Fighting the bear and riding the bull:
Exploitation and exploration during times of recession and recovery

The performance implications of the managerial ability to balance exploitation and exploration are becoming increasingly understood. That is, environmental characteristics varying mainly between industries require specific exploitation–exploration distributions for optimal performance. However, less attention has been given to uncovering whether the exploitation–exploration implications and management requirements change within a given industry over time. We conduct longitudinal research in the information technology industry to investigate the existence of such changes. We find that the relative importance of correctly managing exploitation–exploration varies over the course of a recession and recovery. Overall, the results reveal that different phases of the business cycle provide significantly dissimilar contexts for managing exploitation–exploration. For management practice, the results illustrate how firms can effectively manage recessions and recoveries.

Keywords: exploration–exploitation; recession–recovery; longitudinal research design; managerial attention; performance implications
INTRODUCTION

The global economic recession that started in 2007 and lasted for 18 months resulted in the collapse of large financial institutions and caused significant but unexpected contractions in demand, employment, cash flows, and profits (Hall et al., 2010; Srinivasan, Lilien, and Sridhar, 2011; Steenkamp and Fang, 2011). Such a state of affairs is known as a ‘bear market’ (Barsky and Long, 1990). Subsequently, from 2009 until the end of 2010, many markets recovered, investor confidence was restored, and the financial situation of the surviving firms readily improved. Such an upward market trend is known as a ‘bull market’ (Barsky and Long, 1990). The terminology of bear and bull markets comes from the manner in which each animal attacks its opponent: a bear swipes downward, whereas a bull thrusts its horns upward.

In general, firm performance largely depends on the managerial ability to adapt to and exploit changes in the business environment (Helfat et al., 2007; Ocasio, 1997; Teece, Pisano, and Shuen, 1997). To do so, a firm must maintain ecological fitness by reconfiguring its resource base to cope with emerging threats and explore new opportunities, while exploiting existing resources (O’Reilly and Tushman, 2008; Simsek, 2009). As such, companies engaging in both exploitation and exploration may be more resilient to situations of economic turmoil (Raisch et al., 2009; Walrave, Van Oorschot, and Romme, 2011). Several cross-sectional studies suggest a positive link between the strategic division of exploitation–exploration and firm performance (e.g., He and Wong, 2004; Jansen, Van Den Bosch, and Volberda, 2006; Uotila et al., 2009). Moreover, prior research has shown that environmental influences, such as competitiveness, dynamism, and research-and-development (R&D) intensity, affect the most profitable exploitation–exploration distribution (Auh and Menguc, 2005; Jansen et al., 2006; Uotila et al., 2009). These findings indicate the need to tailor exploitation and/or exploration to specific environmental conditions.
Nevertheless, the mainly cross-sectional nature of prior research (i.e., regarding the performance implications of a chosen exploitation–exploration strategy) does not provide an answer to the questions whether and how the exploitation–exploration implications and management requirements change within a given industry over time (Raisch et al., 2009). A recession and subsequent recovery, due to their opposing macroeconomic indicators, are likely to present management teams with different exploitation–exploration challenges (Lamey et al., 2007; Steenkamp and Fang, 2011). As such, in this paper we investigate how the exploitation–exploration implications and management requirements differ between periods of recession and recovery, within the context of a single industry.

The bear and bull markets of the most recent business cycle constitute a natural experiment. We adopt a longitudinal research approach, which involves system generalized methods of moments (GMM) estimation on a panel data set of 105 firms in the information technology (IT) industry during the 2007–2010 period. Overall, the results indicate that the implications and management requirements of the exploitation–exploration approach within the same industry context strongly depend on the phase of the business cycle (i.e., the relative importance of the exploitation–exploration strategy differs over time). This constitutes our main theoretical contribution to the exploitation–exploration literature and extends previous studies in this field (e.g., He and Wong, 2004; Jansen et al., 2006; Uotila et al., 2009). The findings also provide valuable guidelines for managerial practice in this area, most notably, regarding how to effectively handle bear and bull markets by means of exploitation and/or exploration initiatives.

