosch, & Volberda, 2009; Teece, 2012).

Slack that has been absorbed by the organization represents a "cushion of actual resources […] which allows an organization to adapt successfully" (Bourgeois, 1981: 30). Beyond slack that is typically considered absorbed, there is slack captured in R&D and inventories that frequently remains unused and has the potential to help firms in the reconfiguration process. We thus conceptualize the construct of *stiff slack,* which we define as resources that have been absorbed by the organization for a specific purpose, remained unused, and had potential to generate value if repurposed. This category of slack is "stiff" because deploying inventories is more difficult than deploying regular absorbed slack such as R&D. The increased stiffness of slack captured in inventories is dependent on firms' ability to find an appropriate purpose for it. However, once a new purpose is found, stiff slack not only supports firms' adaptation, but also makes the reconfiguration process unique and idiosyncratic, thus becoming hard for rivals to imitate (Teece, 2012, 2014a).

Previous slack research (Chen, Yang, & Lin, 2013; Latham & Braun, 2008; Lungeanu, Stern, & Zajac, 2016; Marlin & Geiger, 2015a; Tan & Peng, 2003) has not focused on this very stiff category of absorbed slack in the context of balanced sourcing portfolios. It is important to investigate stiff slack for two reasons. First, it creates value by making firms' reconfiguration idiosyncratic. Second, it carries potential to limit the development of some capabilities in balanced sourcing portfolios. The fast-changing nature of the software industry that often creates stocks of stiff slack not only suggests that having balanced sourcing portfolios matters to firm performance (Lavie, Kang, & Rosenkopf, 2011; Lavie, Stettner, & Tushman, 2010; Stettner & Lavie, 2015), but also hints at the possibility that using stiff slack properly may be decisive for how well firms reconfigure capabilities. Therefore, we explore the role of stiff slack in balanced sourcing portfolios.

In the context of the software industry, we address two important but underexplored questions. First, does balancing the development of capabilities across sourcing vehicles improve firm performance compared to balancing the development of capabilities within sourcing vehicles? Second, what are the direct and moderating effects of stiff slack on firm performance? We first suggest that balanced sourcing portfolios improve firm performance by allowing the simultaneous development of sensing and seizing capabilities. Second, given the sticky nature of stiff slack in terms of routine development, we suggest that using stiff slack can be beneficial to firm performance as long as it is not used to reconfigure existing routines (seizing), but only to create new ones (sensing). This implies that for firms balancing the development of sensing and seizing capabilities across sourcing vehicles, using stiff slack may impede proper reconfiguration of routines, lowering performance. Our theoretical model is illustrated in Figure 2.1[1] below.

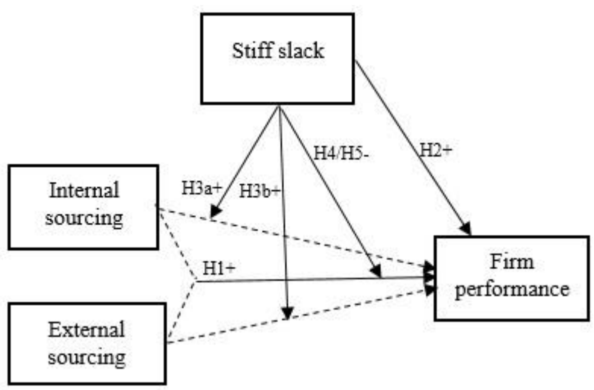

Figure 2.1 Theoretical model

[1] Solid lines represent hypothesized relationships. Dashed lines represent relationships that are not hypothesized.

Our objective is to better understand why and when balanced sourcing portfolios create value and what role stiff slack plays in such balanced sourcing portfolios. We start by outlining internal and external sourcing vehicles as bundles of routines that lead to the development of dynamic capabilities. This conceptualization of sourcing portfolios advances the operationalization of the dynamic capabilities framework, which is known to be difficult to operationalize (Helfat et al., 2006; Peteraf, Di Stefano, & Verona, 2013). To better define the limits and applicability of capabilities developed in sourcing portfolios, we further investigate the role of stiff slack. The findings highlight the duality of stiff slack in balanced sourcing portfolios: while higher levels of stiff slack benefit firms, its use diminishes the advantages of maintaining balanced sourcing portfolios. Overall, we endeavor to show that research on dynamic capabilities, sourcing, and slack can be fruitfully integrated.

A Dynamic Capabilities Perspective of Sourcing Portfolios

In technology-intensive industries, developing dynamic capabilities that systematically support the creation and capture of value from knowledge is essential for firm performance (Cobbenhagen, 2000; Teece, 1986, 2007, 2010). A firm's performance in such industries depends more on how well the firm uses its capabilities to dynamically adapt, and less on the costs incurred in the "production" process (Cusumano, 2004). Particularly in the software industry, a firm's product—software—has a near-zero reproduction cost (Jansen & Cusumano, 2013), leaving firm performance dependent almost entirely on its capabilities to adapt that product over time.

In order to properly develop dynamic capabilities to sustain this adaptation process, firms need to build skills both internally and externally (Capron & Mitchell, 2009, 2013; Helfat et al., 2006; Su, Tsang, & Peng, 2009). Such portfolios of internal and external sourcing vehicles include any configurations of internal R&D and external acquisitions, alliances, or other types of cooperative agreements (Ahuja & Katila, 2001; Capron & Mitchell, 2009; Lungeanu et al., 2016; Van de Vrande, 2013; Van de Vrande, Vanhaverbeke, & Duysters, 2009). While technology sourcing reaches beyond creation and capture of knowledge via internal R&D and external alliances, we focus on these two vehicles because they are most frequently used means that software firms use to create and capture value from knowledge (Lavie et al., 2011; Rothaermel & Deeds, 2004).

Starting with previous theorizing by dynamic capabilities' scholars (Helfat et al., 2006; Teece, 2007, 2010, 2012), we interpret internal and external sourcing as possibly generating both sensing and seizing capabilities. The development of these capabilities is based on the use of the same pool of limited managerial resources such as time or ability (Teece, 2010, 2012). As a result, firms' patenting activity—an indicator of R&D efforts—can focus either (1) on developing sensing capabilities (when firms patent in new domains in which they never patented before), (2) on developing seizing capabilities (when firms patent in known domains in which they patented before), or (3) on developing both capabilities (when firms patent in both new and known domains) (Jansen, Van den Bosch, & Volberda, 2006). Similarly, firms' alliance activity can focus either (1) on developing sensing capabilities (in R&D alliances), (2) on developing seizing capabilities (in licensing alliances), or (3) on developing both sensing and seizing capabilities (in alliances for both R&D and licensing purposes) (Lavie et al., 2010; Stettner & Lavie, 2015; Yang, Lin, & Peng, 2011). While firms may choose to balance the development of both sensing and seizing capabilities within a single sourcing vehicle, we focus on firms that maintain portfolios of internal and external sourcing vehicles. Thus, we advance the idea that firms' involvement with *both* internal and external sourcing vehicles would then comprise of four different portfolio configurations[2] as displayed in Figure 2.2.

		External sourcing	
		Sensing	Seizing
Internal sourcing	Sensing	**Cell 1 FOCUS**	**Cell 2 BALANCE**
	Seizing	**Cell 3 BALANCE**	**Cell 4 FOCUS**

Figure 2.2 Balanced and focused portfolio configurations across sourcing vehicles

When using portfolios of internal and external vehicles, firms have four possible choices. Some firms may choose to pursue both internal and external vehicles for the same purpose and they would generate the same type of capability (either sensing or seizing) with both vehicles. In this case, they would be called to have a *focused sourcing portfolio* (Figure 2.2, Cell 1 & Cell 4). Other firms may choose to pursue both internal and external vehicles for different purposes and

[2] We are aware that firms may simultaneously engage in activities that allow for the development of both sensing and seizing capabilities both internally and externally. Such software firms would develop some new products using the internal R&D unit and develop other new products with alliance partners. They would also commercialize and market some products using their internal R&D unit and other products using alliance partners. Usually, firms devise a separate organizational unit for this purpose (Benner & Tushman, 2003; O'Reilly & Tushman, 2008). We do not believe that organizational separation is prevalent in our setting of small and young software firms (Lubatkin, Simsek, Ling, & Veiga, 2006). Additionally, firms' choice of engaging both sourcing vehicles is taken irrespective of the performance or choice to maintain such separate organizational units (Stettner & Lavie, 2015). Thus, we do not specifically focus on such firms nor we separately identify them in Figure 2.2.

in this case, they would generate different types of capabilities (both sensing and seizing). In this case, they would be called to have a *balanced sourcing portfolio* (Figure 2.2, Cell 2 & Cell 3).

Our conceptualization of sourcing portfolios advances the idea that firms' performance is driven less by the fact that firms use both internal and external sources for knowledge and more by the way firms coordinate the development of sensing and seizing capabilities across sourcing vehicles. If orchestrated properly, such capabilities may be used to search, leverage, and transform resources obtained through internal and external sourcing for higher payoffs (Teece, 2014b). The dynamic capabilities view of sourcing portfolios that we advance endeavors to enhance scholars' understanding of why balanced configurations are preferred over focused configurations. Further we look into how firm performance depends on the chosen configuration.

The Performance of Balanced Sourcing Portfolios

We argue that balanced sourcing portfolios may produce higher performance compared to focused sourcing portfolios by facilitating the simultaneous development of both sensing and seizing capabilities while ensuring adaptability. As opposed to firms with focused sourcing portfolios, firms with balanced sourcing portfolios use both internal and external vehicles to simultaneously develop sensing and seizing capabilities. On the one hand, they use one vehicle to take risks, search, and experiment (Sidhu, Commandeur, & Volberda, 2007), thus enhancing sensing capabilities. On the other hand, they use the other vehicle to gain efficiency and secure market share, thus leveraging seizing capabilities (Lavie et al., 2011). A balanced sourcing portfolio facilitates adaptability which is crucial for good performance (Teece, 2014b).

Balanced sourcing portfolios drive firm performance because they allow firms to use different sourcing vehicles to simultaneously develop different sets of capabilities. This separation across sourcing vehicles allows firms to benefit in the following three ways: (1) it enhances the specialization of routines within each vehicle (Daspit & D'Souza, 2017; Madhok, 1997), (2) it maintains a consistent learning environment (Tsai, 2002), and (3) it lowers the risk for procedural spillover across different routines (Lavie, 2006).

First, the search and leveraging activities that constitute the building blocks for sensing and seizing capabilities are exercised in a repetitive manner. This routinization of activities and processes offers opportunities to streamline activity-specific capabilities and to improve specialization within each sourcing vehicle (Teece, 2010, 2014b). A balanced sourcing portfolio gives firms the chance to choose which set of capabilities to develop internally according to their own strengths and which set of capabilities to develop externally according to their alliance partners' strengths. This way, firms foster experimentation through the internal vehicle and efficiency through the external vehicle or vice-versa. Overall, this separation across sourcing vehicles helps firms foster specialization (Teece, 2014a).

Second, a balanced portfolio nurtures an ideal environment for learning. By separating the development of sensing capabilities from the development of seizing capabilities across sourcing vehicles, firms build a cohesive learning environment within each vehicle (Tsai, 2002). A balanced sourcing portfolio decouples internal learning from external learning, helping firms avoid misapplying learning procedures from the other vehicle's learning procedures (Griffith & Dimitrova, 2014). Negative learning effects can happen when firms unwillingly misapply routines developed while learning while using one sourcing vehicle to the other sourcing vehicle (O'Grady & Lane, 1996). For instance, experimenting with alliance partners develops learning routines that are unlikely to be appropriate for internal use. Because the differences in how learning is performed externally and internally are subtle yet critical, cognitive constraints may determine managers to use some learning routines developed externally when experimenting internally (Gupta, Smith, & Shalley, 2006; O'Reilly & Tushman, 2008). By separating internal from external learning, balanced sourcing portfolios do not face this impediment and nurture an ideal learning environment within each vehicle.

Third, the separation imposed by balanced sourcing portfolios may minimize the risk of spillover of different processes and routines across different sourcing vehicles (Tsai, 2002). For example, while the development of sensing capabilities is generally based on search and experimentation with new products, the way search and experimentation are done internally significantly differs from the way they are done with alliance partners. Internal search and experimentation rely only on firms' "signature processes" and resources (Gratton & Ghoshal, 2005). External search and experimentation rely not only on firms' and alliance partners' expertise and resources, but also on the synergy developed in the process of creating knowledge. Because of this collaborative effort, the alliances develop routines that may not be properly applied when firms search and experiment on their own. Instead, their separation across vehicles makes an overlap unlikely. Additionally, because the resources fueling the internal and external activities are usually kept separate (Benner & Tushman, 2003), balanced sourcing portfolios also relieve some of the managerial burden involved by the integration of internal and external routines and processes (Gibson & Birkinshaw, 2004; Jansen et al., 2009).

In sum, we argue that separating routines that build sensing capabilities from routines that build seizing capabilities across the internal and external vehicles allows firms to maintain the consistency, effectiveness, and control of fundamentally different activities. This separation allows specialization within each sourcing vehicle, encourages consistent learning, and minimizes the potential trade-offs of conflicting processes. All these, in turn, may increase firm performance. Specifically:

H1: Developing sensing and seizing capabilities simultaneously across different sourcing vehicles (balanced sourcing portfolios) leads to higher performance relative to focusing on developing either sensing or seizing capabilities across different sourcing vehicles (focused sourcing portfolios).

Stiff Slack

To better understand how stiff slack plays a role in the relationship between a balanced sourcing portfolio and firm performance, we define *stiff slack* as resources that have been absorbed by the organization for a specific purpose, remained unused, and had potential to generate value if repurposed. These resources are redeployable to the extent that managers have the capabilities to adapt them to new ends. Such resources can be production lines, old hardware or software, or any other types of fixed assets such as inventories. We propose that these resources have the potential to explain the performance heterogeneity among firms with balanced sourcing portfolios.

A discussion on the role that stiff slack plays in balanced sourcing portfolios is fueled by the multidimensionality of slack as a construct (Bourgeois, 1981; Lungeanu et al., 2016; Su et al., 2009; Tan & Peng, 2003; Voss, Sirdeshmukh, & Voss, 2008). Traditionally, slack represents resources available to the firm that are underutilized because it exists beyond what is currently needed to produce a certain level of output (Cyert & March, 1963; Levinthal & March, 1981). Slack can be absorbed (such as R&D resources), or unabsorbed (such as financial resources)

(Lee & Wu, 2016; Paeleman & Vanacker, 2015). We view stiff slack as a subset of absorbed slack that is the most difficult-to-redeploy. Operationally, we measure stiff slack by the resources tied in R&D, inventories, and production lines. It has already been taken into account in the cost of doing business at some point in time and remained unused (Bourgeois, 1981; Voss et al., 2008). Similar to absorbed slack, stiff slack is desirable because it is very difficult to expropriate or imitate (Bourgeois & Singh, 1983). Stiff slack can produce value and increase performance only to the degree that managers have the capabilities to dynamically reconfigure it to fit the right organizational needs or to help the development of other capabilities such as sensing and seizing capabilities.

Stiff slack can produce value and increase performance for two reasons: it creates uniqueness and it increases efficiency. First, among all slack, stiff slack has the highest potential to make firms' adaptation hard to imitate. Stiff slack represents already specialized and routinized resources, defining the context in which value is created (Jansen & Cusumano, 2013; Love & Nohria, 2005). It is characteristic to each firm's unique R&D processes, practices, and routines (Gratton & Ghoshal, 2005; Paeleman & Vanacker, 2015). Its reconfiguration involves a unique set of managerial capabilities (Bradley, Aldrich, Shepherd, & Wiklund, 2011; March, 1981), thus being best reconfigured inside the firm by managers familiar to the firm's successful practices (Bradley et al., 2011). As a contextual resource, stiff slack is difficult to price outside the organization, which makes it inimitable and valuable (Teece, 2012, 2014b). It is also difficult to trade because it has been adapted to the firm's context-specific needs (Chen et al., 2013; Paeleman & Vanacker, 2015). Overall, stiff slack is desirable because the reconfiguration process through which value is created and captured is idiosyncratic.

Second, stiff slack increases performance by creating efficiency. As an embedded resource, stiff slack is easier to be reconfigured and it creates capabilities faster compared to reconfiguring brand new resources. Stiff slack represents absorbed resources that are routinized and familiar to managers. Over time, managers learn to use their resources more efficiently (Bradley et al., 2011) and learn to develop capabilities faster. Managers familiar to a firm's signature processes and routines have a more rapid learning curve when dealing with stiff slack (March, 1981). Further, as a result of managers' expertise, stiff slack may be reconfigured into a set of replicable routines faster, which is critical for the performance of firms facing high competition (Augier & Teece, 2009; Helfat et al., 2006; Teece, 2012). Overall, stiff slack creates value through reconfiguration. Its use permits managers to reconfigure the organization, allowing it to remain adaptable. It encourages idiosyncratic and faster reconfiguration, making a firm's adaptation valuable while improving firm performance. Overall:

H2: Stiff slack increases firm performance.

The Moderating Effect of Stiff Slack When Sourcing Exclusively Internally or Externally

Stiff slack has been introduced as a subset of absorbed slack that includes inventories and other fixed assets. Stiff slack is relevant because it may promote the creation and capture of value in organizations either directly by using it to reconfigure the organization or indirectly by using it to support the development of sensing and seizing capabilities. The sourcing literature informs us that slack is used in organizations mostly to supplement organizational efforts to increase performance (Lee & Wu, 2016). Given that stiff slack is difficult-to-redeploy, organizations use it specifically to supplement either resource-consuming or high-risk activities. We expect that software firms access stiff slack when sourcing knowledge exclusively internally as this involves resource-consuming activities (He & Wintoki, 2016). We also expect that software firms use stiff slack when sourcing knowledge exclusively externally as this carries a high risk for expropriation (Harryson, Dudkowski, & Stern, 2008). Both resource-consuming activities and expropriation risks can be mitigated by using highly contextual resources such as stiff slack. In the following, we investigate the moderating role of stiff slack for firms that source knowledge using a single sourcing vehicle, either internal or external.

Firms that source knowledge by the means of a single vehicle both create and capture value from knowledge through the means of that only vehicle. Firms using internal sourcing exclusively generate new knowledge and leverage that knowledge on their own (Jansen et al., 2006; Sidhu et al., 2007). Firms using external sourcing exclusively generate new knowledge and leverage that knowledge with alliance partners (Lavie et al., 2011; Lavie & Rosenkopf, 2006). A direct implication of focusing on a single sourcing vehicle is that firms develop both sensing and seizing capabilities within that sourcing vehicle. We argue that for firms balancing the development of sensing and seizing capabilities *within* a single sourcing vehicle, higher levels of stiff slack may foster the development of one set of capabilities at the expense of developing the other set of capabilities, regardless of the vehicle used.