In the next sections, we review the literature and develop several hypotheses. Then, we describe the research method and present the main empirical findings. Finally, we discuss the
theoretical contributions and managerial implications of our findings, after which we present issues for further research.

THEORETICAL BACKGROUND

The choices senior executives make about which issues to pay attention to have profound implications for the strategic direction of the firm (Bouquet and Birkinshaw, 2008). The underlying theoretical perspective—the attention-based view—provides an increasingly important lens into organizational decision making (Ocasio, 1997, 2011), which we adopt in this study. Top executives play a decisive role in establishing a supportive context for managing the tension between exploitation and exploration (Gibson and Birkinshaw, 2004; Jansen et al., 2008; Smith and Tushman, 2005). For example, these managers have the power to prevent short-term performance pressures, salient to lower-level managers, from overwhelming the need for more explorative developments (Adler, Goldoftas, and Levine, 1999). Sidhu, Volberda, and Commandeur (2004) provide empirical evidence that managerial attention significantly influences an organization’s explorative orientation. As such, the allocation of managerial attention to matters (e.g., exploitation–exploration) is often used to explain firm behavior (e.g., Barnett, 2008; Bouquet and Birkinshaw, 2008; Gavetti et al., 2012).

Managerial attention to exploitation helps a firm reduce its knowledge variety, increase its efficiency, and, therefore, generate profits in the short run (March, 1991). Exploitation, in a broad sense, captures things such as ‘refine, choice, production, efficiency, selection, implementation, and execution’ (March, 1991, p. 71). In contrast, attention to exploration serves to gather and develop firm knowledge that is different from the current knowledge base (Lavie, Stettner, and Tushman, 2010). As such, executives focused on exploration can enhance their firm’s adaptability by developing new knowledge (March, 1991). Exploration is characterized by
‘search, variation, risk taking, experimentation, play, flexibility, discovery, and innovation’ (March, 1991, p. 71).

Prior research treats the exploitation–exploration relationship in two distinct ways: either as a zero-sum game (e.g., March, 1991; Uotila et al., 2009; Walrave et al., 2011) or as two fundamentally different orthogonal aspects (e.g., He and Wong, 2004; Katila and Ahuja, 2002; Rothaermel, 2001). Gupta, Smith, and Shalley (2006) suggest that the correct choice depends on the level of analysis. In this respect, although large and resource-rich organizations are ideally able to conduct both activities in parallel (i.e., orthogonal perspective), this is not necessarily the case at the individual level. For example, Amabile (1996) suggests that a focus on creativity and experimentation (i.e., exploration) requires a different mind-set than attention to short-term rewards (i.e., exploitation). Thus, at the individual level, ‘withdrawal from some things [is necessary] in order to deal effectively with others’ (James, 1890, p. 404). As such, Gupta et al. (2006) conclude that at the individual or subsystem level (e.g., executive team), exploration and exploitation are mutually exclusive. Given our focus at the managerial level, and in line with March’s (1991) original characterization, we consider exploitation–exploration two ends of the same continuum (i.e., the exploitation–exploitation ratio).

The managerial failure to achieve a sound exploitation–exploration ratio can have destructive consequences for firm performance. On the one hand, excessive attention to exploration can be extremely costly because the outcomes of the belonging investments are highly uncertain. Moreover, such emphasis can result in the so-called failure trap (Levinthal and March, 1993; March, 1991). On the other hand, a strong focus on exploitation can result in relatively certain returns, but it also discourages more radical learning, inhibiting the sustained
development of a competitive advantage (Barney, 1991). Furthermore, a too-strong focus on exploitation can easily result in the so-called success trap (Levinthal and March, 1993).

Empirical work illustrates that a carefully orchestrated combination of exploitation and exploration has a significant, positive effect on firm performance (e.g., Auh and Menguc, 2005; He and Wong, 2004; Jansen et al., 2006; Uotila et al., 2009). For example, He and Wong (2004) demonstrate that equal levels of exploitation and exploration are required for a superior sales growth rate. Auh and Menguc (2005) show that the costs associated with neglecting either exploitation or exploration negatively influence firm performance. Subsequent research further develops the ‘ambidexterity hypothesis’ by abandoning the idea that equal levels of exploitation and exploration are necessary for superior performance. For example, Jansen et al. (2006) find that the level of environmental dynamism and competitiveness dictates the most profitable mix of exploitation–exploration. Most recently, Uotila et al. (2009) show the relationship between the exploitation–exploration ratio and firm performance is U-shaped; they further demonstrate that the R&D intensity of the industry moderates this relationship.

Nevertheless, these studies provide limited insight into whether the exploitation–exploration implications and management requirements change within a given industry over the course of its business cycle. Here, we focus specifically on recessions and recoveries. The National Bureau of Economic Research (Hall et al., 2010, p. 1) defines an economic recession as ‘A period of falling economic activity spread across the economy, lasting more than [six] months, normally visible in real [gross domestic product], real income, employment, industrial production, and wholesale-retail sales.’ Conversely, it defines an economic recovery as ‘A period of [rising] economic activity spread across the economy, lasting more than [six] months, normally visible in real [gross domestic product], real income, employment, industrial production, and wholesale-retail sales.’
sales’ (Hall et al., 2010, p. 1). In this respect, recessions and recoveries are characterized by many opposing macroeconomic indicators (Grewal and Tansuhaj, 2001; Smart and Vertinsky, 1984). These two phases of the business cycle are therefore likely to present top executive teams, attempting to obtain the right exploitation–exploration ratio, with highly dissimilar challenges and implications.

**HYPOTHESES**

To develop hypotheses on the differences between the exploitation–exploration ratio implications and management requirements within a given industry over time, we build on the work of Uotila et al. (2009). They measure managerial attention to exploitation–exploration as a continuum and uncover an inverted U-shaped relationship between the exploitation–exploration ratio and firm performance (i.e., for R&D-intensive industries in the 1989–2004 period). As such, we assume the existence of two inverted U-shaped relationships—one for the bear market and one for the bull market—and investigate three differences between these relationships: (1) a difference in the position of the inflection point on the y-axis, reflecting a difference in the absolute performance outcomes given an exploitation–exploration ratio; (2) a difference in the steepness between the slopes of the two inverted U shapes, which reflects a difference in the relative importance of the exploitation–exploration ratio for firm performance; and (3) a difference in the position of the inflection point on the x-axis, which reflects variation in the optimal exploitation–exploration ratio for firm performance. These differences translate directly into varying exploitation–exploration ratio implications and management requirements between the bear and bull markets and result in three hypotheses.

**Bear-bull market affects absolute performance effects of the exploitation–exploration ratio**

The two assumed inverted U-shaped relationships can differ in their position along the y-axis. This implies a difference in the performance implications of a given exploitation–exploration
ratio. More specifically, as outlined previously, business cycles have a profound effect on macroeconomic indicators (Deleersnyder et al., 2004; Grewal and Tansuhaj, 2001; Lamey et al., 2007; Lee and Makhija, 2009; Steenkamp and Fang, 2011). A recession is characterized by an industrywide contraction, which strongly reduces the amount of opportunities available to realize firm growth by means of exploitation–exploration (Deleersnyder et al., 2004; Lamey et al., 2007; Srinivasan et al., 2011; Steenkamp and Fang, 2011). In contrast, a recovery triggers a general rise in the economic conditions and, as such, is characterized by an increasing amount of firm growth opportunities (Deleersnyder et al., 2004; Lamey et al., 2007).

The bear and bull markets differ in terms of their environmental munificence (Dess and Beard, 1984). Munificence refers to ‘the extent to which the environment can support sustained growth’ (Dess and Beard, 1984, p. 55) and thus reflects the amount of firm growth opportunities available to top management. This difference in munificence between a bear and a bull market implies a difference in the absolute performance outcomes of a given exploitation–exploration ratio. That is, the anticipated inverted U-shaped relationship between a given exploitation–exploration ratio and firm performance is likely to be more positive in a bull market than in a bear market. Figure 1 graphically depicts this expected effect.