On the positive side, the use of stiff slack may help firms develop more efficient sensing capabilities. Sensing helps managers better *understand*, *identify*, and *assess* new opportunities (Teece, 2007). First, stiff slack helps managers to better their understanding of new opportunities by offering backup resources for experimentation (Pitelis, 2007). Firms sourcing either exclusively internally or externally may reconfigure idle inventories or computer hardware/software to increase the amount of search that is done internally or in their upstream collaborations with alliance partners (March, 1981).

Second, because stiff slack represents slack resources that have already been routinized (Jansen et al., 2009; Love & Nohria, 2005), managers can use it to improve firms' performance by helping the process of opportunity recognition and identification. First, stiff slack may enhance firms' ability to speed up the identification and assessment of new opportunities (Bradley et al., 2011). For firms choosing to source either exclusively internally or externally, managers familiar with such routines may also use their expertise to assess and identify the most appropriate avenues for growth. Given stiff slack's familiarity with firms' "signature processes" (Gratton & Ghoshal, 2005), managers may use stiff slack to better assess the value that identified opportunities may possibly bring. Even further, the routinized resources introduced by the use of stiff slack may enforce consistent patterns of learning and behavior that are essential for the efficient use of organizational routines, either internally or externally (Lavie et al., 2011). Overall, using stiff slack allows firms to improve their performance by enhancing managers' capabilities to better understand, assess, and incorporate new knowledge.

On the negative side, the use of stiff slack may impede the development of more efficient seizing capabilities due to its redundant nature (Love & Nohria, 2005). Seizing refers to the mobilization of existing resources, mobilization that relies heavily on firms' capabilities to *integrate* and *coordinate* active resources with stiff slack resources (Teece, 2012, 2014b). First, the use of stiff slack may impede the integration and coordination of resources by widening the pool of resources that can be mobilized. A wider resource pool increases complexity and impedes managerial coordination (Benner & Tushman, 2003), while offering alternate and likely less appropriate paths for routine development (Pentland, Feldman, Becker, & Liu, 2012).

Second, for firms exclusively relying either on internal or external sourcing, stiff slack may diminish firms' capabilities to seize value from identified opportunities. As a routine-embedded resource bundle, stiff slack erodes the development of seizing capabilities by introducing obsolescence in the process of value capture (Paeleman & Vanacker, 2015). This increases the chance for redundancies with some of the more current resources being used, impeding the integration of active and stiff resources (Chen & Huang, 2010; Chen et al., 2013; Gratton & Ghoshal, 2005; Love & Nohria, 2005). Overall, we argue that for firms relying exclusively on a single sourcing vehicle for the development of both sensing and seizing capabilities, using stiff slack enhances the positive effect that balancing sensing and seizing capabilities within a single sourcing vehicle has on firm performance. Thus:

H3a: For firms sourcing exclusively <u>internally</u>, stiff slack positively moderates the relationship between balancing sensing and seizing within a single vehicle and firm performance.

H3b: For firms sourcing exclusively <u>externally</u>, stiff slack positively moderates the relationship between balancing sensing and seizing within a single vehicle and firm performance.

The Moderating Effect of Stiff Slack in Balanced Sourcing Portfolios

Previous research has shown that using multiple sourcing vehicles is more beneficial to firm performance compared to using a single sourcing vehicle (Helfat et al., 2006; Helfat & Peteraf, 2015; Paeleman & Vanacker, 2015). In the software industry, very young firms typically only use external sourcing because they do not have sufficient in-house resources (Lungeanu et al., 2016; Rothaermel & Hess, 2007). Very large firms typically only use internal sourcing because it protects from expropriation risks (Ahuja, 2000; Capron & Mitchell, 2013; Lavie, 2007). Most firms, however, use a portfolio of both internal and external sourcing vehicles. Among these, significant differences in performance can be observed. Firms like Adobe (software solutions) reap significantly improved outcomes while others like Atari (gaming) or Netscape (Internet browsing) do not. We investigate whether the use of stiff slack may explain this heterogeneity of performance given that these firms all balance their sourcing portfolios across internal and external sources.

In balanced sourcing portfolios, firms source one activity internally and the other one externally. Given that stiff slack is a highly context-dependent resource bundle, the use of stiff slack outside organizational boundaries may introduce process and routine conflicts. Thus, firms may use stiff slack to help only the activity that is performed in-house, which supports the development of either sensing or seizing capabilities (Figure 2.2, Cell 2 and Cell 3). For firms such as Netscape that use their internal R&D function to develop sensing capabilities and their alliance partners to develop seizing capabilities (Figure 2.2, Cell 2), using stiff slack may impede a proper reconfiguration of sensing routines while other active sensing routines are already in place for the same purpose (Vanacker, Collewaert, & Paeleman, 2013). Using stiff slack introduces sensing routines that increase the complexity of firms' resource pool, putting a burden on managerial shoulders (Benner & Tushman, 2003; Gratton & Ghoshal, 2005) and undermining integration and coordination (Pentland et al., 2012). This may have resulted in Netscape's poor performance.

For firms such as Atari that use their alliance partners to develop sensing capabilities and their internal R&D unit to develop seizing capabilities (Figure 2.2, Cell 3), using stiff slack may also undermine performance, but for different reasons and in a smaller magnitude. Using stiff slack—maintained in R&D inventories and outdated production lines—to save on costs, makes it more difficult to integrate new knowledge developed externally into already streamlined routines (Daspit & D'Souza, 2017; Madhok, 1997; Teece, 2010). In this case, the stickiness of stiff slack hinders firms' ability to capture value from externally developed knowledge by impeding adaptation, obstructing cohesiveness of operations, and undermining specialization advantages (Teece, 2014b).

To sum up, the amount of available stiff slack may be responsible for the unexplained performance heterogeneity among firms with balanced sourcing portfolios, mainly because stiff slack's stickiness introduces difficulties in routine coordination.

H4: Stiff slack weakens the positive effect of balanced sourcing portfolios on firm performance.

The negative effect on firm performance is smaller for firms that use the internal vehicle to seize externally developed knowledge than it is for firms that use the external vehicle to seize internally developed knowledge. This is due to higher managerial capabilities to orchestrate the development of sensing and seizing internally compared to orchestrating it with alliance partners (Helfat & Peteraf, 2015; Jensen & Meckling, 1976; Kor & Mesko, 2013; Latham & Braun, 2008). When value capture is performed internally, the efficiency of developing seizing capabilities depends exclusively on firm's managers and their capabilities to mobilize a wider pool of active and stiff resources (Benner & Tushman, 2003) and to integrate them properly (Pentland et al., 2012). When value capture is performed externally, the efficiency of developing seizing capabilities depends on the combined managerial capabilities of both the firm and its alliance partners to mobilize a wider pool of active and stiff resources (Jansen & Cusumano, 2013; Love & Nohria, 2005). We argue that for firms that capture value inside organizational boundaries the negative effect may be smaller compared to firms that capture value outside organizational boundaries because the integration of stiff slack resources is not dependent on orchestrating this integration with alliance partners. Therefore:

H5: Stiff slack weakens the positive effect of balanced sourcing portfolios on firm performance less for firms using the external vehicle for sensing than for firms using the external vehicle for seizing.

Methods

Research Context and Sample

We focus on software firms for three reasons. First, software firms face a new type of competition that is IT-driven and requires them to completely rethink their value chain (Porter & Heppelmann, 2015). As the industry is in its early stages of “smart, connected products” (Porter & Heppelmann, 2015), profound changes in organizational structure, functions, and cross-functional collaboration happen. As a result, firms must stay abreast of these changes by carefully stimulating the role that dynamic capabilities have in their processes of creating and capturing value. Second, as the software industry matures, firms increasingly focus on services to generate additional profits (Suarez, Cusumano, & Kahl, 2013; Teece, 1986). Yet, to increase profits, this shift must be substantial—with services representing more than half of firms’ sales

(Suarez et al., 2013). To do so, firms are required to sense, seize, and reconfigure, pushing for an aggressive development of dynamic capabilities. Third, software firms display both active alliance and active patenting behaviors with a high likelihood to engage in both simultaneously (Stettner & Lavie, 2015), making our study comparable to previous research on the software industry (Chatterjee, 2017; Lavie et al., 2010; Stettner & Lavie, 2015; Zahavi & Lavie, 2013).

We test our hypotheses on a sample of publicly listed U.S. software firms between 1996 and 2007 (inclusive). Out of a population of 289 software firms, we keep only those that have at least one patent granted or one active alliance during the time frame of interest. To better capture dynamic capabilities, we focus on firms with below average financial slack. High levels of financial slack are found to lead firms to downscope their sourcing portfolio (Lungeanu et al., 2016), potentially lowering the effects that dynamic capabilities have on these choices.[3] This process reduces the panel to a final data set of 230 firms and 942 firm-year observations. We use Compustat and Mergent Online to collect firms' characteristics and performance data, USPTO to measure patent data, and SDC Platinum to extract alliance characteristics.

Dependent Variable

Our dependent variable is firm performance as reflected by return on assets (ROA). This accounting measure is consistent with previous research on organizational slack (Daniel, Lohrke,

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[3] We consider recent findings claiming that firms decide whether to diversify their sourcing portfolio or downscope their sourcing portfolio depending on the levels of financial slack they can access (Lungeanu et al., 2015). Firms with less financial slack choose to focus on the internal vehicle that is more familiar and easier to control. By selecting a sample of firms with low levels of financial slack allows us to minimize possible confounding effects that higher levels of slack may have on firms' decision to diversify their sourcing portfolio. We compute financial slack as a ratio of working capital to sales (Miller, Lant, Milliken, & Kom, 1996) and split the sample by the mean.

Fornaciari, & Turner, 2004; Latham & Braun, 2008; Marlin & Geiger, 2015a; Tan & Peng, 2003) and dynamic capabilities (Arthurs & Busenitz, 2006; Lin & Wu, 2014). Internal and external sourcing vehicles have multidimensional effects on software firms and in this context, an objective (accounting) measure can capture the overall performance better than a subjective (perceptual) measure of performance (Lin, Yang, & Arya, 2009).

Independent Variables

Internal sourcing. We capture internal sourcing with firms' patenting. We go beyond a simple count measure (Jansen et al., 2006; Kaplan & Vakili, 2015; Yayavaram & Chen, 2015) and unveil a more relevant measure to reflect the sensing, seizing, and recombinatory capabilities of firms' strategy. We use USPTO's Cooperative Patent Classification (CPC)[4] to compile an internal sourcing variable that measures a firm's internal orientation towards creating value with new knowledge or capturing value from existent knowledge. We capture internal sourcing with a continuous variable ranging from 0 (seizing—reflected by patents filed within level 3 classifications that are already existent in a firm's patent pool) to 1 (sensing—reflected by patents filed within classifications new to the firm), and assuming that sensing and seizing are

[4] Each patent filed with the USPTO is assigned codes according to a preestablished Cooperative Patent Classification (CPC) system. Each code assigns a patent to each of the five mandatory hierarchical levels: section (level 1), class (level 2), subclass (level 3), group (level 4), and subgroup (level 5). A patent is usually assigned to multiple level 2, level 3, level 4, and level 5 classifications. These codes uniquely describe how a firm's patents relate to each other. We use General Architecture for Text Engineering (GATE) open source software to design queries that automatically retrieve the complete classification information of the entire patent pool of all software firms in our dataset. We pool the data at subclass level (level 3 classifications) and use the aggregated measure to compute the internal sourcing variable.

two activities that inhibit each other (Greve, 2007; Sidhu et al., 2007; Uotila, Maula, Keil, & Zahra, 2009).

We operationalize internal sourcing with a Herfindahl index of firms' classifications at the subclass level pooled by firm and by year, with higher values reflecting sensing and lower values reflecting seizing. The operationalization reflects firms' diversity in patenting at level 3 classification (subclass level) [5]. A more diverse patenting at the subclass level suggests that firms have an intense focus on experimenting new knowledge domains, thus widening their knowledge base. This behavior is likely to support the development of sensing capabilities because the newly discovered knowledge may help firms better identify new opportunities. A less diverse patenting at the subclass level suggests that firms, instead of widening their knowledge base, choose to focus on deepening it, therefore clustering their patenting in fewer subclasses. This behavior is likely to support the development of seizing capabilities because firms' expertise with familiar knowledge may help them better capture value from opportunities.

$$Internal\ sourcing_{j,t} = 1 - \sum_{j}^{n_i} p_{ij,t}^2 \qquad (1)$$

where $p_{ij,t}$ denotes the percentage of times each level 3 classification appears in total number of subclasses (level 3 classifications) with which each patent *i* of firm *j* in year *t* is filed.

[5] We choose to measure the diversity at the subclass level (level 3) as opposed to measuring it at the section (level 1) or class (level 2) level because the number of sections and classes available within the USPTO's CPC system is not diversified enough to reflect software firm's capabilities towards search or seizing. Also, we do not choose to measure this variable at the group (level 4) or subgroup (level 5) level because the combinations available at these levels are too diversified. Measuring internal sourcing at these levels it would incorrectly classify most patenting as focused on search for new knowledge when in reality the differences between two patents classified within same section, class, subclass, but different groups or subgroups is one of matter rather than kind. We believe that operationalizing the measure at the middle level (3 out of 5) most accurately reflects software firms' capabilities.

External sourcing. We capture external sourcing by investigating the composition of firms' alliance portfolios. We focus on capturing not only the quantity (Baum, Calabrese, & Silverman, 2000; Lavie, 2007), but also the purpose of these alliances (Stettner & Lavie, 2015; Yang et al., 2011). Software firms may form alliances to augment their capabilities with new knowledge (sensing) or to refine their existent capabilities by leveraging existent routines (seizing). Using alliances' description provided in the SDC database, we code each alliance as either focused on sensing (coded 1), seizing (coded 0), or both (coded 0.5). Following previous research (Stettner & Lavie, 2015; Yang et al., 2011), we consider alliances to develop sensing capabilities (coded 1) if their alliance description is either "Research and Development Services," "Software Development Services," or "Computer Programming Services." We consider all other alliance descriptions such as "Licensing Services", "Marketing Services", or "Consulting Services" indicative of alliances focused on developing seizing capabilities (coded 0). Alliance descriptions mentioning both types of descriptions are indicative of alliances focused on developing both sensing and seizing capabilities (coded 0.5). To consider the cumulative effect of firms' entire alliance portfolio, we use a five-year moving average (Kogut, 1988). The external sourcing variable is calculated as the average value of all alliances in firms' alliance portfolio over the last five years and can take any value between 0 (seizing) and 1 (sensing).

Stiff slack. We focus on internal slack resources that have been absorbed by the organization but now lay idle and can be redeployed (Bourgeois, 1981). Stiff slack does not necessarily refer to immutable or unchangeable slack, but slowly adaptable slack—adaptable to the degree that management has the capabilities to reconfigure it. Its main characteristic is that stiff slack offers room for dynamic adaptation. As a subset of absorbed slack that has been traditionally measured with the ratio of excess costs carried by general business activities in sales—such as costs with R&D personnel, training, advertising, or charity (Bourgeois & Singh, 1983; Lee & Wu, 2016; Wiseman & Bromiley, 1996) —, stiff slack also takes into account excess costs carried by maintaining unused inventories.

The definition we suggest is more relevant for the software firms that invest and usually keep excess amounts in their R&D (Finkelstein & Boyd, 1998) and inventories (Marlin & Geiger, 2015a; Stan, Peng, & Bruton, 2014). Important R&D-related amounts and inventories remain idle when R&D processes change and can be repurposed for future endeavors. We thus conceptualize stiff slack as the ratio of R&D and inventories over total sales. This conceptualization of stiff slack fits our dynamic capabilities framing as it depicts a more realistic image of managerial adaptation within existing constraints of firm configuration (Teece, 2010). Specifically:

$$Stiff\ slack = {}^{(R\&D + Inventories)}/_{Total\ sales} \tag{2}$$

Control Variables

We control for five firm-level variables that may affect the financial performance of software firms. We consider the possibility that firms learn to become better and more efficient inventors (Mowery, Sampat, & Ziedonis, 2002) with *internal sourcing experience*. The measure reflects the cumulative effect of patenting compared to a base year (base = 1995), which is a one year before the first year in our dataset (Montgomery, 1982). The formula assigns smaller weights to more current years considering that more recent years contribute less to firms' experience compared to earlier years.

$$Internal\ sourcing\ experience_{i,t} = \sum_{t=1996}^{2007} \left\{ \left[{}^{1}\!/_{t-b} \right] * \left[1 - {}^{\sum_k^n P_{ikt}^2}\!/_{(\sum_k^n P_{ikt})^2} \right] \right\} \quad (3)$$

where *b* is the base year 1995, *t* is the current year, P_{ikt} is the proportion of patents of firm *i* in class *k* in year *t.* We account for *external sourcing experience* because firm performance may be pushed by their partners' experience instead of their own intrinsic ability to leverage the alliance (Leiponen & Helfat, 2010). Since larger firms may be better equipped to perform well in alliances as well as at in-house R&D (Ahuja, Lampert, & Tandon, 2008) we control for *firm size* measured as the natural logarithmic function of firms' total assets. We control for *firm age* (number of years from incorporation). Last, we consider *R&D expenses* as they affect firms' openness to experimentation and generally impact firm overall performance.

We control for portfolio characteristics. *Portfolio breadth* takes into account the number of vehicles used (patents, alliances, acquisitions) (Lungeanu et al., 2016). *Portfolio dissimilarity* captures how the change in importance of each vehicle may affect overall performance. We sum up the absolute differences between the weights of each vehicle in firms' portfolio over time.

Finally, we include two behavioral controls. First, *attainment discrepancy* may explain higher involvement with certain vehicles depending on how well firm performance meets firms' aspirations (Alessandri & Pattit, 2014). The variable is the difference between firms' aspiration level and performance, with a positive discrepancy when the performance is below aspirations. Second, *distance from bankruptcy*—included in Heckman's first stage regression—is measured with the Altman's Z score (Chen & Miller, 2007) with a lower Z-score indicating a higher likelihood of bankruptcy and hence, a higher incentive to play safe and engage the internal vehicle instead of external ones (Lungeanu et al., 2016). We control for time effects with *year dummies* and address any remaining heterogeneity inside firms with fixed effects regression.

Analytical Strategy

To test our hypotheses, we estimate a fixed effects model with year controls. We address possible endogeneity with a Heckman two-stage model (Heckman, 1979). Software firms' tendency to engage a particular sourcing vehicle may be influenced by the inherent benefits of that vehicle. These benefits influence firms' choice of a vehicle *irrespective* of its contribution to overall performance. To account for this endogeneity effect, we first run two different probit models, one for firms' patenting propensity and one for firms' alliance propensity, by regressing the probability of using a certain vehicle on firm size, age, experience in that mode, R&D expenses, fear of bankruptcy, importance of that vehicle in firms' portfolio, and year effects. The predicted values are used to compute the inverse Mills ratios (λ *Internal* and λ *External*).