Hypothesis 1: The performance implications of a given exploitation–exploration ratio are more positive during a bull market than during a bear market.

Bear-bull market affects differential performance effects of exploitation–exploration ratio

The two anticipated inverted U-shaped relationships can also differ in the steepness of their slopes. This involves a difference in the relative importance of managing the exploitation–
exploration ratio (Raisch et al., 2009). For example, in the 2001 bear market, 20 percent of the firms that were initially in the bottom quartile of performance statistics rose to the top quartile in their respective markets, and more than 20 percent in the top quartile fell to the bottom quartile (Srinivasan et al., 2011). In addition, 70 percent of the firms that increased performance in the bear market sustained those gains in the ensuing economic recovery, while fewer than 30 percent of the firms that lost ground regained their positions (Srinivasan et al., 2011; Steenkamp and Fang, 2011). In this respect, especially recessions may provide opportunities for accelerated firm growth or, alternatively, reinforce decline if management fails to exploit these opportunities (Srinivasan et al., 2011; Steenkamp and Fang, 2011). This observation resonates with the organizational decline literature (e.g., Porter and Harrigan, 1983; Rosenblatt, Rogers, and Nord, 1993) and suggests that correctly handling the exploitation–exploration ratio is an even more important managerial task in a bear than a bull market.

These patterns of firm growth and decline can be explained by the industry-wide contraction reducing the number of prospects for firm growth (Block, 1979; Grewal and Tansuhaj, 2001; Srinivasan et al., 2011). That is, the decreased level of munificence makes for a severe external selection regime. Therefore, successfully seizing business opportunities in a bear market is extremely critical because such chances are scarce (Grewal and Tansuhaj, 2001). Marketing scholars have long maintained that contractions, compared with expansions, present managers with the rare opportunity to boost their firms’ market share and long-term profitability (e.g., Steenkamp and Fang, 2011). In contrast, the general rise in output levels in bull markets provides ample opportunities for top executives to achieve profitable growth. Therefore, correctly managing the exploitation–exploration ratio during the recovery is relatively less important.
Moreover, managerial failure to take advantage of the reduced amount of opportunities in a bear market, in combination with the general decline in output levels, causes a rapid performance decrease (Walrave et al., 2011). This decrease can give rise to a vicious feedback loop in which the negative performance trend further deteriorates the development of a profitable exploitation–exploration ratio, which in turn accelerates organizational decline (i.e., the success trap) (Leonard-Barton, 1992; Levinthal and March, 1993). In responding to external threats, such as a bear market, managers frequently let their firms slip into such a vicious process (Walrave et al., 2011). In contrast, this vicious feedback loop is less likely to develop in a bull market because of the general rise in output levels (Deleersnyder et al., 2004).

These reasons suggest that mismanagement of the exploitation–exploration ratio in a bear market is likely to have a larger negative impact on firm performance than mismanagement during a bull market, and vice versa. We thus expect that the relative importance (i.e., differential performance effects) of correctly managing the exploitation–exploration ratio is greater during an economic recession than during a recovery.

*Hypothesis 2: The differential performance effects of the exploitation–exploration ratio are greater in a bear market than in a bull market.*

---

**Figure 2**

Building on Figure 1, Figure 2 graphically illustrates the expected effect. In this figure, the steepness of the two graphs has changed. The steeper curve in the bear market reflects the larger differential performance effects—that is, firms can lose more by deviating from the vertex (i.e., for any given $c$, $a < b$).

**Bear-bull market affects the optimal exploitation–exploration ratio itself**
Finally, the two anticipated inverted U-shaped relationships can differ in their position on the x-axis. That is, the third expected effect of the business cycle on the relationship between exploitation–exploration ratio and firm performance involves a *shift in the vertex* (i.e., the optimal exploitation–exploration ratio).