To account for self-selection bias of engaging in a particular vehicle, in the second-stage models we incorporate the computed inverse Mills ratios as controls. We use the second stage models to test the hypotheses. To control for potential interdependence among observations, we consider a one-year lag for all our predictor and control variables relative to the dependent variable. To avoid an increase in multicollinearity, we build seven models by sequentially adding variables. All models' individual VIFs are below the recommended threshold of 10 with full model's VIF of 6.27 being the highest, suggesting that multicollinearity is not significant.

Findings

Table 2.1 presents descriptive statistics, and Table 2.2 the Heckman first stage results.

Table 2.1 Descriptive statistics and correlations

Variables	Mean	*s.d.*	1	2	3	4	5	6	7	8	9	10	11	12	13
1 Return on assets	-0.126	0.524													
2 Stiff slack	0.005	0.051	0.06												
3 Internal sourcing	0.431	0.289	0.06	0.14											
4 External sourcing	0.135	0.165	0.04	-0.13	0.06										
5 Internal sourcing experience	0.209	0.247	0.07	0.17	0.56	0.11									
6 External sourcing experience	4.389	13.196	0.03	-0.07	0.12	0.23	0.25								
7 Firm age (ln)	2.075	0.553	0.19	0.05	0.17	0.11	0.20	0.12							
8 Firm size (ln)	5.350	1.861	0.20	-0.16	0.22	0.32	0.21	0.37	0.49						
9 Attainment discrepancy	0.041	0.539	-0.33	0.01	-0.02	-0.00	-0.03	-0.00	-0.02	-0.10					
10 Portfolio breadth	1.947	0.474	0.03	-0.23	0.02	0.34	0.03	0.18	0.14	0.44	-0.05				
11 Portfolio dissimilarity	0.237	0.180	-0.05	0.01	0.19	-0.07	-0.23	-0.11	-0.19	-0.23	0.05	-0.15			
12 R&D expenses	0.223	0.208	-0.19	0.05	0.05	-0.08	0.02	-0.05	-0.11	-0.33	0.28	-0.18	0.05		
13 λ Internal	0.541	0.463	-0.16	0.06	-0.59	-0.18	-0.68	-0.16	-0.43	-0.56	0.05	-0.16	-0.38	0.05	
14 λ External	0.984	0.487	-0.07	0.17	-0.12	-0.42	-0.27	-0.43	-0.20	-0.63	0.10	-0.49	0.18	0.18	0.27

N = 942; p < 0.05 for correlations above 0.06; two-tailed test

Table 2.2 Heckman first stage results (stage 1)

Variables	Internal sourcing likelihood Model 1	External sourcing likelihood Model 2
Intercept	-1.077	-0.761
	(0.00)	*(0.00)*
Year fixed effects	Yes	Yes
Internal sourcing experience	4.029	
	(0.00)	
External sourcing experience		0.095
		(0.00)
Firm age (ln)	-0.092	-0.040
	(0.29)	*(0.48)*
Firm size (ln)	0.251	0.101
	(0.00)	*(0.00)*
Fear of bankruptcy	0.001	0.009
	(0.57)	*(0.00)*
R&D expenses (ln)	*0.114*	*0.017*
	(0.03)	*(0.67)*
Internal sourcing weight	0.497	
	(0.00)	
External sourcing weight		0.201
		(0.05)
Observations	2314	2314
Walk-chi2	405.19	443.51
	(0.00)	*(0.00)*
LL	-1126.16	-1220.33

Random effects probit regression
p-values in parentheses

Table 2.3 Panel fixed effects regression results (stage 2)

		Return on Assets							
Variables		**Base model**	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
Intercept		0.608	0.862	0.630	0.981	0.769	0.376	0.841	0.644
		(0.00)	*(0.01)*	*(0.00)*	*(0.00)*	*(0.02)*	*(0.11)*	*(0.01)*	*(0.06)*
Year fixed effects		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Main effects									
Internal sourcing			0.016		-0.110	-0.123		-0.122	0.022
			(0.85)		*(0.17)*	*(0.12)*		*(0.11)*	*(0.79)*
External sourcing			0.376		-0.034		-0.029	-0.027	0.413
			(0.05)		*(0.76)*		*(0.79)*	*(0.81)*	*(0.03)*
Internal sourcing × External sourcing	H1		-0.978						-1.119
			(0.00)						*(0.00)*
Stiff slack	H2			2.236	2.267	0.984	0.393	-0.615	-0.100
				(0.00)	*(0.00)*	*(0.08)*	*(0.45)*	*(0.31)*	*(0.87)*
Interactions									
Stiff slack × Internal sourcing	H3a					4.487		3.923	1.624
						(0.00)		*(0.00)*	*(0.23)*
Stiff slack × External sourcing	H3b						9.783	9.349	3.665
							(0.00)	*(0.00)*	*(0.23)*
Stiff slack × [Internal sourcing × External sourcing]	H4&H5								17.102
									(0.01)
Control variables									
Internal sourcing experience		0.424	0.426	0.187	0.011	-0.240	0.284	-0.104	0.333
		(0.23)	*(0.35)*	*(0.59)*	*(0.98)*	*(0.59)*	*(0.40)*	*(0.81)*	*(0.46)*
External sourcing experience		-0.001	-0.002	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
		(0.40)	*(0.32)*	*(0.50)*	*(0.37)*	*(0.51)*	*(0.51)*	*(0.51)*	*(0.70)*
Firm age (ln)		0.195	0.158	0.189	0.153	0.133	0.229	0.166	0.163
		(0.05)	*(0.14)*	*(0.05)*	*(0.15)*	*(0.19)*	*(0.02)*	*(0.11)*	*(0.11)*
Firm size (ln)		-0.196	-0.212	-0.193	-0.205	-0.203	-0.161	-0.176	-0.177
		(0.00)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*
Attainment discrepancy		0.075	0.076	0.080	0.082	0.081	0.058	0.061	0.057
		(0.03)	*(0.03)*	*(0.02)*	*(0.01)*	*(0.01)*	*(0.08)*	*(0.07)*	*(0.08)*
Portfolio breadth		-0.003	-0.001	0.008	0.006	0.005	0.011	0.007	0.012
		(0.87)	*(0.95)*	*(0.73)*	*(0.78)*	*(0.83)*	*(0.64)*	*(0.76)*	*(0.58)*
Portfolio dissimilarity		0.084	0.123	0.079	0.123	0.128	0.065	0.113	0.099
		(0.34)	*(0.18)*	*(0.36)*	*(0.17)*	*(0.15)*	*(0.44)*	*(0.20)*	*(0.25)*
R&D expenses		-0.037	-0.056	-0.073	-0.090	-0.057	-0.045	-0.039	-0.069
		(0.78)	*(0.67)*	*(0.57)*	*(0.49)*	*(0.66)*	*(0.72)*	*(0.75)*	*(0.58)*
λ Internal			-0.154		-0.182	-0.232		-0.221	-0.163
			(0.17)		*(0.09)*	*(0.03)*		*(0.04)*	*(0.13)*
λ External			-0.009		0.008		0.075	0.048	0.040
			(0.91)		*(0.91)*		*(0.33)*	*(0.53)*	*(0.60)*
Observations		942	942	942	942	942	942	942	942
R-square		17.93%	19.27%	20.84%	21.34%	22.82%	24.84%	26.44%	28.24%
F		7.97	6.84	9.11	7.78	8.86	9.90	9.48	9.62
Increase in R-square			1.34%	2.91%	3.41%	4.89%	6.91%	8.51%	10.31%

p-values in parentheses
λ represents the Inverse Mills Ratio

Table 2.3 presents the panel fixed effects regression results. We start with the baseline model that includes control variables only. We start testing hypotheses with Model 1. Hypothesis 1 suggests that firms with balanced sourcing portfolios (using one vehicle for sensing and another vehicle for seizing) achieve higher performance than firms with focused sourcing portfolios (using both internal and external vehicles to develop only one type of capability—either sensing or seizing). The significant coefficient in Model 1 (β = -0.978, $p < 0.001$) provides support for this hypothesis. The negative sign of this coefficient indicates that a balanced sourcing portfolio improves firm performance compared to a focused sourcing portfolio.

Nevertheless, the sign of the interaction term reported in the regression does not give any indication about how much more beneficial a balanced strategy is compared to developing similar capabilities across internal and external sourcing vehicles (denoted by focused strategies in Cell 1 and Cell 4 in Figure 2.2) and neither says which configuration of a balanced strategy is preferable (Cell 2 or Cell 3). To find support for Hypothesis 1, it is additionally required to use graphical representations and comparison tests to evaluate these differences in performance and interpret the interaction (Hoetker, 2007). Consequently, we model firm performance as a function of internal and external sourcing:

$$\hat{Y} = b_0 + b_1 \cdot X_1 + b_2 \cdot X_2 + b_3 \cdot X_1 \cdot X_2 + b_i \cdot K_i \tag{3}$$

with X_1 and X_2 denoting internal and external sourcing and K_i is a vector of control variables.

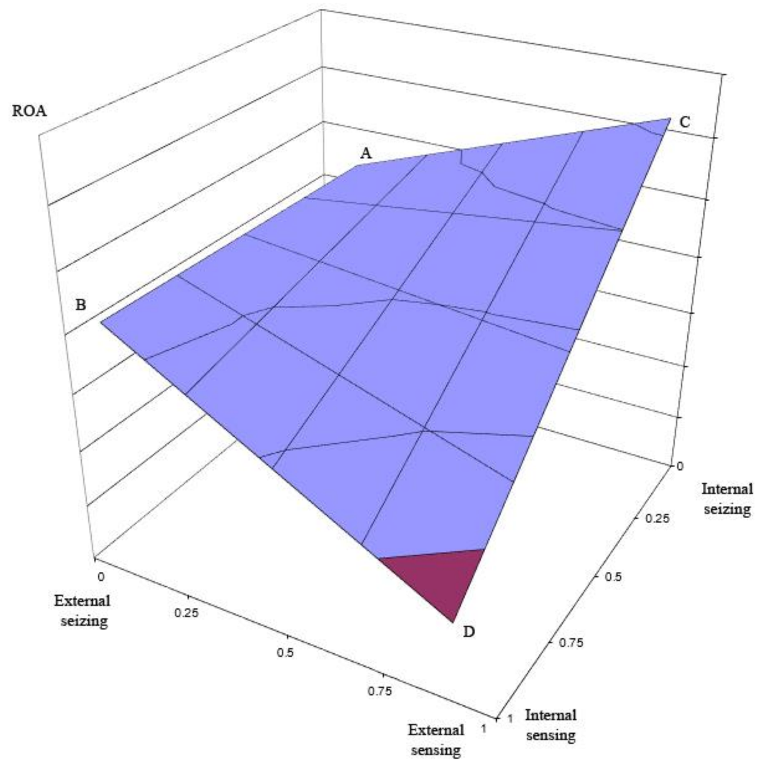

Figure 2.3 Performance across internal and external sourcing

Figure 2.3 exemplifies the performance function defined above at the corresponding sourcing variables and mean levels of covariates. The two focus points (A and D) represent focused strategies when both internal and external sourcing are used to develop same category of capabilities—either sensing or seizing. The two balance points (B and C) represent balanced strategies when firms develop sensing capabilities through one vehicle and seizing capabilities through the other. Hypothesis 1 is supported if at least one balance point produces higher performance than at least one focus point as long as the other focus point does not produce significantly higher performance than the referred balance point (Stettner & Lavie, 2015). Table 2.4 provides the results for two-sided *t*-tests to evaluate the significance of performance differences between points. In support of Hypothesis 1, balance point C reports significantly higher performance than both focus points A ($\Delta\hat{Y}_{CA}$= 376.44, p < 0.001) and D ($\Delta\hat{Y}_{CD}$= 897.04, p < 0.001). Consistent with Hypothesis 1, the other balance point, B, is also significantly superior to both focus points A ($\Delta\hat{Y}_{BA}$= 15.36, p < 0.001) and D ($\Delta\hat{Y}_{BD}$= 535.96, p < 0.001) but with lower performance compared to Point C. Overall, the graphical representation and the regression results support Hypothesis 1.

Table 2.4 Balance vs focus across internal and external sourcing

Performance difference	Balance versus focus across vehicles			
	$\Delta\hat{Y}$ (mil.)	s. e.	p	t
Points B vs. A	$15.36	0.0295	*0.000*	4.086
Points C vs. A	$376.44	0.0607	*0.000*	14.579
Points B vs. D	$535.96	0.0311	*0.000*	-13.850
Points C vs. D	$897.04	0.0614	*0.000*	5.420

Note: Points A and D are focus points.
Points B and C are balance points.

Hypothesis 2 claims that stiff slack has a positive direct effect on the performance of software firms. Models 2 and 3 test the direct performance effects of stiff slack by itself and in the presence of internal and external sourcing. The positive and significant coefficients in Model 2 (β = 2.236, p < 0.001) and Model 3 (β = 2.267, p < 0.001) support Hypothesis 2.

Models 4-6 test Hypotheses 3a and 3b. These models report the individual two-way moderating effects of stiff slack on internal and external sourcing. Hypothesis 3a suggests that in the presence of high levels of stiff slack, software firms achieve higher performance by sourcing knowledge internally. Model 4 reports a positive and significant interaction coefficient (β = 4.487, p < 0.001) which supports Hypothesis 3a. Hypothesis 3b suggests that as levels of stiff slack increase, firms may also achieve higher returns by sourcing knowledge externally. Model 5 shows a positive and significant interaction coefficient (β = 9.783, p < 0.001) supporting Hypothesis 3b. Results are corroborated by Figure 2.4. Model 6 serves to support results by testing both interactions simultaneously under the assumption that firms concurrently develop portfolios of internal and external sources (Van de Vrande et al., 2009). This model shows that the sign and significance of interactions obtained previously hold ($\beta_{slack \times internal}$ = 3.923, p < 0.001 and $\beta_{slack \times external}$ = 9.349, p < 0.001).

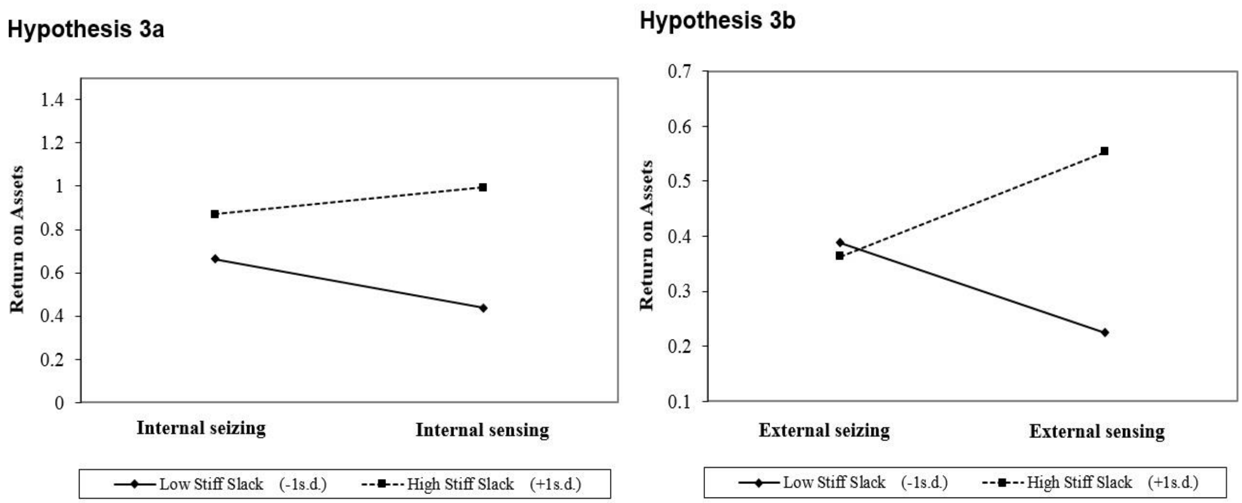

Figure 2.4 Two-way interaction plots

We test Hypothesis 4 in Model 7. The hypothesis proposes that for firms with a balanced sourcing portfolio, high levels of stiff slack lead to lower performance compared to low levels of stiff slack. To find support for this hypothesis, two conditions must be met. First, the regression coefficient for the three-way interaction must be positive and significant, showing a double negative effect (Table 2.3 Model 7). Second, the graphical representation (Figure 2.5) must show both balanced configurations (Cells 2 and 3) with significantly lower performance than the two focused configurations (Cells 1 and 4).

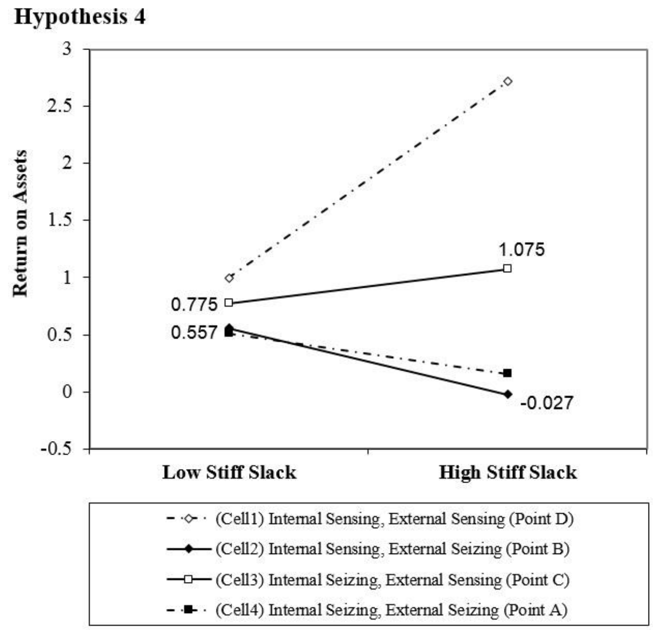

Figure 2.5 Three-way interaction plot

The three-way interaction coefficient reported by Model 7 (β = 17.102, $p < 0.01$) is positive and significant. This result reflects a double negative effect meaning that the performance effect hypothesized in Model 1 is weakened. In other words, a balanced strategy—using the internal vehicle to develop sensing capabilities and the external vehicle to develop seizing capabilities as described in Cell 2 or vice versa as described in Cell 3—becomes less important as levels of stiff slack increase. Figure 2.5 provides details. As slack increases, both straight lines corresponding to the two balanced configurations (Cell 2 and Cell 3) lead to decreasing ROA compared to the two focused configurations (dotted lines corresponding to focus on sensing (Cell 1) and focus on seizing (Cell 4)). Therefore, Hypothesis 4 is supported.