As argued previously, a recession is characterized by a decreasing amount of opportunities due to decreasing munificence (Block, 1979; Grewal and Tansuhaj, 2001; Srinivasan *et al.*, 2011). Management teams that steer their firms toward discovery and innovation are more likely to uncover new business opportunities than firms that focus on exploiting their current, but diminishing number of, firm growth opportunities. Therefore, during a recession, management should expand the scope of information acquisition by initiating more exploration to realize firm growth (Sidhu *et al.*, 2004). Furthermore, if management decides to reduce R&D spending during a recession, it risks losing its long-term technological advantage (Srinivasan *et al.*, 2011).

This line of reasoning is consistent with observations that an increase in R&D activities during contractions is a more effective strategy for building profit than an increase in R&D effort during expansionary periods (Steenkamp and Fang, 2011). As such, managers directing their firm to build more explorative knowledge are likely able to adapt their firms’ overall operations in line with the requirements imposed by the recession, in clear contrast with firms without such explorative activities (Grewal and Tansuhaj, 2001; Lee and Makhija, 2009).

Conversely, the increasing level of munificence in a bull market means that firm growth opportunities are more likely to be discovered than in a bear market. As such, management should take advantage of this situation and give relatively more attention to exploitation to bring firm performance back to pre-recession levels. We therefore expect the deflection point between
recession and recovery to be the (ideal) moment top management (modestly) changes its balance of attention to more exploitation.

_Hypothesis 3: For optimal firm performance, more managerial attention should be directed toward exploration in a bear market than in a bull market._

**METHOD**

**Data collection**

Although business cycles affect the entire economy, not all industries are equally affected (Deleersnyder _et al._, 2004; Steenkamp and Fang, 2011). For example, firms in the high-tech sector tend to allocate greater resources to exploration to manage ongoing technological change (Grewal and Tansuhaj, 2001). The IT industry is an exemplar of high-tech sectors characterized by continuous product innovation, high growth rates, and high product differentiation (Mendelson, 2000). As such, IT firms need to be more responsive to environmental fluctuations and generate a return on (explorative) investments faster than firms in many other industries (e.g., gas or food industry) (Mendelson, 2000). Consequently, within the IT industry, performance implications arising from different exploitation–exploration configurations are likely to be observed more clearly and within a shorter time span than those in most other industries. As such, we selected the IT industry as the context for our empirical study.
To test the hypotheses, longitudinal data covering both a bear and a bull market are required. As such, we collected data during the years 2007–2010 for companies active in the IT sector (16 quarters in total). The Global Industry Classification Standard (GICS) lists these firms under codes 4510–4530. In view of the global character of the business cycle under investigation, we collected data on both U.S.- and European-based companies. Moreover, we focused on publicly owned corporations because they generate a regular flow of documents (e.g., annual reports, letters to shareholders) that include data on the attentional focus of top management. Finally, to make the sample somewhat consistent in terms of firm size, a net income in excess of US$75 million (in 2007) was required. In summary, our sample includes firms that (1) were listed in GICS codes 4510–4530, (2) were based in U.S. or Europe, (3) were publicly owned, (4) traded at the beginning of 2007, and (5) reported a net income of more than US$75 million in 2007.

With these criteria, we first selected 89 U.S.-based firms from the Standard & Poor’s (S&P) 500 index and 11 European-based firms from the S&P 350 EURO index. To improve the geographical balance in the sample, we then supplemented the data with all European-based IT firms (not listed in the S&P indexes) that had a net income in excess of US$75 million in 2007 (from Thomson ONE Banker). These 21 firms were too small to be listed in the S&P EURO index but complied with our sample selection criteria. This process resulted in an initial sample of 121 firms.