Hypothesis 5 is tested using Model 7 of the regression, slope difference tests in Table 2.5, and the graphical representation in Figure 2.5. Hypothesis 5 claims that the two balance configurations are not equal and that firms using the internal vehicle to sense and the external vehicle to seize (Point B) achieve lower performance when using their stiff slack compared to those using the external vehicle to sense and the internal vehicle to seize (Point C). Hypothesis 5 is supported if firms perform in point C significantly better than in Point B (confirmed in Figure 2.5) and a significant three-way coefficient in Model 7 (β = 17.102, p < 0.01). Table 2.5 provides support by confirming significant slope differences in performance between these two balance points when considering the effect of stiff slack. Thus, Hypothesis 5 is supported.

Table 2.5 Slope difference tests for the three-way interaction.

Pairs of slopes	t	p
(1) and (2)	8.100	*0.000*
(1) and (3)	6.640	*0.000*
(1) and (4)	9.063	*0.000*
(2) and (3)	-3.977	*0.000*
(2) and (4)	-1.152	*0.250*
(3) and (4)	2.279	*0.023*

Robustness Checks

We test the robustness of our analyses by running additional tests. First, in Table 2.6 we test our dynamic capability framing of balanced sourcing portfolios by using return on sales (ROS) as a dependent variable (Daniel et al., 2004). All hypotheses remain supported.

Table 2.6 Sample robustness check with return on sales as dependent variable

	Return on Sales			
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Intercept	1.677	1.991	1.407	0.926
	(0.03)	*(0.00)*	*(0.04)*	*(0.18)*
Internal sourcing	-0.193	-0.439	-0.464	-0.139
	(0.33)	*(0.01)*	*(0.00)*	*(0.43)*
External sourcing	0.485	-0.215	-0.203	0.740
	(0.26)	*(0.38)*	*(0.37)*	*(0.05)*
Internal sourcing × External sourcing	-1.793			-2.474
	(0.01)			*(0.00)*
Stiff slack		7.874	-0.431	0.947
		(0.00)	*(0.72)*	*(0.46)*
Stiff slack × Internal sourcing			7.600	1.762
			(0.00)	*(0.52)*
Stiff slack × External sourcing			32.583	16.982
			(0.00)	*(0.00)*
Stiff slack × [Internal sourcing × External sourcing]				45.725
				(0.00)
Control variables and year fixed effects	Yes	Yes	Yes	Yes
F	7.99	11.42	16.75	16.93
R-square	21.80%	28.49%	38.83%	40.93%
Increase in R-square	1.39%	8.08%	18.42%	20.52%

N = 942 obs.; *p*-values in parentheses

Second, in Table 2.7 we test robustness of results on the entire population of software firms, regardless of the level of financial slack they maintain. Models 1–4 display the results with ROA as dependent variable and Models 5–8 display the results with ROS as dependent variable. We find consistent support for our hypotheses on the entire population of firms. Third, earlier work shows that the effect of slack may be contemporaneous, meaning that current levels of slack may affect results in the same time period (Marlin & Geiger, 2015b). We use non-lagged variables to test hypotheses. Results remain broadly robust, supporting our measures' generalizability across time periods.

Table 2.7 Robustness check with return on assets and return on sales as dependent variables

	Return on Assets				**Return on Sales**			
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
Intercept	1.541	1.554	1.577	1.332	2.663	2.726	2.812	1.934
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.17)*	*(0.15)*	*(0.14)*	*(0.31)*
Internal sourcing	-0.061	-0.194	-0.197	0.010	0.005	-0.552	-0.564	-0.276
	(0.63)	(0.04)	(0.04)	(0.93)	*(0.99)*	*(0.15)*	*(0.14)*	*(0.59)*
External sourcing	0.192	0.047	-0.033	0.211	0.234	-0.380	-0.437	0.327
	(0.15)	(0.58)	(0.69)	(0.11)	*(0.67)*	*(0.27)*	*(0.20)*	*(0.54)*
Internal sourcing × External sourcing	-0.340			-0.559	-1.439			-2.268
	(0.15)			*(0.01)*	*(0.13)*			*(0.01)*
Stiff slack		1.396	-0.195	0.276		5.520	-1.069	0.407
		(0.00)	*(0.78)*	*(0.70)*		*(0.00)*	*(0.71)*	*(0.89)*
Stiff slack × Internal sourcing			0.000	-3.218			0.945	-10.038
			(0.98)	*(0.05)*			*(0.85)*	*(0.14)*
Stiff slack × External sourcing			4.807	2.070			18.895	10.008
			(0.00)	*(0.22)*			*(0.00)*	*(0.15)*
Stiff slack × [Internal sourcing × External sourcing]				10.880				36.814
				(0.00)				*(0.02)*
Control variables and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F	8.32	8.81	8.95	8.89	5.67	6.08	6.32	6.29
R-square	26.42%	27.54%	29.57%	31.07%	19.67%	20.78%	22.86%	24.20%
Increase in R-square	1.08%	2.20%	3.23%	5.73%	0.97%	2.08%	4.16%	5.50%

N =796 obs.; *p*-values in parentheses

Discussion

Contributions

Overall, three contributions emerge. First, this study is among the first to use a dynamic capabilities perspective to better understand why firms with balanced sourcing portfolios are heterogeneous in performance. While the question has been previously discussed in the learning literature (Lavie et al., 2010; Makri, Hitt, & Lane, 2010; Stettner & Lavie, 2015), we tackle it by disaggregating capabilities in *clusters of processes*—sensing and seizing (Teece, 2007, 2014b)—and by assigning specific managerial capabilities to these clusters—sensing capabilities and seizing capabilities. Following scholars interested in how firms source their knowledge and what configurations are the most productive (Lungeanu et al., 2016; Van de Vrande, 2013; Van de Vrande et al., 2009), we link dynamic capabilities research to ambidexterity research. We interpret exploration and exploitation activities as possible launching pads for, respectively, developing sensing and seizing capabilities. Building on previous ambidexterity work (Lavie et al., 2011; Stettner & Lavie, 2015), we hypothesize and find support for the claim that developing sensing and seizing capabilities *across* vehicles benefits firm performance. Compared to focused sourcing portfolios, balanced sourcing portfolios bring the advantages of flexibility of reconfiguration (Augier & Teece, 2009; Teece, 2007, 2014b). Balanced sourcing portfolios offer the opportunity to match sensing and seizing capabilities with the appropriate vehicle. This flexibility allows a better match of capability development and vehicle use, giving firms the opportunity to reconfigure themselves as they see fit. Henceforth, we extend the applicability of dynamic capabilities perspective and hope that revealing these choices, our study yields powerful insights into advancing a relatively new research perspective.

Second, we propose, operationalize, and validate *stiff slack* as a new construct to help us better understand what exactly makes the performance effects of balanced sourcing portfolios differ between software firms. By using a stricter operationalization of slack and focusing on a sample of firms with below average financial slack, we find that stiff slack can explain why some firms with balanced sourcing portfolios see increased performance while others do not. Specifically, we find interesting contradictory effects of stiff slack. First, due to its familiarity with firms' "signature processes" (Gratton & Ghoshal, 2005) and usage at near-zero marginal cost (Pitelis, 2007), stiff slack allows for experimentation and investigation of smarter ways, enhancing firms' sensing capabilities. Yet, due to its stickiness (Paeleman & Vanacker, 2015) and routine conflicts (Pentland et al., 2012), stiff slack creates redundancies and decreases the efficiency of seizing capabilities (Chen & Huang, 2010; Chen et al., 2013; Gratton & Ghoshal, 2005; Love & Nohria, 2005).

Third, while our conceptualization of stiff slack is the first of its kind, it holds the power to explain why firms with balanced sourcing portfolios can reconfigure themselves to outperform competitors. Firms that make use of stiff slack while balancing the development of sensing and seizing capabilities across sourcing vehicles find that the obsolescence introduced by stiff slack makes it increasingly difficult to coordinate routines and processes, negatively affecting firm performance. We find that this effect is smaller for firms performing the seizing inside organizational boundaries and sensing outside than it is for firms performing the seizing outside organizational boundaries and sensing in-house. The findings consolidate with previous findings of the slack literature claiming context-dependent effects of slack (Chen et al., 2013; Cheng &

Kesner, 1997; Latham & Braun, 2008; Marlin & Geiger, 2015a; Tan & Peng, 2003; Voss et al., 2008).

Limitations and Future Research Directions

While one step closer in clarifying the individual and combined performance of internal and external sourcing vehicles, our focus on software firms and data constraints associated with it compels us to restrict our study to the examination of the two major sourcing vehicles (internal and external). We recognize that alternative sources exist. We hope that our study encourages researchers to extend our line of investigation to other vehicles as well (Stettner & Lavie, 2015).

Similarly, a study of firms active in a different industry may reveal a different configuration of vehicles as the preferred choice. While engineering-based industries such as software may pay more attention to expanding their sensing capabilities, manufacturing-based industries may place a heavier weight on developing seizing capabilities to improve efficiency of operations (Wadhwa & Kotha, 2006). We believe that a study of firms in manufacturing-based industries that target efficiency would nicely complement our findings.

A question to consider relates to the long-term performance effects of maintaining balanced sourcing portfolios. Our study focuses on short-term performance effects (ROA, ROS) and does not capture the lasting effects of engaging in internal and external sourcing. Future researchers may consider that firm's choice of vehicles may be different depending on whether short-term or long-term performance is targeted (Rothaermel & Hess, 2007). A test of the effects of engaging in internal and external sourcing separately or simultaneously on firms' market value—which theoretically captures investors' opinion on firms' future potential—would help clarify the matter and inform us whether the results remain consistent or not.

Conclusion

Adopting a dynamic capabilities perspective, we conceptualize internal and external sourcing as conducive to the development of sensing and seizing capabilities and investigate how possible configurations of sourcing vehicles affect performance. Further, we conceptualize and operationalize a new construct—stiff slack—and explore its potential to affect firm performance. We find that for firms with balanced sourcing portfolios, stiff slack has contradictory effects depending on which activity is performed in-house. We reveal that for firms using a single vehicle, stiff slack supports the development of sensing capabilities but it weakens the development of seizing capabilities. For firms using balanced sourcing portfolios, stiff slack undermines the advantages of separating activities across vehicles, lowering performance. We conclude that from a dynamic capabilities perspective, stiff slack may explain firms' heterogeneity in performance while bridging the perspective to slack and sourcing research.

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CHAPTER 3

RACIAL DIVERSITY, REGULATORY FOCUS, AND ALLIANCE PORTFOLIO COMPOSITION

Abstract

We investigate the individual and joint effects that the racial diversity in the upper management group (UMG) and the regulatory focus of the CEO have in deciding the composition of firms' alliance portfolios—which we define as the distribution of exploratory, exploitative, and mixed alliances. Grounded in social categorization, information elaboration, and social contact mechanisms, we find that racially homogeneous UMGs have a higher propensity to maintain more exploratory alliance portfolios compared to very heterogeneous UMGs and subsequently to moderately racially diverse UMGs. Further, by leveraging regulatory focus mechanisms and by adopting the recently proposed racial diversity congruence approach, we posit that matching and mismatching levels of UMG racial diversity and CEO regulatory focus at low levels of racial diversity (as opposed to high levels) tilt the composition of firms' alliance portfolios in a more exploratory direction. A two-stage analysis on a panel of 128 pharma and software firms accompanied by polynomial regression and response surface analysis, yields support to our theorizing.

Introduction

The decisions regarding firms' alliance portfolio composition have received recent strategic alliance interest (Hoehn-Weiss & Karim, 2014; Mouri, Sarkar, & Frye, 2012; Stettner & Lavie, 2015). Alliances are critically important in science- and engineering-based industries (e.g. pharmaceuticals and software) where firms rely heavily on experimentation and cooperation and where attracting external resources is crucial (Koza & Lewin, 1998; Laursen & Salter, 2014; Li, 2013; Rothaermel & Deeds, 2004). Strategic alliance research claims that the alliance decision is grounded in firms' resource and capability needs and ultimately rests with the decision maker (Ahuja, Lampert, & Tandon, 2008; Das & Teng, 1998; Lavie & Rosenkopf, 2006; Tsang, 1998).In the literature, the composition of firms' alliance portfolios—defined here as the distribution of exploratory, exploitative, and mixed alliances within a firm's alliance portfolio—is mainly guided by firms' resource and capability needs (Ahuja, 2000; Ahuja et al., 2008; Baum, Calabrese, & Silverman, 2000; Harryson, Dudkowski, & Stern, 2008; Lavie, 2006).I It remains unexplained why some pharma and software firms keep alliance portfolios with a composition that does not seem to fulfill a resource or capability gap. In an attempt to explain the determinants of such alliance decisions, in this study we focus on the decision maker as the guiding element in the alliance portfolio composition.

While previously, scholars have mostly considered only the top management team (TMT) as the decisive factor in alliance decisions (Chatterjee & Hambrick, 2011; Hambrick & Mason, 1984; Harryson et al., 2008; Jiang, Bao, Xie, & Gao, 2016; Koza & Lewin, 1998; Ozcan & Eisenhardt, 2009; Schilke & Goerzen, 2010), few studies have shown that as a cooperative partnership, the alliance involves a high degree of cooperation and understanding, beyond what the TMT can provide (Das & Teng, 1998). Whereas the alliance decision-making process may differ among firms, the recent decrease in the early termination rate of strategic alliances (Das & Rahman, 2010; Das & Teng, 1998) can be explained by the profound understanding and tacit knowledge that the upper management as a group, beyond the TMT, can have. Following this line of reasoning, in this study we consider that upper management as a group (e.g. chief information officer, director of research) is involved in the alliance decision. In particular, the racial diversity at the upper management level dictates how, why, and what information is shared with the alliance partner (Gillespie et al., 2017; Jiang et al., 2016). Their attitude toward information sharing, collaboration, and risk ultimately guides firms' alliance preferences, with a deep impact on the alliance portfolio composition.

The burden of alliance decisions is carried by firms' upper management group (UMG) and the chief executive officer (CEO), with the UMGs' racial diversity and CEOs' motivational characteristics controlling firms' decision-making (Gillespie, De Jong, Williamson, & Gill, 2017; Hambrick, 1994; Hambrick & Mason, 1984; Richard, Barnett, Dwyer, & Chadwick, 2004). Demographic and motivational characteristics of both UMG and CEO have been found to shape firms' motivation and attitude behind strategic decisions (Brockner, Higgins, & Low, 2004; Crowe & Higgins, 1997; Richard et al., 2004). Given the seemingly equal importance of both decision factors, we adopt a congruence approach to characteristic matching. Following Richard, Stewart, McKay, and Sackett (2017), we define characteristic congruence as the matching between the levels of UMG racial diversity and CEO regulatory focus (e.g. high [low] UMG racial diversity and high [low] CEO regulatory focus). Characteristic incongruence is defined as the mismatching between the levels of UMG racial diversity and CEO regulatory focus (e.g. high [low] UMG racial diversity and low [high] CEO regulatory focus). Considering the scant attention that the matching/mismatching levels of demographic and motivational characteristics received in strategic alliance decisions, we ask: How does UMG racial diversity and CEO regulatory focus independently and jointly affect firms' alliance portfolio composition?

Previous literature showed that when upper management makes decisions, it is influenced by the demographic and psychological characteristics of its members (Hambrick & Mason, 1984). With the proportion of racial minorities in the UMG growing, we consider that racial diversity holds significant potential to influence the composition of firms' alliance portfolios. Despite the abundant research on racial diversity (Andrevski, Richard, Shaw, & Ferrier, 2014; Richard, Murthi, & Ismail, 2007), the research linking UMG racial diversity and firms' alliance portfolio composition is limited. To some degree, racial diversity has been linked to firms' ability to compete and innovate (Andrevski et al., 2014; Cox, 1996; Richard et al., 2004). Racially diverse groups have been shown to stimulate social contact, enlarge resource access, and diversify firms' perspectives (Blau, 1977). Upper management is responsible with allocating resources for alliances and with helping the CEO make alliance decisions. We expect that various configurations of social categorization, information elaboration, and social contact processes determine how different levels of UMG racial diversity favor or inhibit firms' perception of and propensity for risk taking and opportunism in alliances.

Beyond demographic characteristics of the UMG, CEO psychological attributes have also been shown to account for differences in risk taking and strategic choices of firms (Brockner et al., 2004; Chatterjee & Hambrick, 2007; Delgado-García & De La Fuente-Sabaté, 2010). Recently, CEO regulatory focus stood out as one personality attribute that influences "how people evaluate strategic options for their firm and what courses of action they choose to pursue" (Gamache, McNamara, Mannor, & Johnson, 2015: 1262). Regulatory focus is defined as "an individual's tendency to achieve either positive outcomes (promotion focus) or avoid negative outcomes (prevention focus)" (Das & Kumar, 2010: 4). As a self-regulation mechanism, an individual's regulatory focus drives that individual's motivation behind certain courses of action (Johnson & Yang, 2010). According to theory, the effects of CEOs' self-regulation mechanism may interact with situational characteristics (Higgins, 2000) such as the racial diversity of the UMG. To the degree that one individual—the CEO—has enough influence in the alliance decision-making (Chatterjee & Hambrick, 2007; Crowe & Higgins, 1997; Higgins & Spiegel, 2004), CEO regulatory focus may interact with UMGs' strategic alliance decisions.

This study endeavors to raise scholars' attention on the potential significance that the interaction between UMG racial diversity and CEO motivational characteristics may have in deciding the composition of firms' alliance portfolios. We test our hypotheses on a panel of pharmaceutical and software firms over a time frame of six years (2006-2011 inclusive). The study claims a number of important contributions to existing theory and research. By building on the categorization-elaboration model (CEM) (van Knippenberg, De Dreu, & Homan, 2004) and on social contact mechanisms (Blau, 1977), we investigate a possible J-shaped effect of UMG racial diversity on firm alliance portfolio composition, with homogeneous UMGs displaying the highest propensity for maintaining exploratory alliance portfolios compared to extremely to moderate heterogeneous UMGs.

Further, by investigating possible congruence/incongruence effects between UMG racial diversity and CEO regulatory focus, we extend very recent research on the racial diversity congruence approach (Richard et al., 2017), with a high potential to explain how categorization-elaboration (Tajfel & Turner, 1986; Turner, Hogg, Oakes, Reicher, & Wetherell, 1987; van Knippenberg et al., 2004), social contact (Blau, 1977), and regulatory focus mechanisms (Gamache, McNamara, Mannor, & Johnson, 2015; Higgins, 2000; Higgins & Spiegel, 2004) interact. Even more, the polynomial regression used helps us explain potential non-linear effects that group demographics—individual personality characteristics congruence has in strategic decision making and that have been shown to characterize diversity when defined as degree of variation in membership to a certain racial group (Blau, 1977; Harrison & Klein, 2007).

Theoretical Background

As a widely dispersed organizational form in the last decade (Lavie, 2007b), alliances imply either a short-term, rent-seeking relationship (exploitative) (Li, 2013; Sakakibara, 2002), a long-term, trust-based relationship (exploratory) (Jiang et al., 2016; Zanarone, Lo, & Madsen, 2015), or a combination of both (mixed) (Lavie, 2007a; Lavie & Rosenkopf, 2006). On one side, exploratory alliances require partner firms to be open, to trust, and to fully cooperate for longer periods of time (Inkpen & Tsang, 2007). On the other side, exploitative alliances imply a more superficial relationship, usually for a shorter period of time, and for a specific rent-seeking purpose such as licensing or marketing (Jiang et al., 2016; Laursen & Salter, 2014).

By their nature, exploratory alliances involve a profound exchange of tacit knowledge which makes them susceptible to partners' opportunistic behavior and increased likelihood of expropriation of their more intimate knowledge (Inkpen & Tsang, 2007; Jiang et al., 2016). Exploitative alliances, while susceptible to opportunism, do not imply the transfer of tacit knowledge and carry lower risks (Das & Teng, 1998; Inkpen & Tsang, 2007; Lin, Yang, & Arya, 2009; Rothaermel & Deeds, 2004; Schilke & Goerzen, 2010).

For pharmaceutical and software firms, alliance engagement is a risky but necessary proposition. Research shows that it is crucial for firms in rapidly evolving environments to use alliances to tackle external knowledge and capabilities (Laursen & Salter, 2006; Laursen &

Salter, 2014). The positive effect of alliances in helping such firms lower their knowledge gaps overcomes the negative effects these alliances may pose through knowledge expropriation (Mouri et al., 2012). However, alliances are not equally risky (Hoffmann, 2007) and the motivations behind tilting the composition of firms' alliance portfolio into a more exploratory or more exploitative direction lie with the upper management group (Hambrick, Humphrey, & Gupta, 2015) and the decision maker—usually the CEO (Papadakis & Barwise, 2002). The types of alliances (R&D or licensing) in firms' alliance portfolio carry various degrees of risk that the firm must assume, with R&D alliances presenting higher rewards but also higher risks compared to licensing alliances (Vassolo, Anand, & Folta, 2004). In the following, we introduce the literature and develop arguments on UMG racial characteristics and CEO motivational characteristics (regulatory focus) that may explain the role of upper management dynamics and individual motivations behind firms' alliance portfolio composition.

Theoretical Perspectives on Group Diversity

While diversity research has been abundant, how racial diversity interacts with various firm level outcomes is complicated (De Dreu, Nijstad, & van Knippenberg, 2008; Richard & Charles, 2013). It is important to understand how racial diversity relates to organizational behavior and outcomes because these processes shape firm behavior and explain firm choices (Wooten, 2008). Although no research to date has investigated the effects of UMG racial diversity on firms' alliance portfolio composition, there has been some research showing that strategic choice is a function of leaders' characteristics (Golden & Zajac, 2001; Wiersema & Bantel, 1992). The categorization-elaboration model (van Knippenberg et al., 2004) identifies two mechanisms with potential to affect the composition of firms' alliance portfolios. The first one is grounded in the social contact theory (Blau, 1977). The second one draws simultaneously from the social categorization perspectives (Tajfel, 1981; Turner et al., 1987) and the information-processing models (Mannix & Neale, 2005; Williams & O'Reilly, 1998).

Regarding the social contact mechanism, Blau's theory of heterogeneity argues that low and high degrees of racial differences help social interaction among people, while medium levels of diversity impede it (Blau, 1977). Accordingly, homogeneous and heterogeneous UMGs have fewer barriers to overcome in making decisions or reaching agreement on a strategic direction compared to moderately diverse UMGs. The theory claims that groups in which members have more opportunities to socialize face lower cultural barriers with regards to action and thus develop relations among them. Members of homogeneous groups display similar norms and preconceptions (DiStefano & Maznevski, 2000), have low cultural barriers, and develop more cohesive groups in terms of communication and positive social relations (Richard et al., 2004).

In UMGs with low racial diversity, members are likely to share unified views that they develop together as a result of sharing perceptions and developing positive feelings of inclusion in the group (Dahlin, Weingart, & Hinds, 2005). As heterogeneity increases, subgroups are likely to form, and the barriers to social communication with members of other subgroups increase (Earley & Mosakowski, 2000). These communication barriers impede the flow of information between different subgroups (Alexander, Nuchols, Bloom, & Lee, 1995; Wiersema & Bird, 1993). The segregation between subgroups increases each group's inertia and deprive each individual subgroup of information diversity. With further increases in heterogeneity, groups become diverse enough to encourage open communication. At very high levels of diversity, the effect of racial minorities is minimized. The flow of informational resources is improved and even if diverse groups do not share common perceptions and attachments to any particular context, their social contact facilitates the sharing of information among them.

Beyond social contact processes, social categorization and information elaboration processes arise in work groups. The categorization-elaboration model (CEM) (Van Knippenberg et al., 2004) proposes that people categorize themselves and exchange information depending on how they categorize others into in-group/out-group (Chen, Peng, & Saparito, 2002). The social categorization mechanism refers to people's tendency to categorize similar others as part of the in-group and dissimilar others as part of the out-group (Chen et al., 2002; Tajfel & Turner, 1986; Turner et al., 1987). The information-processing mechanism refers to the exchange and integration of others' perspectives (Harrison & Klein, 2007; Thomas & Ely, 1996; Van Knippenberg et al., 2004). As defined by van Knippenberg et al., (2004: p.1011), information-elaboration is "the exchange of information and perspectives, individual-level processing of information and perspectives, the process of feeding back the results of this individual-level processing into the group, and discussion and integration of its implications."

According to CEM, social categorization may harm decision making and information-elaboration may benefit it. Low diversity is expected to enhance social integration through low categorization but undermine decision making through lack of access to information. At the same time, high diversity is expected to weaken social integration through high categorization but benefit decision making through an expanded access to diverse information.

Racial Diversity Effects on Alliance Portfolio Composition

To the degree that UMGs shape strategic decision making (Finkelstein, Hambrick, & Cannella, 2009; Hambrick, 1994; Hambrick & Mason, 1984), UMG racial diversity may have a significant impact on the alliance portfolio composition. In this hypothesis, we claim that homogeneous UMGs that do not suffer from social categorization tend keep more exploratory alliances in their alliance portfolios compared to heterogeneous UMGs that suffer from social categorization inhibiting information elaboration (Tajfel, 1981; van Knippenberg et al., 2004). Further, using social contact mechanisms proposed by Blau's theory of heterogeneity, we propose that both homogeneous and heterogeneous UMGs may embrace exploratory alliances easier than moderately diverse UMGs that face medium categorization and information elaboration but lack social contact. Thus, we argue for a non-linear, J-shaped effect of UMGs racial diversity on firms' alliance portfolio composition.

To decide in favor of an exploratory alliance (e.g. R&D alliance) implies willingness to engage in a long-term relationship based on trust. Such endeavors require the ability and willingness to develop interpersonal communication with alliance partners (Lavie, 2007a; Lavie, Stettner, & Tushman, 2010; Zahavi & Lavie, 2013). Homogeneous and heterogeneous UMGs are better equipped to enter such trust-based relationships compared to moderately diverse UMGs due to a higher ability to foster social contact (Blau, 1977). In moderately diverse UMGs where categorization and social comparison processes occur, the formation of subgroups raises social barriers and hinder communication (Ely & Thomas, 2001; Tajfel & Turner, 1986). Additionally, social categorization processes that dominate at moderate levels of diversity do not allow for much information elaboration (Turner et al., 1987). The segregation resulting from social categorization cannot lead to exploratory-seeking behavior because categorization neither stimulates constructive debate nor fosters information-elaboration (Barkema & Shvyrkov, 2007; Harrison & Klein, 2007; Jehn, 1997; Richard et al., 2017; Thomas & Ely, 1996). Constructive debate is essential in reaching consensus and moderately diverse UMGs suffering from segregation cannot reach it.

According to Blau's theory of heterogeneity, opportunities for social contact are more numerous in homogeneous and heterogeneous groups compared to moderately diverse groups. They are better at transferring information thus minimizing the chances that social categorization processes take place and helping the development of positive social association among UMG members (Lau & Murnighan, 2005). In homogeneous UMGs for example, managers do not face cultural barriers to social action and develop deep solidarity within their racial group (K. Williams & O'Reilly, 1998). They relate to other similar managers in the group easier, transfer knowledge without inhibition, and develop stronger interdependencies (Richard et al., 2007). These in turn, make the upper management as a group more effective in making difficult and risky decisions such as choosing in favor of a long-term R&D alliance (Dahlin et al., 2005).

In homogeneous UMGs, managers identify with the social group and see each other as being part of the same social category (Hogg & Terry, 2000; Tajfel & Turner, 1986; Turner et al., 1987; Van Knippenberg et al., 2004). Because members of homogeneous UMGs identify as part of the same in-group, they do not develop feelings of discrimination against others in the way that moderately diverse or very heterogeneous UMGs do (Earley & Mosakowski, 2000; Lau & Murnighan, 2005; Richard et al., 2004). Even if in homogeneous UMGs the access to a wide array of viewpoints and diverse information is limited, members develop increased trust among members of the in-group leading to unanimity in decisions. The lack of intergroup bias makes homogeneous UMGs transfer information faster, have more positive-affective evaluative reactions to others' behavior, and have a higher propensity to collaborate (Harrison & Klein, 2007; Thomas & Ely, 1996). Compared to very heterogeneous or moderately diverse UMGs, homogeneous UMGs, as a result of low categorization processes and very good social contact, are more open to engage in long-term, trust-based relationships such as exploratory alliances and less open to engage in short-term, exploitative alliances (Jiang et al., 2016).

On the other side of the spectrum, very heterogeneous UMGs suffer from higher categorization but benefit from highest elaboration derived from a very good access to a wide pool of perspectives, skills, and preferences (Jackson, 1992; Tajfel & Turner, 1986; Turner et al., 1987). Access to an extensive range of perspectives makes them more capable to identify external opportunities and make novel strategic decisions (Barkema & Shvyrkov, 2007; Boeker, 1997). However, due to high social categorization, information-elaboration processes are inhibited to some degree. Even if very heterogeneous UMGs are likely to perceive less risk in entering alliances that involve intensive knowledge sharing—such as R&D alliances— access to a diversity of perspectives makes these UMGs more aware of issues possibly out of their control. Social categorization processes are also likely to negatively affect heterogeneous UMGs' collaboration capability, decision-making, and trust in the alliance partner.

Overall, based on the social categorization, information elaboration, and social contact mechanisms, we claim a J-shape relationship between racial diversity at the UMG level and firms' alliance portfolio composition. First, moderately diverse teams that cannot reach consensus have the least exploratory alliance portfolios compared to homogeneous and heterogeneous UMGs that benefit from improved social contact. Second, by comparison, very heterogeneous UMGs that benefit from highest information-elaboration advantages may foster better collaboration and may be more open to engage in trust-based relationships such as exploratory alliances (Jiang et al., 2016). Third, very homogeneous UMGs, despite the homogeneous knowledge they possess, but thanks to very low categorization processes and very good social contact, may be the most open to engage in exploratory alliances that require intensive knowledge sharing on the long-term. Thus, we hypothesize:

H1: UMG racial diversity is J-shaped associated with firms' alliance portfolio composition, such that homogeneous UMGs have a higher propensity for exploratory alliance portfolios compared to very heterogeneous UMGs, which have a higher propensity for exploratory alliance portfolios than moderately diverse UMGs.

Regulatory Focus Theory

Although regulatory focus is a micro level concept, it has the potential to drive firm action and affect macro level behavior (Das & Kumar, 2010; Gamache et al., 2015). It does that by shaping the motivational attributes of individuals with power to decide firms' actions such as the CEO (Lanaj, Chang, & Johnson, 2012). The regulatory focus theory (Higgins, 1998) introduces regulatory focus as an individual level psychological characteristic with a profound impact on organizational decision making and behavior. The term *regulatory focus* refers to "an individual's tendency to achieve either positive outcomes (promotion focus) or avoid negative outcomes (prevention focus)" (Das & Kumar, 2010: 4). Regulatory focus pertains to self-regulation and goal attainment and encompasses the motivation that drives an individual to prefer certain courses of action over others (Johnson & Yang, 2010).

Regulatory focus theory claims that there are two different types of individuals: those focused on obtaining positive outcomes and those focused on avoiding negative outcomes (Higgins, 1998; Molden, Lee, & Higgins, 2008). While individuals focused on obtaining positive outcomes regulate their behavior by adopting a promotion-focused perspective, individuals focused on avoiding negative outcomes regulate their behavior by adopting a prevention-focused perspective (Higgins, 1998; Higgins & Spiegel, 2004). Promotion focused individuals are sensitive to "accomplishments, hopes, and aspirations", whereas prevention focused individuals pay more attention to "safety, responsibilities, and obligations" (Higgins, 1998: 16). Due to the intrinsic specifics of each type, a promotion focus will direct an individual's attention toward opportunities for growth and accomplishment, consideration of alternatives, and achievement of ideals (Das & Kumar, 2010; Liberman, Molden, Idson, & Higgins, 2001; Molden et al., 2008). In contrast, a prevention focus will direct an individual's attention toward ways to avoid negative outcomes, to minimize losses, and to ensure security, stability, and accuracy in decisions (Crowe & Higgins, 1997; Higgins & Spiegel, 2004; Liberman, Idson, Camacho, & Higgins, 1999).

Individuals' regulatory focus has been linked to the organizational choices these individuals make (Galinsky, Leonardelli, Okhuysen, & Mussweiler, 2005). Because regulatory focus shapes people's motivations for certain types of actions, it differs from other personality traits (e.g. narcissism, affectivity, charisma) identified in the literature. First, while personality traits such as narcissism or charisma have an indirect effect on firm action (Barrick, Stewart, & Piotrowski, 2002), regulatory focus is a motivational attribute with direct effects on firm action (Gamache et al., 2015; Lanaj et al., 2012). Second, regulatory focus differs from other personality traits because it directly affects how much people strive to achieve their goals instead of affecting the difficulty that people perceive in attaining their goals. For example, people's focus on maximizing gains (promotion focus) underlie their judgement, making these individuals more eager and open to risk instead of making them perceive less risk in certain decisions. Third, regulatory focus shapes people's eagerness or vigilance strategies (Crowe & Higgins, 1997) that directly impact people's actions (Scholer & Higgins, 2008). Overall, regulatory focus as opposed to other personality characteristics is more proximal to individuals' behavior and actions.

Regulatory focus is a more flexible individual-level characteristic than deep-level personality traits such as narcissism (Gamache et al., 2015). Scholars have identified promotion and prevention foci as two different ways people use to attain their goals (Förster, Higgins, & Bianco, 2003; Lanaj et al., 2012). The literature has treated them as two separate variables, independent of each other, based on the fact that the approach and avoidance strategic orientations that lay behind the promotion and prevention foci stem from "biological dispositions" developed in early life (Higgins, 1997), and are, to some degree, consistent over an individual's life time (Higgins et al., 2001). However, promotion and prevention preferences can coexist and they evolve and change with organizational norms, past performance or interpersonal relationships (Brockner et al., 2004; Higgins, 2000; Johnson & Yang, 2010). We conceptualize regulatory focus as one continuous variable and propose to measure it as a difference between promotion and prevention foci. In our conceptualization, a positive regulatory focus reflects a promotion focus and a negative regulatory focus reflects prevention focus.

As shown in Table 3.1, we expect categorization-elaboration mechanisms, social contact mechanisms, and individuals' regulatory focus mechanisms to affect the composition of firms' alliance portfolios. We expect that matching levels of UMG racial diversity and CEO regulatory focus—further referred to as congruence—at low levels (Cell 1) to yield the highest propensity to enter exploratory alliances and matching levels of UMG racial diversity and CEO regulatory focus at high levels (Cell 4) to yield the lowest propensity to enter exploratory alliances.

Furthermore, we expect that mismatching levels of UMG racial diversity and CEO regulatory focus—further referred to as incongruence—at high levels of UMG racial diversity (Cell 3) to yield a higher exploratory propensity compared to low levels of UMG racial diversity (Cell 2).

Table 3.1 The congruence and incongruence effects of UMG racial diversity – CEO regulatory focus on firm alliance portfolio composition.

	CEO regulatory focus	
UMG racial diversity	Low (more prevention-focused)	High (more promotion-focused)
Low	CELL 1 (congruence) + low elaboration, high categorization + social contact + loss avoidance	CELL 2 (incongruence) + low elaboration, high categorization - social contact - gain maximization
High	CELL 3 (incongruence) - high elaboration, low categorization + social contact + loss avoidance	CELL 4 (congruence) - high elaboration, low categorization - social contact - gain maximization

Note: A positive sign (+) indicates an increase in firms' exploratory propensity and a negative (-) sign indicates a decrease in firms' exploratory propensity.

UMG Racial Diversity – CEO Regulatory Focus Congruence Effects

The regulatory fit mechanism claims that regulatory focus and salient contextual characteristics reinforce each other (Higgins, 2000). In particular, a salient and immediate characteristic of the environment is UMG racial diversity (Johnson & Yang, 2010; Ling, Simsek, Lubatkin, & Veiga, 2008). As a powerful driver of organizational behaviors and outcomes (Richard et al., 2004; Richard & Charles, 2013), UMG racial diversity drives the alliance portfolio composition into a more exploratory or exploitative direction depending on whether the regulatory focus of the CEO is consistent with the social categorization and information elaboration allowed by it (Crowe & Higgins, 1997; Higgins, 1998; Higgins et al., 2001). On one hand, the safety needs of more prevention focused CEOs encourage homogeneous UMGs promoting social contact toward trust-based alliances and, on the other hand, the accomplishment needs of more promotion focused CEOs encourage heterogeneous UMGs promoting information-elaboration toward rent-seeking alliances (Jiang et al., 2016).

Using regulatory focus mechanisms (Das & Kumar, 2010; Das & Teng, 1998; Higgins, 1998; Molden et al., 2008), the CEM model (Van Knippenberg et al., 2004), and the social contact mechanisms (Blau, 1977), we predict that the congruence between racial and motivational characteristics will determine the composition of firms' alliance portfolios depending on whether the congruence meets at high or low levels. As such, prevention focused CEOs of homogeneous UMGs (low-low congruence) have a higher propensity for long-term, trust-based alliances (exploratory) compared to promotion focused CEOs of very heterogeneous UMGs (high-high congruence). The primary mechanisms are a lower tolerance for opportunistic actions and a higher willingness to share knowledge.