We collected the firm-level data from two main sources: Thomson ONE Banker and annual letters to shareholders. We omitted 14 firms from the analysis because no letters were available. Moreover, two firms had fewer than six (quarterly) observations (compared with an average of 14 per firm), and thus we omitted them from the sample because such a limited number would provide a misfit with our longitudinal research design. (Nevertheless, inclusion of these two
firms as a robustness check resulted in highly similar findings; see the Appendix under the heading ‘Extra observations.’) Another 125 quarterly financial performance observations were not available, mostly because of stock market exits. This resulted in a final sample of 105 companies (75 in U.S. and 30 in Europe) and 1,555 valid observations over 16 quarters.

**Measures**

*The recession and recovery phase*

We analyzed the economic recession that started in 2007. According the National Bureau of Economic Research, this recession lasted 18 months (Hall et al., 2010). The subsequent recovery that unfolded during 2009–2010 was of such strength and length that any subsequent recession will be considered a new one (Hall et al., 2010), though this does not mean that the economic conditions since the ‘through’ point have been particularly favorable. Thus, we merely determined that the economic recession ended and a period of recovery began.

Global economic upheavals tend to be synchronized at large (Claessens, Kose, and Terrones, 2009), and thus we presumed no delay between U.S. and European firms in the analyses. This assumption is reinforced by the notion that all firms in our sample are global players and therefore affected by global crises simultaneously. Nevertheless, we tested whether this assumption is valid for the selected firms by calculating the average relative Tobin’s q for the U.S. and European subsamples. Subsequently, we applied the Zivot and Andrews unit root test, which treats the breakpoint endogenously, to the two subsamples (Zivot and Andrews, 2002). We found that the breakpoint (i.e., the minimum t-statistic, based on the slope) was at quarter 9 for both the U.S.-based firms ($t = -4.138$, $p < .10$) and the European firms ($t = -5.645$, $p < .01$).

Therefore, we split the data into a bear and a bull phase with a deflection point in quarter 9 at large. As such, for quarters 1 through 8 (i.e., years 2007–2008), we coded a dummy variable
(‘bear dummy’) as 0 to indicate a bear market and, for quarters 9 through 16 (i.e., years 2009–2010), coded a bull market as 1.

**Dependent variable: relative Tobin’s q**

The exploitation–exploration literature uses various performance measures. Some studies draw on self-reported subjective measures (e.g., Gibson and Birkinshaw, 2004; Lubatkin et al., 2006) or accounting-based measures (e.g., He and Wong, 2004), whereas others rely on market-value-based measures (e.g., Uotila et al., 2009). In view of their retrospective bias, self-reported subjective measures are not appropriate in a longitudinal research setting in which historic data are collected (Golden, 1992). Accounting-based measures are also less suitable because of the time lag for the results of exploration to manifest, compared with the more immediate effect of exploitation (Lavie et al., 2010; Uotila et al., 2009). In contrast, market-value-based measures adequately capture both the short-term performance and the long-term prospects of managerial decision making (Lee and Makhija, 2009; Lubatkin and Shrieves, 1986). In this respect, empirical studies investigating performance effects longitudinally have often employed market-value-based measures (e.g., Uotila et al., 2009). As such, we calculated the widely used Tobin’s q as the market-value-based index by dividing the market value of a company by its book value (Lee and Makhija, 2009).

Our conceptualization and measurement of performance were guided by Reibstein and Wittink (2005). That is, to directly compare performance variations between firms as they arise from managerial attention to exploitation–exploration, we calculated and used the relative Tobin’s q. More specifically, all firms had the same Tobin’s q (i.e., 1) at $t = 1$; we calculated subsequent values relative to this initial value. A robustness check with several alternative operationalizations of the relative Tobin’s q (e.g., Gozzi, Levine, and Schmukler, 2008)
demonstrated that the operationalization we adopted did not significantly influence the results (see the Appendix).