Opportunism is a serious threat for firms choosing to enter an alliance (Das & Rahman, 2010). The higher the regulatory focus of the CEO, the higher the emphasis the CEO puts on attaining his/her aspirations by downplaying the possible negative effects of partners' opportunism in exploitative alliances (Das & Rahman, 2010). The lower the regulatory focus of the CEO, the lower the forbearance for opportunistic behavior (Das & Kumar, 2010). As the main decision factor in the UMG, the CEO imprints his/her opportunism-avoidance or achievement-attainment characteristic on a homogeneous UMG. Good in-group communication and social contact will encourage a prevention focused CEO to liberally share the opportunism-avoidance with a homogeneous UMG that will mirror the concerns (Eggers & Kaplan, 2009; Molden et al., 2008; Van Knippenberg et al., 2004). Homogeneous knowledge of homogeneous UMGs and the opportunism-avoidance trait of prevention focused CEOs will guide them toward exploratory alliances based on building trust and cooperation (Jiang et al., 2016).

Prevention focused CEOs are motivated by needs for safety, stability, and avoidance of negative outcomes (Crowe & Higgins, 1997). Prevention focus is a self-regulation mechanism that sensitizes people about possible losses (Crowe & Higgins, 1997). In response to this concern, prevention focused CEOs adopt an attitude that minimizes the vulnerabilities to which the individual is exposed (Higgins, 1998). Very good social contact and low categorization processes characteristic to homogeneous UMG fit well with prevention focus CEOs' need for stability and trust. Homogeneous UMG dominated by a supportive attitude as a result of very low social categorization, prevention focus CEOs will gear their decision making toward long-term, trust-based relationships as opposed to short-term, rent-seeking relationships.

In contrast, more promotion focused CEOs like change because change gives them the opportunity to maximize their gains (Liberman et al., 1999). They are less worried about making a mistake and more worried about losing an opportunity (Crowe & Higgins, 1997). Promotion focused CEOs will push for exploitative alliances because this is the action that will quickly maximize their gains. Very heterogeneous UMGs, despite the heterogeneous knowledge they hold, face social categorization that impedes the elaboration of information among members of the UMG (Tajfel & Turner, 1986; Van Knippenberg et al., 2004). Impeded communication and promotion focused CEOs' concern with immediate accomplishment (Brockner et al., 2004) make very heterogeneous UMGs more prone to exploitation because it brings immediate results and satisfies CEOs' need for achievement. The opportunism that promotion focused CEOs are prone to, is likely to be mirrored by alliance partners (Jiang et al., 2016), determining heterogeneous UMGs to choose in favor of short-term relationships as opposed to long-term relationships (Das & Teng, 1998).

In sum, the low-low congruence between the UMG racial diversity and CEO regulatory focus denotes a configuration of demographic and motivational characteristics that is more open to knowledge sharing and has a lower tolerance for opportunistic behavior. The low-low congruence configuration has a higher preference for long-term alliances thus tilting the alliance portfolio composition in a more exploratory direction. The high-high congruence denotes a configuration of demographic and motivational characteristics that is faces increase social categorization processes, being less open to knowledge sharing but with a higher tolerance for opportunistic behavior. The high-high congruence configuration has a higher preference for short-term alliances, tilting the alliance portfolio composition in a more exploitative direction.

H2: The congruence of low UMG racial diversity and low CEO regulatory focus is associated with a more exploratory alliance portfolio composition than the congruence of high UMG racial diversity and high CEO regulatory focus.

UMG Racial Diversity – CEO Regulatory Focus Incongruence Effects

In this hypothesis we suggest that the incongruence between racial diversity characteristics of the UMG and motivational characteristics of the CEO at low levels of UMG racial diversity is more conducive to exploitative alliance portfolios compared to the incongruence at high levels of UMG racial diversity which is more conducive to exploratory alliance portfolios. Homogeneous UMGs fostering social contact but not information-elaboration are attentive to more promotion focused CEOs' need for support in their goal achievement process (Das & Teng, 1998). This homogeneity in perspectives resonates with more promotion focused CEOs who are open and need a sympathetic audience (Das & Rahman, 2010; Das & Kumar, 2010). The vigilance of promotion focused CEOs against losing an opportunity is enhanced and perpetuated by homogeneous UMGs that are over concerned about maintaining unanimity (Barkema & Shvyrkov, 2007; Das & Rahman, 2010).

Moreover, the solidarity between group members makes them work together to achieve common goals (Earley & Mosakowski, 2000; Richard et al., 2007). Supportive homogeneous UMGs are likely to decide in favor of engaging with a possibly opportunistic partner due to their knowledge homogeneity (Harrison & Klein, 2007; Thomas & Ely, 1996). The improved decision-making processing and speed that homogeneous UMGs foster resonates well with promotion focused CEOs who are constantly on the lookout to reach quick agreements that propel them closer to realizing their goals (Das & Kumar, 2010). In the light of previous arguments, we conclude that racially homogeneous UMGs led by promotion focused CEOs (Table 3.1 Cell 2: low-high incongruence) are likely to keep exploitative alliance portfolios.

By contrast, very heterogeneous UMGs introduce increasingly diffuse cultural barriers (Richard et al., 2004). They foster information-elaboration (van Knippenberg et al., 2004) and social contact that opens the transfer of information across social categories (Richard, McMillan, Chadwick, & Dwyer, 2003). The heterogeneous knowledge that heterogeneous UMGs possess opens the range of resources and opportunities the CEO can access (Richard et al., 2007). A prevention focused CEO that is concerned with avoiding losses (Brockner et al., 2004; Crowe & Higgins, 1997; Lanaj et al., 2012), will find the access to a wide range of experiences, connections, and perspectives informative and beneficial. The information-elaboration that heterogeneous UMGs allow for expands the field of alliance opportunities that more prevention focused CEOs can trust and evaluate as positive.

Prevention focused CEOs, because they are focused on avoiding losses at all costs, are constantly on the lookout for cues that may better inform them about possible risks. Very heterogeneous UMGs provide more prevention focused CEOs access to various external salient cues that enhance these CEOs' perception and information processing (Cesario & Higgins, 2008). Multiple out-group contacts and perspectives of UMG members activate these cues (Dimotakis, Davison, & Hollenbeck, 2012), further reassuring prevention focused CEOs about the appropriateness of their decisions. Ultimately, a better-informed prevention focused CEO will more leniently engage in long-term, exploratory alliance endeavors without a supportive homogeneous UMG.

Overall, we expect that heterogeneous UMGs led by prevention focused CEOs (high – low incongruence) have a higher preference for exploratory alliance portfolios compared to homogeneous UMGs led by promotion focused CEOs (low – high incongruence).

H3: The incongruence of high UMG racial diversity and low CEO regulatory focus is associated with a more exploratory alliance portfolio composition than the incongruence of low UMG racial diversity and high CEO regulatory focus.

Methodology

Sample and Data Collection

We start by identifying U.S.-based science and engineering firms in pharmaceutical (SIC 2833, 2834, 2835, 2836) and software (SIC 7372, 7373, 7374, 7375) industries. We use Dun and

Bradstreet that is considered the most exhaustive database of U.S.-based firms (Hmieleski & Baron, 2008; Kalleberg, Marsden, Aldrich, & Cassell, 1990).

This multi-industry dataset gives us the opportunity to capture firms' alliance behavior for three reasons. First, firms in pharmaceutical and software industries display an intense alliance involvement (Lavie, Kang, & Rosenkopf, 2011), minimizing data availability issues. Second, these industries have been dominated by U.S.-based firms and many previous studies on alliances have been based in these industries (Hess & Rothaermel, 2011; Lavie, 2006, 2007b), making our study highly relevant to previous work. Third, science and engineering-based firms are more likely to be racially diverse (Zhou & Rosini, 2015), representing a proper context to test our hypotheses.

To avoid possible inconsistencies introduced by the Sarbanes-Oxley Act of 2002, we retrieve data for the period after the introduction of this act, leaving a one-year delay for the new regulation to settle. Therefore, we cover years 2006-2011 inclusive with some data traced back to 2003.

We collect alliance data from SDC Platinum Database (Lavie et al., 2010; Stettner & Lavie, 2015). Information on upper management racial and gender diversity and controls are extracted from Institutional Shareholder Services (ISS) database. CEO characteristics that are used to measure regulatory focus are extracted using the General Architecture for Text Engineering (GATE) tool (Vlas & Robinson, 2012) from letters to shareholders collected using EDGAR Online (government fillings) platform. Firm-level financial controls are collected from Compustat/CRSP database, patent-related controls from the U.S. Patent and Trademark Office (USPTO), and alliance-specific controls from SDC database.

Analytical Strategy

Our final dataset is a panel of 128 firms analyzed between 2006 and 2011 inclusive with alliance and patent data traced back to 2003. A one-year lag for all predictor and control variables relative to the dependent variable helps us deal with the potential interdependence among multiple firm observations over a number of years. A Hausman test yields the fixed effects model appropriate (Hausman 1978).

To test our hypotheses, we estimate a fixed effects model with year controls. We address possible endogeneity with a Heckman two-stage model (Heckman 1979). Firms' tendency to explore in alliances may be influenced by the inherent benefits this activity irrespective of UMG racial diversity or CEO regulatory focus. To account for this endogeneity effect, we first run a probit model for firms' exploratory propensity, by regressing firms' probability of exploration in alliances on firm performance (sales productivity), firm age (logged), firm R&D intensity, patenting experience, joint venture experience, acquisition experience, UMG average age, UMG size, CEO duality, year 2008 effect, and year effects. Patenting experience, joint venture experience, acquisition experience variables were computed as dummies taking a value of 1 if the firm patented or engaged in a joint venture/acquisition in that respective year, and 0 otherwise. Year 2008 effect variable takes a value of 1 if the alliance event year comes after 2008 and a value of 0 if the alliance event year precedes 2008. The predicted values are used to compute the exploration inverse Mills ratio (λ Exploration).

To account for the exploration self-selection bias, we incorporate the computed inverse Mills ratio as control in the second-stage model. Potential interdependence among observations is dealt with by the one-year lag between all our predictor and control variables and the dependent variable. To avoid an increase in multicollinearity, we sequentially add variables. All models' individual VIFs are well below the recommended threshold of 10 with full model's VIF of 7.04 being the highest, suggesting that multicollinearity is not significant.

To test our hypotheses, we use polynomial regression and graphical representation (Edwards, 1994, 2007; Edwards & Parry, 1993; Shanock, Baran, Gentry, Pattison, & Heggestad, 2010). Polynomial regression allows us to investigate predictors' linear and non-linear effects as well as their interaction. Graphical representation in the form of response surface analysis allows us to better interpret and understand the relationships between different configurations of the two predictor variables (UMG racial diversity and CEO regulatory focus) and the outcome variable (alliance portfolio composition). For the purpose to run the polynomial regression analysis, we first mean-center the two predictors and then use hierarchical regression by sequentially adding variables to avoid an increase in multicollinearity (Bashshur, Hernández, & González-Romá, 2011; Richard et al., 2017). The polynomial function takes the following form:

$$APF = b_0 + b_1 \times RD + b_2 \times RF + b_3 \times RD^2 + b_4 \cdot (RD \times RF) + b_5 \times RF^2 + e \quad (2)$$

where APF denotes alliance portfolio composition, RD denotes UMG racial diversity, RF denotes CEO regulatory focus. We construct two models: a model with first order terms (RD and RF) and a model with first order, second order, and interactive terms. A potential congruence effect is denoted by a significant and positive interactive term (RD × RF), alongside the two positive and significant quadratic terms (RD^2 and RF^2) (Edwards & Parry, 1993).

Following the polynomial regression analysis, we engage graphical representation to aid our understanding of results. We conduct response surface analysis tests to interpret the slopes and curvatures of both the congruence line (RD = RF) and the incongruence line (RD = -RF) (Shanock et al., 2010). The response surface analysis tests retrieve four values: slope and curvature along the congruence line and slope and curvature along the incongruence line.

The slope along the congruence line (running from the front corner of the surface plane to the back corner of the surface plane) helps us interpret the increase in the outcome variable (alliance portfolio composition) as both predictors (RD and RF) increase (a positive slope) or decrease (a negative slope). The significant curvature along the congruence line indicates a non-linear effect. A positive value suggests an upward curved surface (convex) and a negative value suggests a downward curved surface (concave). Both the slope and curvature of the congruence line helps our understanding of the effects that the congruence between the UMG racial diversity and CEO regulatory focus at high levels compared to low levels has on alliance portfolio composition (Hypothesis 2).

The slope along the incongruence line (running from the left corner of the surface plane to the right corner of the surface plane) helps us interpret the increase in the outcome variable (alliance portfolio composition) as one predictor increases and the other one decreases (high – low and low – high configurations). A positive and significant slope indicates how much the outcome variable increases for low UMG racial diversity – high CEO regulatory focus configuration (left corner) compared to high UMG racial diversity – low CEO regulatory focus configuration (right corner) (Hypothesis 3). The significant curvature along the congruence line indicates a non-linear effect, either convex (positive curvature) or concave (negative curvature) as well as whether congruence (high – high and low – low configurations) is significantly different than incongruence (high – low and low – high configurations).

Variables

Alliance Portfolio Composition

Our dependent variable is firms' alliance portfolio composition. This represents the degree of exploration undertaken by a firm through its entire alliance pool. Given the average alliance span, we capture firms' alliance portfolio by pooling all alliances formed in the last five years (Kogut, 1988). firms can form alliances either to explore to gain access to partners' knowledge or to exploit to leverage firms' existent knowledge (Koza & Lewin, 1998; Lavie & Rosenkopf, 2006; Rothaermel & Deeds, 2004). We expect firms' alliance portfolios to be composed of a variety of alliance types, such as licensing, marketing, or R&D alliances.

Following Rothaermel and Deeds (2004), we define alliances that involve joint R&D activities as exploratory, alliances that involve joint marketing, licensing, resale or production activities as exploitative, and alliances that combine both activities as mixed. Our conceptualization assumes that exploration and exploitation are two separate indicators of activities that inhibit each other because they use resources from firms' limited pool of resources (Uotila, Maula, Keil, & Zahra, 2009). Thus, when coding the alliance descriptions mentioned in the SDC Database, we code exploration alliances as 1, exploitation alliances as 0, and mixed alliances as 0.5 (Hess & Rothaermel, 2011; Rothaermel & Deeds, 2004). After summing up all alliances formed by each firm over the last five years (Kogut, 1988), we compute a ratio reflecting the percentage of exploration in firms' alliance portfolio. For example, a firm with one R&D alliance and four licensing alliances will have an alliance portfolio composition index of 0.2, reflecting that the firm's alliance portfolio is 20% exploratory and the remaining 80% exploitative. This index serves as our dependent variable and ranges from 0 to 1, with values closer to 1 reflecting firms' exploratory endeavors and values closer to 0 reflecting firms' exploitative endeavors.

UMG Racial Diversity

Our first independent variable is operationalized using Blau's heterogeneity index (Blau, 1977). Blau's index is a commonly used measure for categorical variables such as race because it captures qualitative distinctions of diversity as variety (Harrison & Klein, 2007). It has been widely used to measure the diversity of management teams (Andrevski et al., 2014; Bunderson & Sutcliffe, 2002; Richard & Charles, 2013; Richard et al., 2007), and is recommended by researchers as a measure that attributes equal weights to all racial categories without skewing the distribution in the favor of any category (Harrison & Klein, 2007; Richard et al., 2007). In our sample, UMG racial diversity encompasses five racial categories (e.g. Caucasian, African-American, Hispanic, Asian, and American-Indian) and thus the index theoretically ranges from 0 to 1, with an index of 0 reflecting racial homogeneity (only one racial category represented) and an index of 1 reflecting racial heterogeneity (all racial categories equally represented). The index is calculated at the upper management level, as $1 - \sum_{i=1}^{5} P_i^2$ where P_i represents the proportion of upper management members in each racial category *i*. The minimum value for UMG racial diversity in our sample is 0 and the maximum is 0.67 with a mean of 0.34. The average group ranges from 3 to 32 with a mean of 9.73.

CEO Regulatory Focus

Following recent research in management (Gamache et al., 2015; Johnson, Chang, Meyer, Lanaj, & Way, 2013), we use content analysis of letters to shareholders for the firms in our data set for the fiscal years 2006-2011. Compared to interviews, this approach is more appropriate considering that individuals are not fully aware of their regulatory focus (Uhlmann et al., 2012). However, individuals' regulatory focus is reflected in an individual's language (Johnson & Steinman, 2009) and therefore can be captured by analyzing the content of that individual's written communication. The advantage of analyzing letters to shareholders is that they represent a consistent form of communication used by CEOs (Duriau, Reger, & Pfarrer, 2007), are non-intrusive and publicly available (Eggers & Kaplan, 2009). These letters are also highly relevant for CEOs' communication as it has been shown that CEOs are highly involved in wording the letters (Eggers & Kaplan, 2009; Kaplan, 2008).

In this study, we use the GATE Platform to automatically track promotion and prevention characteristics that define CEO regulatory focus (Cunningham, Maynard, Bontcheva, & Tablan, 2002; Vlas & Robinson, 2012). The tool allows users to create dictionaries based on words' ontological family or to work with built-in dictionaries (Vlas & Robinson, 2012). Using Gamache et al. (2015) regulatory focus words listed in Table 3.2, we develop a dictionary that includes all synonyms, alternate tenses, and alternate parts of speech.

Table 3.2 Regulatory focus words* (from Gamache et al., 2015)

Promotion Words	**Prevention words**
Accomplish	Accuracy
Achieve	Afraid
Advancement	Careful
Aspiration	Anxious
Aspire	Avoid
Attain	Conservative
Desire	Defend
Earn	Duty
Expand	Escape
Gain	Escaping
Grow	Evade
Hope	Fail
Hoping	Fear
Ideal	Loss
Improve	Obligation
Increase	Ought
Momentum	Pain
Obtain	Prevent
Optimistic	Protect
Progress	Responsible
Promoting	Risk
Promotion	Safety
Speed	Security
Swift	Threat
Toward	Vigilance
Velocity	
Wish	

*Alternative tenses and parts of speech are included in our dictionary.

Using this created dictionary, we run GATE and identify the number of promotion and prevention words in each letter. We then use these counts when computing the CEO regulatory focus variable as the ratio of the difference between the number of promotion and prevention words and firm size. The operationalization weights the word frequency with firm size (as reflected by firm's total assets in millions of U.S. dollars) under the assumption that firm size is directly correlated to the length of letters to shareholders. A positive value of the CEO regulatory focus ratio is characteristic to a CEO that is more promotion focused and a negative value is characteristic to a CEO that is more prevention focused. For our dataset, the CEO regulatory focus variable ranges from -42.88 to 1.19 with a mean of -0.43. This reflects the fact that on average, the CEOs of firms in our dataset are prevention-focused.

$$CEO\ regulatory\ focus = \frac{no.of\ promotion\ words - no.of\ prevention\ words}{firm\ size} \quad (3)$$

Control Variables

In order to minimize possible alternative explanations, we include controls for firms' characteristics, alliance-related, and diversity-related variables as they may significantly correlate with UMG racial diversity. Specifically, we control for firm *previous performance* as reflected in firms' sales growth which is logged because the variable is highly skewed.

We control for firm *size* as reflected in firms' total assets (in billions of dollars) because successful or larger firms have a higher propensity to enter exploratory alliances, tilting the alliance portfolio composition to a more exploratory end (Shan, Walker, & Kogut, 1994).

We control for firm *alliance experience* measured with the total number of alliances formed in the last 5 years (Kogut, 1988) because more experienced firms are more capable to develop and implement knowledge from their alliance partners.

We control for firm *solvency* because it captures the available financial slack resources that might make it easier to explore in alliances.

Given that *UMG gender diversity* has been found to share variation with racial diversity (Richard et al., 2003), we include it as control. We use the same Blau index that we used to compute UMG racial diversity to measure UMG gender diversity as well.

Finally, we include mills ratios computed in the first stage to control for potential endogeneity. We control for time effects with alliance event year and any remaining heterogeneity with regression fixed effects.

Findings

Table 3.3 details means, standard deviations, the minimum and maximum for all variables. Table 3.4 presents the Pearson correlations between variables. We notice some noticeable correlations. Alliance portfolio composition and firm previous performance are negatively correlated at 45% (β = 0.45). This tells us that, as expected, software and pharma firms that perform better are those keeping exploitative alliance portfolios as opposed to exploratory alliance portfolios. Alliance portfolio composition is positively correlated with firm alliance experience (β = 0.42), suggesting that in our dataset, firms with more alliance experience keep more exploratory alliance portfolios. Also, as expected and predicted by previous literature (Richard et al., 2003), UMG gender and racial diversity indices are correlated (β = 0.58). For this reason, we replicate the regression tests using UMG gender diversity and find consistent results

Table 3.3 Descriptive statistics.

Variables	Mean	*s.d.*	Min	Max
1 Alliance portfolio composition	0.504	0.368	0	1
2 UMG racial diversity	0.342	0.154	0	0.672
3 CEO regulatory focus	-0.433	2.473	-42.88	1.199
4 Previous performance(ln)	0.394	3.443	-8.70	9.254
5 Firm size (mil $)	20.97	46.46	0.005	275.64
6 Alliance experience	9.117	14.07	1	152
7 Form solvency (thousands)	0.295	3.903	0	69.66
8 UMG gender diversity	0.358	0.124	0.142	0.5
9 λ Exploration	1.356	0.327	0.678	2.19
10 Exploration propensity	0.574	0.495	0	1
11 Firm productivity	426.1	320.9	1.176	1987.35
12 Firm age (ln)	3.148	0.756	1.098	4.905
13 R&D intensity [a]	0.691	0.462	0	1
14 Patenting experience [a]	0.879	0.326	0	1
15 Joint venture experience [a]	0.105	0.307	0	1
16 Acquisition experience [a]	0.347	0.476	0	1
17 UMG average age [a]	0.537	0.499	0	1
18 UMG size [a]	0.368	0.483	0	1
19 CEO duality	0.374	0.485	0	1
20 2008 effect [a]	0.673	0.469	0	1

N = 331

[a] dummy variable

Table 3.4 Pearson correlations.

Variables	1	2	3	4	5	6	7	8
1 Alliance portfolio composition								
2 UMG racial diversity	**0.28**							
3 CEO regulatory focus	**-0.12**	**-0.17**						
4 Previous performance(ln)	**-0.45**	**-0.20**	0.03					
5 Firm size (mil $)	-0.06	-0.00	0.07	**0.18**				
6 Alliance experience	**0.11**	-0.09	0.06	0.00	**0.42**			
7 Firm solvency (000)	-0.07	-0.02	-0.03	-0.02	-0.03	-0.04		
8 UMG gender diversity	**0.39**	**0.58**	**-0.15**	**-0.35**	0.01	-0.05	-0.04	
9 λ Exploration	**-0.45**	**-0.18**	-0.05	**0.64**	**-0.12**	**-0.29**	0.03	**-0.28**

p < 0.05 for correlations in bold; two-tailed test

Table 3.5 presents the Heckman first stage results were firms' exploratory propensity is regressed on firm performance (sales productivity), age (logged), R&D intensity, patenting experience, joint venture experience, acquisition experience, UMG average age, UMG size, CEO duality, 2008 effect, and year effects. The random effects probit regression reports a highly significant Wald chi-square of 32.12 ($p < 0.001$) and a log-likelihood of -801.20.

Table 3.5 First stage regression results.

Variables	Exploration propensity Model 1
Intercept	-1.651 ***
	(0.44)
Year fixed effects	Included
Firm productivity	0.0001 †
	(0.00)
Firm age (ln)	0.146
	(0.15)
R&D intensity [a]	0.466 **
	(0.18)
Patenting experience [a]	0.204
	(0.14)
Joint venture experience [a]	0.422
	(0.26)
Acquisition experience [a]	*0.305* *
	(0.15)
UMG average age [a]	0.196
	(0.17)
UMG size [a]	*-0.235*
	(0.20)
CEO duality	*-0.152*
	(0.18)
2008 effect [a]	-0.452 **
	(0.15)
Observations	1673
Walk-chi2	32.12 ***
LL	-801.20

Random effects probit regression
Standard errors in parentheses
[a] dummy variable
†$p < 0.1$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Table 3.6 shows the results of panel fixed effects regression. We start with the baseline model with control variables only. Table 3.6 Model 1 and Figure 3.1 are both used to test Hypothesis 1 discussing the J-shape effect between racial diversity and alliance portfolio composition. Hypothesis 1 proposes that as a result of high elaboration, low categorization processes allowing for social contact opportunities, very heterogeneous UMGs tend to keep more exploratory alliance portfolios compared to homogeneous UMGs which in turn tend to keep more exploratory alliance portfolios compared to moderately racially diverse UMGs. Model 1 confirms a curvilinear effect ($\beta_{UMG\ racial\ diversity} = -2.414$, $p = 0.015$ and $\beta_{UMG\ racial\ diversity\ squared} = 3.287$, $p = 0.019$). The model shows an improvement of the baseline model R-square of 2.78%.

Table 3.6 UMG racial diversity J-shape and (in)congruence effects on alliance portfolio composition.

	Alliance portfolio composition			
Variables	**Base model**	**Model 1**	**Model 2**	**Model 3**
Intercept	0.365 *	0.730 ***	0.514 **	0.098
	(0.16)	*(0.22)*	*(0.18)*	*(0.262)*
UMG racial diversity (RD)		-2.414 *	-0.129	-1.930 *
		(0.98)	*(0.17)*	*(0.868)*
CEO regulatory focus (RF)			-0.093 †	-0.184 **
			(0.05)	(0.068)
RD^2		3.287 *		3.164 *
		(1.38)		*(1.393)*
RD × RF				0.945 *
				(0.40)
RF^2				0.062 *
				(0.02)
Control variables				
Previous performance (ln)	0.001	0.001	0.001	0.002
	(0.01)	*(0.01)*	*(0.01)*	*(0.01)*
Firm size	-0.000	-0.000	-0.000	-0.000
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
Alliance experience	*-0.001*	*-0.001*	*-0.001*	*-0.001*
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
Firm solvency	-0.000	-0.000	-0.000	0.000
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
UMG gender diversity	0.614 *	0.643 *	0.633 *	0.616 *
	(0.27)	*(0.27)*	*(0.27)*	*(0.26)*
λ exploration	-0.023	-0.038	-0.022	-0.040
	(0.10)	*(0.10)*	*(0.10)*	*(0.10)*
Year fixed effects	Included	Included	Included	Included
Congruence line				
Slope				-2.10 *
Curvature				4.18 **
Incongruence line				
Slope				-1.73 *
Curvature				2.28
R^2	3.62%	6.40%	5.10%	10.60%
ΔR^2		2.78%	1.48%	6.98%
VIF	3.68	3.99	3.81	7.04

N: 331
Standard errors in parentheses
λ represents the inverse Mills ratio
†$p < 0.1$
*$p < 0.05$
**$p < 0.01$
***$p < 0.001$

However, to investigate a possible J-shape effect, both the regression results as detailed above and graphical representation must be investigated. In terms of graphical representation, we start by computing the alliance portfolio composition index ($\hat{Y}$) for the minimum, mean, and maximum values of UMG racial diversity using the formula below.

$$\hat{Y} = b_0 + b_1 \cdot X_1 + b_2 \cdot X_1^2 + b_i \cdot K_i \qquad (4)$$

with X_1 representing racial diversity, X_2 representing racial diversity squared, and K_i is a vector of control variables. We find that homogeneous UMGs have an alliance portfolio composition index of 0.32 which is lower than the alliance portfolio composition index of 0.68 of heterogeneous UMGs but higher than the alliance portfolio composition index of 0.18 of moderately diverse UMGs. Since the mean of the alliance portfolio composition index is 0.504, moderately diverse UMGs (index = 0.41) have the lowest proclivity for exploratory alliances compared to heterogeneous UMGs (index = 0.86) and homogeneous UMGs (index = 0.72). The graphical representation in Figure 3.1 endorses the regression results. Hypothesis 1 is supported.

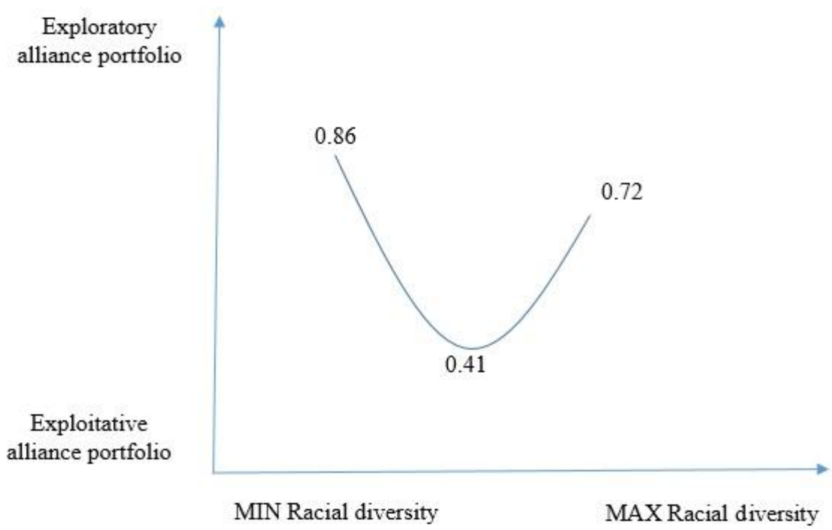

Figure 3.1 Graphical representation and check for the hypothesized J-shape effect.

For the purpose of testing Hypotheses 2 and 3, we first run the polynomial regression as detailed in Table 3.6 Models 2 and 3. Model 2 considers the simultaneous linear direct effects of UMG racial diversity and CEO regulatory focus. Model 3 reports the full polynomial regression results that include the linear, quadratic, and interactive terms of both UMG racial diversity and CEO regulatory focus (Cohen, Nahum-Shani, & Doveh, 2010; Richard et al., 2017). Table 3.6 Model 3 shows the unstandardized coefficients and the slopes and curvatures along the congruence line (running from the nearest front to the farthest back corners of the plane) and incongruence line (running from the left to the right corners of the plane). As displayed, the linear terms of both UMG racial diversity and CEO regulatory focus are negative and significant along with positive and significant quadratic terms ($\beta_{\textit{UMG racial diversity}}$ = -1.93, p = 0.027 and $\beta_{\textit{UMG racial diversity squared}}$ = 3.164, p = 0.024 and $\beta_{\textit{CEO}\text{ regulatory focus}}$ = -0.184, p = 0.008 and $\beta_{\textit{CEO}\text{ regulatory focus squared}}$ = 0.062, p = 0.018). The interactive term reported is positive and significant ($\beta_{\textit{UMG racial diversity x CEO regulatory focus}}$ = 0.946, p = 0.019). Further, we analyze the congruence and incongruence effects based on the slopes and curvatures reported in Model 3.

Hypothesis 2 proposes that congruence at low levels of both UMG racial diversity and CEO regulatory focus leads to a higher propensity to maintain exploratory alliance portfolios as opposed to the congruence at high levels of both variables. As shown in Table 3.6 Model 3, the slope along the congruence line (RD = RF) is negative and significant (slope test statistic = -2.10, $p < 0.05$). This tells us that low UMG racial diversity – low CEO regulatory focus congruence results in a higher preference for exploratory alliance portfolios relative to high UMG racial diversity – high CEO regulatory focus congruence. In Figure 3.2, the response surface corresponding to the congruence line (running from the nearest front to the farthest back corners of the plane) is higher in the front (low-low congruence) than in the back (high-high congruence). Additionally, the positive and significant curvature reported in Table 3.6 Model 3 (curvature test statistic = 4.10, $p < 0.01$) confirms that the response surface is upward curved (convex). As the preference for exploratory alliance portfolios rises with lower average levels of diversity – regulatory focus congruence, it does so at an increasing rate. We conclude that Hypothesis 2 is supported.

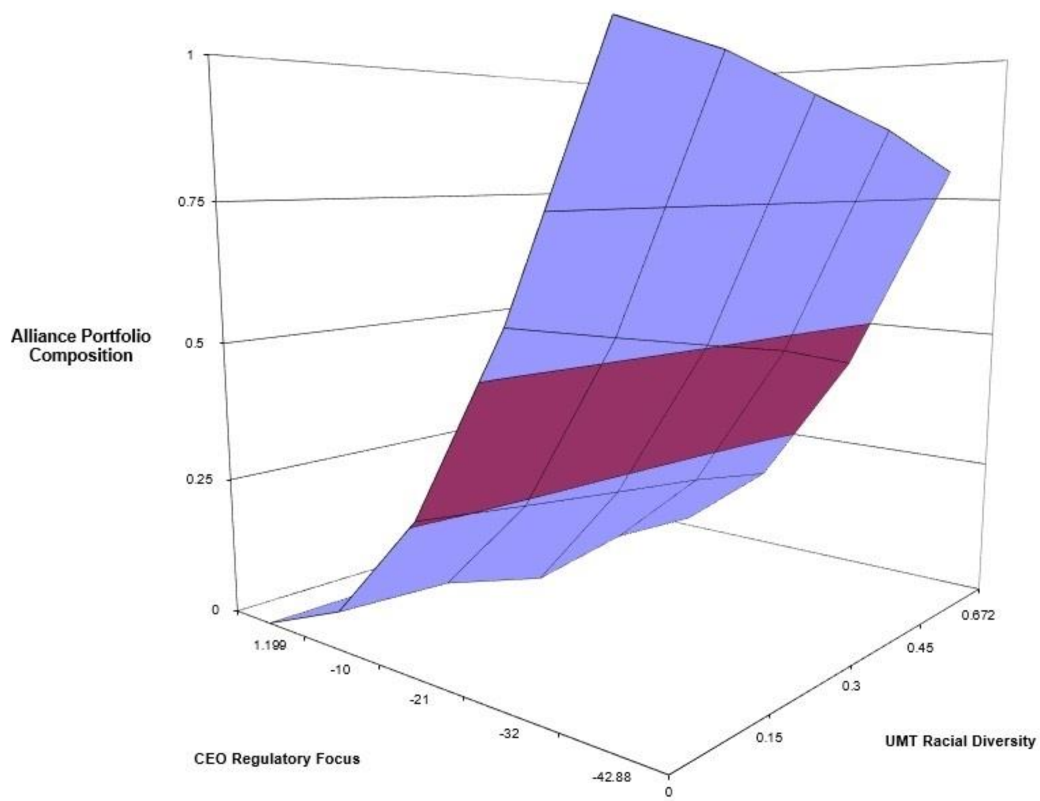

Figure 3.2 The UMG racial diversity – CEO regulatory focus congruence and incongruence effects on alliance portfolio composition.

Hypothesis 3 predicts a higher preference for exploratory alliance portfolios for high UMG racial diversity – low CEO regulatory focus incongruence than for low UMG racial diversity – high CEO regulatory focus incongruence. As shown in Table 3.6 Model

3, the slope along the incongruence line (RD = - RF) is negative and significant (slope test statistic= -1.73, $p < 0.05$). In Figure 3.2, the response surface corresponding to the incongruence line (running from the left to the right corners of the plane) is higher on the right (high – low incongruence) than on the left (low – high incongruence). Concluding, high UMG racial diversity – low CEO regulatory focus incongruence leads to a higher preference for exploratory alliance portfolios compared to the low UMG racial diversity – high CEO regulatory focus incongruence. Hypothesis 3 is supported. For robustness, given that racial and gender characteristics share a great portion of variance, we test our hypotheses using UMG gender diversity and find consistent results.

Table 3.7 Robustness results using UMG gender diversity.

	Alliance portfolio composition			
Variables	**Base model**	**Model 1**	**Model 2**	**Model 3**
Intercept	0.584 ***	0.505 **	0.800 ***	0.937 **
	(0.16)	*(0.16)*	*(0.18)*	*(0.34)*
UMG gender diversity (GD)		1.349 ***	-0.635 *	1.301 ***
		(0.36)	*(0.26)*	*(0.36)*
CEO regulatory focus (RF)			-0.096 †	-0.172 *
			(0.05)	(0.06)
GD^2		6.537 **		6.349 **
		(2.26)		*(2.23)*
GD × RF				0.857 *
				(0.40)
RF^2				0.066 *
				(0.02)
Control variables				
Previous performance (ln)	0.005	-0.001	0.001	-0.001
	(0.01)	*(0.01)*	*(0.01)*	*(0.01)*
Firm size	-0.000	-0.000	-0.000	-0.000
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
Alliance experience	*-0.001*	*0.000*	*-0.001*	*0.000*
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
Firm solvency	0.000	0.000	-0.000	0.000
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
UMG racial diversity	-0.109 *	-0.152	0.126	1.964 *
	(0.18)	*(0.17)*	*(0.17)*	*(0.86)*
λ exploration	-0.008	0.000	-0.034	-0.001
	(0.10)	*(0.10)*	*(0.09)*	*(0.09)*
Year fixed effects	Included	Included	Included	Included
Congruence line				
Slope				1.13 **
Curvature				7.27 ***
Incongruence line				
Slope				1.47 ***
Curvature				5.56 *
R^2	1.40%	7.60%	4.46%	11.83%
ΔR^2		6.20%	3.06%	10.43%
VIF	3.15	3.61	2.80	6.66

N: 331
Standard errors in parentheses
λ represents the inverse Mills ratio
†$p < 0.1$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Discussion

Contributions

Our study claims three important contributions to existing theory and research. First, grounded in the social categorization (Tajfel & Turner, 1986; Turner et al., 1987) and information elaboration research (Harrison & Klein, 2007; Thomas & Ely, 1996; van Knippenberg et al., 2004) and social contact (Blau, 1977), we contribute to diversity research by theorizing an innovative J-shape effect of UMG racial diversity on firms' alliance portfolio composition. This level of detail enriches scholars understanding of the effects of racial diversity and is important both for diversity research and alliance research since the exact effects of UMG racial diversity on macro level decision making are still unclear (Andrevski et al., 2014; Richard et al., 2017). By building on the CEM model (van Knippenberg et al., 2004) and on the social contact mechanisms (Blau, 1977; De Dreu et al., 2008), our study offers additional guidance into how micro level research may be usefully and meaningfully integrated with firms' strategic decision making.

Second, this study's findings extend recent research on the role of CEOs' motivational attributes in firms' strategic decision making (Gamache et al., 2015). We specifically investigate CEO regulatory focus as a key dimension that explains firms' strategic decision making (Higgins, 1998; Higgins & Spiegel, 2004; Scholer & Higgins, 2008). We propose a new operationalization for CEO regulatory focus as a difference between the promotion and prevention foci, thus taking into account the real possibility that an individual possesses both motivational characteristics simultaneously but in different degrees (Dimotakis et al., 2012; Lanaj et al., 2012). Using this proposed conceptualization, we investigate how matching and mismatching levels between the racial diversity in the UMG and the CEO regulatory focus—recently coined by Richard et al. (2017) as congruence and incongruence effects—may be decisive in firms' alliance decision making. Third, grounded in the CEM model (van Knippenberg et al., 2004) and regulatory focus theory (Higgins, 1998), and tested using 2-stage regression, polynomial regression and response surface techniques (Edwards, 1994, 2007; Edwards & Parry, 1993; Heckman, 1979; Shanock et al., 2010), we investigate congruence and incongruence effects between different levels of UMG racial diversity and CEO regulatory focus. By adopting the view that cohesion and opportunities for social contact are more important for individuals than access to information (Richard et al., 2017), we predict a higher exploratory tendency when congruence and incongruence happens at low UMG racial diversity compared to high UMG racial diversity. Findings are robust and show that congruence at low levels of racial diversity leads to a more exploratory alliance portfolio composition compared to congruence at high levels of UMG racial diversity. Interesting enough, incongruence at high levels of UMG racial diversity leads to a more exploratory alliance portfolio composition compared to incongruence at low levels of UMG racial diversity.

Limitations and Future Research

There are three noteworthy limitations to this study that open the way to interesting future research for the field of diversity in particular and strategic management in general. First, the current study focuses on the impact of UMG racial diversity on firms' alliance strategic decisions. However, it has been shown that racial and gender diversity share a high degree of variance (Richard et al., 2004). To provide a more complete testing of theory, future research may consider the interplay of racial diversity and other demographic characteristics such as gender or age. In this study, we retested our models using UMG gender diversity and found broadly robust results confirming that results hold across demographic characteristics.

Second, given the international nature of alliance partnerships especially in high velocity engineering-based industries such as software and pharmaceuticals, another interesting avenue for future research may be the investigation of the determinants of alliance portfolio composition for firms emerging from transition economies (Yamakawa, Khavul, Peng, & Deeds, 2013; Zoogah & Peng, 2011). In this stream of research, scholars have highlighted the existence of significant differences in institutional influences and behavior between firms in developed and firms in emerging countries (Yamakawa, Peng, & Deeds, 2015; Zoogah, Vora, Richard, & Peng, 2011). Such research has the potential to enrich the strategic alliance literature by cross-fertilizing it with concepts from institutional theory.

Third, it would be theoretically arousing and methodologically challenging to have a mediating factor explaining the mechanism that leads UMG racial diversity to affect the composition of firms' alliance portfolio. Scholars have shown relevant effects by investigating a number of such mediators including competitive intensity (Andrevski et al., 2014). While measuring the alliance formation underlying processes was outside the scope of the current study, future research may consider quantifying the more proximal effects of social contact, social categorization, and information elaboration as the vital links accounting for diversity effects.

Conclusion

Our study endeavors to explore the direction and the degree to which UMG racial diversity and CEO regulatory focus affect firms' alliance portfolio composition. To investigate firms' alliance decision making, we draw on categorization-elaboration, social contact, and regulatory focus mechanisms. Relevant diversity research allows us to theorize a novel J-shaped relationship between UMG racial diversity and the composition of firms' alliance portfolio for which we find a strong support. Further, by leveraging the recently proposed racial diversity congruence concept and regulatory focus theory mechanisms, we posit that, contrary to expectations, while congruence at low levels of UMG racial diversity lead firms into more exploratory alliance endeavors, incongruence at low levels of UMG racial diversity lead firms into more exploitative alliance endeavors. The study encourages scholars to further investigate the different weights that social categorization, information elaboration, social contact, and individual personality characteristics exercise on UMG diversity, further being elemental in firms' alliance decision making.

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Zoogah, D. B., Vora, D., Richard, O., & Peng, M. W. (2011). Strategic alliance team diversity, coordination, and effectiveness. *International Journal of Human Resource Management, 22*(3), 510-529.

BIOGRAPHICAL SKETCH

Cristina O. Vlas is a PhD candidate of International Management Studies in the Department of Organizations, Strategy, and International Management at the Naveen Jindal School of Management, the University of Texas at Dallas. She holds a Master in Business Administration degree from the University of Nebraska at Omaha and a Bachelor of Science degree from the Academy of Economic Studies, Bucharest, Romania. Cristina's research interests lie mainly in the areas of innovation, entrepreneurship, and international business. Her research focuses on the antecedents, moderators, and consequences of organizational innovation in knowledge-intensive firms through the lenses of organizational learning, resource-based and knowledge-based perspectives, and dynamic capabilities. Cristina has an impressive number of papers presented and a number of awards won at prominent conferences. She has published papers in journals such as Entrepreneurship Theory and Practice and Strategic Organization. Cristina has taught Strategic Management and International Business courses at the University of Texas at Dallas for which she received the highest student evaluations in her department. Starting Fall 2018, she will serve as Assistant Professor of Management at the University of Massachusetts Amherst.

CURRICULUM VITAE

EDUCATIONAL HISTORY

Doctor of Philosophy in International Management Studies August 2018 (expected)
The University of Texas at Dallas, Richardson, Texas
Major: Strategic Management | Minor: Organization Theory
Dissertation: *Antecedents, Moderators, and Outcomes of Internal Innovation*
Chair: Mike W. Peng | Co-chair: Emily W. Choi
Committee members: Toyah Miller, Orlando Richard
Proposal defense date: May 2016

Master in Business Administration May 2006
The University of Nebraska at Omaha, Omaha, Nebraska
Major: General Management

Bachelor of Science June 2001
The Academy of Economic Studies, Bucharest, Romania
Major: Marketing

RESEARCH INTERESTS

Research Stream 1: Strategy (resource-based view, dynamic capabilities, knowledge-based view)

Research Stream 2: Entrepreneurship and innovation (innovation in alliances, knowledge transfer, learning, exploration/exploitation, soft power, open source projects' attractiveness)

Research Stream 3: International business (emerging markets, institution-based perspective)

ARTICLES PUBLISHED IN SCHOLARLY JOURNALS

Peng, MW, Sun, W, **Vlas, C**, Minichilli, A, and Corbetta, G (2018) "An institution-based view of large family firms: A recap and overview" *Entrepreneurship Theory and Practice*, vol. 42, issue 2, pp: 187-205.

Peng, MW and **Vlas, C** (2017) "Diffusion of a twentieth-century innovation" *Academy of Strategic Management Journal*, vol. 16, issue 1, pp: 172-174.

Yuan, C, Li, Y, **Vlas, C**, and Peng, MW (2017) "Dynamic capabilities, subnational environment, and university technology transfer" *Strategic Organization*, vol. 16, issue 1, pp: 35-60.

Vlas, R and **Vlas, C** (2016) "The role of internal and network constraints on alliance ambidexterity decisions in technology-intensive industries" *Asia Pacific Journal of Information Systems*, vol. 26, issue 2, pp: 299-321.

ARTICLES UNDER REVIEW

Vlas, C, Choi, EW, and Peng, MW "Patenting velocity and patterns in market signaling" *Organization Science* (review and resubmit)

Peng, MW, Lebedev, S, **Vlas, C**, Wang, J, and Shay, J "The growth of the firm in (and out of) emerging economies" *Asia Pacific Journal of Management* (review and resubmit)

Vlas, R, Robinson, W, and **Vlas, C** "The effects of new requirements engineering factors on open source attractiveness" *Journal of Management Information Systems* (under first round of review)

PAPERS UNDER DEVELOPMENT

Vlas, C, Peng, MW, and Choi, EW "Balanced sourcing portfolios, stiff slack, and dynamic capabilities" In preparation for submission to *Strategic Management Journal* (dissertation paper; final preparation stage – 42 pages)

Vlas, C and Richard, O "Racial diversity, regulatory focus, and alliance portfolio composition" In preparation for submission to *Strategic Entrepreneurship Journal* (dissertation paper; final analysis stage – 42 pages)

Vlas, C, Su, W, and Richard, O "Racial and gender diversity: Independent and joint effects on organizational innovation and firm performance" In preparation for submission to *Strategic Management Journal* (final preparation stage – 30 pages)

Vlas, C "Soft power and entrepreneurial growth" Targeted for *Journal of Small Business Management* (theoretical paper; final preparation stage – 24 pages)

Vlas, C and Vlas, R "The impact of CEO self-monitoring on new ventures' performance" Targeted for *Entrepreneurship Theory and Practice* (preparing data stage)

Vlas, C "When institutions collide: Innovation in alliances under institutional relatedness and knowledge ambiguity" Targeted for *Journal of World Business* (preparing data stage)

Vlas, C and Vlas, R "Ambiguity and innovation in alliance partnerships" Targeted for *Research Policy* (preparing data stage)

Vlas, C "Entrepreneurs' personality, managerial discretion, and new ventures' strategic change" Targeted for *Strategic Entrepreneurship Journal* (preparing data stage)

Kemp, A, **Vlas C,** and Vlas, R "The effects of CEO shame-proneness and guilt-proneness on financial misrepresentation" Targeted for *Strategic Management Journal* (preparing data stage)

Vlas, C and Peng, MW "Learning and knowledge transfer in (and out of) emerging economies" In preparation for submission to *Asia Pacific Journal of Management* (invited—theoretical framing stage)

CONFERENCE PRESENTATIONS

Academy of Management Conference, Chicago, IL August 2018
Vlas, C "CEO's personality, managerial discretion, and strategic change"

Academy of Management Conference, Chicago, IL August 2018
Vlas, C "TMT diversity and CEO regulatory focus as determinants of alliance portfolio composition"

Strategic Management Society Conference, Houston, TX September 2017
Vlas, C "Beyond two shades of grey: The contradictory effects of recoverable slack in balanced portfolios"

Academy of Management Conference, Atlanta, GA August 2017
Vlas, C "Slack and sourcing: A dynamic capabilities perspective"

Hawaii International Conference on Systems Sciences January 2017
Vlas, R, Robinson, W, and **Vlas, C** "Evolutionary software requirements factors and their effect on open source project attractiveness"
BEST PAPER NOMINEE (OST TRACK)

Strategic Management Society Conference, Berlin, Germany September 2016
Vlas, C "Risky decision making: The role of top management team's diversity, self-monitoring, and interdependence"
BEST CONFERENCE PAPER NOMINEE

Academy of Management Conference, Anaheim, CA August 2016
Vlas, C "Patenting velocity and patterns in market signaling"
BEST PAPER FINALIST TIM DIVISION

Academy of Management Conference, Anaheim, CA August 2016
Vlas, C "Mode focus versus mode ambidexterity: Solving a dilemma"

Theories of Family Enterprise Conference, Alberta, Canada May 2016
Peng, MW, Sun, W, and **Vlas, C** "An institution-based view of family ownership and control in large firms"

Southwest Academy of Management Conference, Oklahoma City, OK March 2016
Vlas, C "Soft power and entrepreneurial growth"
BEST CONFERENCE PAPER FINALIST

Southwest Academy of Management Conference, Oklahoma City, OK March 2016
Vlas, C "Mode focus as the preferred choice: A niche theory approach"

Southwest Academy of Management Conference, Oklahoma City, OK March 2016
Vlas, C "A conceptual perspective on alliance exploration: Extracting the benefits of diversity, self-monitoring, and interdependence in top management teams"

Strategic Management Society Conference, Denver, CO October 2015
Vlas, C "The internal coexistence of high velocity innovation and diversification: A moderation model"

Eastern Academy of Management International Conference, Lima, Peru June 2015
Vlas, C, and Vlas, R "Balancing internal and network constraints in alliance ambidexterity decisions"

Eastern Academy of Management International Conference, Lima, Peru June 2015
Vlas, C, Nguyen, H, and Vlas, R "A theoretical explanation of out-group versus in-group perspectives on the dynamics of team effectiveness"

ASE/IEEE Conference on Privacy, Security, Risk, and Trust, Washington, DC August 2013
Yang, A, Vlas, R, Yang, A, and **Vlas, C** "Risk management in the era of BYOD"

Innovation Conference on Automation and Robotics, Houston, TX October 2012
Vlas, R and **Vlas, C** "A multi-dimensional analysis of technological innovation in the context of U.S. social networking patents"

Americas Conference on Information Systems, Detroit, MI August 2011
Vlas, R, Robinson, W, and **Vlas, C** "A requirements-based analysis of success in open-source software development projects"

Midwest Association for Information Systems Conference, Omaha, NE March 2011
Vlas, R and **Vlas, C** "A threefold user-based software evaluation framework"

TEACHING INTERESTS

I teach most subjects within the strategy and management domains, including:

- Strategic Management
- Global Business/International Business
- Entrepreneurship Fundamentals
- Entrepreneurial Business Development
- Social Entrepreneurship
- Technology and Innovation Management
- Organization Theory
- Cross-cultural Management
- Diversity Issues in Management

TEACHING EXPERIENCE

The University of Texas at Dallas

BPS 4305 – Strategic Management Fall 2017
Undergraduate level capstone course
Evaluation ratings 4.69 out of 5; 35 students enrolled

BPS 4305 – Strategic Management — Fall 2015
Undergraduate level capstone course
Evaluation ratings 4.83 out of 5; 46 students enrolled

IMS 3310 – International Business — Summer 2014
Undergraduate level capstone course
Evaluation ratings 4.81 out of 5; 43 students enrolled

Teaching Assistant – The University of Texas at Dallas — Fall 2013 – Spring 2016
Strategic Management, International Business, Entrepreneurship,
Corporate Finance, Information Technology Strategy and Management

The University of Nebraska at Omaha
MKT 3310 – Principles of Marketing — Fall 2004 – Spring 2006
Undergraduate level capstone course
Led the laboratory section

The Academy of Economic Studies, Bucharest, Romania
MKT – Statistical Analysis Techniques — Fall 2001 – Spring 2002
Undergraduate level core course
Led the laboratory section

ACADEMIC AND PROFESSIONAL SERVICE

Reviewing activities

- Reviewer for *Strategic Organization*
- Reviewer for *Academy of Strategic Management Journal*
- Reviewer for *Journal of Entrepreneurship Education*
- Reviewer for *Asia-Pacific Journal of Information Systems*
- Reviewer for Academy of Management Conference (AOM)
- Reviewer for Eastern Academy of Management International Conference (EAM-I)
- Reviewer for Southwest Academy of Management Conference (SWAM)
- Reviewer for International Conference on Information Systems (ICIS)
- Reviewer for Americas Conference on Information Systems (AMCIS)
- Reviewer for Southern Association for Information Systems Conference (SAIS)

Program ranking and development

Closely worked with the Innovation and Entrepreneurship Program Director Madison Pedigo (see reference) on the following tasks related to the Program's Growth, Retention, and Ranking:

- Reviewed course descriptions
- Assessed opportunities for course cross-listings
- Assessed competing programs' performance on the Princeton Review's undergraduate- and graduate-level program ranking metrics
- Developed and maintained a comprehensive database of UT Dallas' startups and business founders

- Outcomes:
  - 2013 – UT Dallas was not ranked among Top 25 Entrepreneurial Schools in U.S.
  - 2015 – feedback from the Princeton Review confirms that on 2 out of 3 ranking metrics UT Dallas qualifies to be ranked in Top 25 Entrepreneurial Schools in U.S.
  - 2017 – The graduate innovation and entrepreneurship programs were ranked #22 in Princeton Review's ranking of the "Top Schools for Entrepreneurship Studies for 2017"
  - 2018 – The graduate innovation and entrepreneurship programs were ranked #19 in Princeton Review's ranking of the "Top Schools for Entrepreneurship Studies for 2018"

Conference chairing

Session Chair at the Academy of Management Conference 2016 (session: "Learning")

Academic memberships

Academy of Management (AOM), Academy of International Business (AIB), Strategic Management Society (SMS), INFORMS

Volunteering

Member of the organizing team of the UT Dallas' Business Plan Competition 2015, 2016

Worked with the UT Dallas's Entrepreneurship Program's Assistant Director to develop the program's webpage 2015

Developed the "Ex-Offender's Guide to Rehabilitation" as part of a program managed by Orion-PFM for the successful re-integration of offenders into the society 2006

Helped international students file their taxes as assistant for the federal VITA program 2005, 2006

Developed and conducted marketing analysis for the advancement of the MBA program at The University of Nebraska at Omaha 2005

Auditor for the "95 Viilor Street" Owners Association 2001 – 2004

HONORS AND AWARDS

Academy of Management Annual Meeting

"Above and Beyond the Call of Duty" Reviewer Award 2016

"Patenting velocity and patterns in market signaling"

BEST PAPER FINALIST TIM DIVISION 2016

Strategic Management Society Conference

"Risky decision making: The role of top management team's diversity, self-monitoring, and interdependence"

BEST CONFERENCE PAPER NOMINEE 2016

Southwest Academy of Management Conference

"Soft power and entrepreneurial growth"

BEST CONFERENCE PAPER FINALIST 2016

The University of Texas at Dallas

PhD Scholarship – Jindal School of Management 2013 – 2018

Outstanding Teaching Award – Strategic Management Course 2015

Outstanding Teaching Award – International Management Course 2014

The University of Nebraska at Omaha

MBA Scholarship 2004 – 2006

Business Plan Competition Finalist – 2nd place 2006

Best Performing Team at the Simulation Workshop for Sustainable Decision Making 2005

The Academy of Economic Studies, Bucharest, Romania

Merit-Based Scholarship 1997 – 2001

Special Award for "Commerce – The Foundation of Modern Economies" 2000

Special Award for "The Internet at the Edge between Ignorance and Omniscience" 1999

Special Award for "Foreign investments in Romania" 1998

Special Award of the Efficient Publishing House for winning the *Students With Exceptional Paper Writing Abilities* Competition 1998

INDUSTRY EXPERIENCE

Omnis Prime, LLC. – Houston, TX May 2008 – Present

Business Consultant and Owner

C&D Marketing, Inc. – Atlanta, GA October 2006 – May 2008

Marketing Manager

Marketing and Business Solutions Specialist

New Vision, Inc. – Bucharest, Romania January 2002 – July 2004

Director of Marketing and IT