**Independent variable: attention to exploitation–exploration ratio**

Prior research has operationalized exploitation and exploration in many different ways. For example, Katila and Ahuja (2002) use the depth and breadth of technological search activity as a proxy. Other studies have relied on questionnaires that target key personnel (He and Wong, 2004; Jansen *et al*., 2006; Sidhu, Commandeur, and Volberda, 2007). These operationalizations are frequently highly specific and therefore lack generalizability and applicability outside their respective contexts (Uotila *et al*., 2009). Moreover, whether and how they resonate with the original definitions of exploitation and exploration remains unclear (March, 1991).

As argued previously, the capability of firms to simultaneously exploit and explore inherently manifests itself in the decision-making processes at the top management level. As such, we documented the chief executive officers’ (CEOs’) attentional focus, in terms of the exploitation–exploration ratio, by content analysis of the letters to shareholders. Content analysis of linguistic media is useful for reconstructing beliefs and perceptions of their authors (D’Aveni and MacMillan, 1990).

Letters to shareholders are a relatively homogeneous communication channel that is carefully controlled by top managers (D’Aveni and MacMillan, 1990; Ocasio, 1997). As such, these letters embody the ‘corporate speak’ of top management more than any other form of communication. Research finds that executive attention, as reflected in these letters, affects firm activities, such as technological responsiveness to competitions (Eggers and Kaplan, 2009), technological innovations (Kaplan, 2008), and speed of response to sector and task changes (Nadkarni and Barr, 2008). Previous research has successfully undertaken content analysis of
letters to shareholders to uncover the strategic direction set by top management (D’Aveni and MacMillan, 1990; Yadav, Prabhu, and Chandy, 2007).

The operational definition of exploitation and exploration in our content analysis is based on March’s (1991) original work. This ensured that our operationalization of the exploitation–exploration ratio aligned well with the conceptual definitions adopted. Moreover, Uotila et al. (2009) demonstrate that March’s definition statistically and accurately differentiates between attention to exploitation and exploration. Thus, we captured managerial attention to exploitation by (the roots of) the keywords ‘refinement,’ ‘choice,’ ‘production,’ ‘efficiency,’ ‘selection,’ ‘implementation,’ and ‘execution.’ We captured managerial focus to exploration by (the roots of) the keywords ‘search,’ ‘variation,’ ‘risk,’ ‘experimentation,’ ‘play,’ ‘flexibility,’ ‘discovery,’ and ‘innovation.’ Moreover, manual inspection of a randomly chosen selection of letters to shareholders, comprising 5 percent of all 405 letters, revealed that the keywords ‘new’ and ‘technology’ indicated attention to exploration and ‘cost’ and ‘reduction’ represented a focus on exploitation. Therefore, we also included (the roots of) these four words in the investigation. A preliminary analysis of the letters indicated that contractions of the keywords selected are rarely used in the context of other meanings, except in the case of ‘executive’, which we therefore excluded from the analysis.

To construct the exploitation–exploration variable, researchers have employed an array of mathematical methods (e.g., subtraction, summation, multiplicative interaction) (e.g., Auh and Menguc, 2005; He and Wong, 2004). No compelling rationale exists for choosing one mathematical operation over the other, but this choice may greatly influence the results (e.g., Auh and Menguc, 2005; He and Wong, 2004). The assumption that attention to exploration and exploitation are two ends of a continuum helps avoid this problem (Lavie et al., 2010).
Following Uotila et al. (2009), we defined the attention to exploitation–exploration ratio as the total number of matched keywords for exploration divided by the sum of matched keywords for exploitation and exploration. Thus, a firm exclusively directed toward exploitation received a score of 0, and a firm exclusively focused on exploration received a score of 1. In total, we matched the keywords to 4,799 instances (42% to exploration). We used the year a letter was published to denote the exploitation–exploration ratio of that year. We assume that the letters adequately represent and reflect the CEOs’ attentional focus on exploitation and exploration.

The length of the letters may influence the independent variable (Yadav et al., 2007); it could be argued, for example, that shorter letters result in extreme exploitation–exploration ratios. That is, finding one additional keyword in a shorter text, in which relatively fewer keywords are likely to appear, would have a greater influence on the exploitation–exploration ratio than finding one additional keyword in a longer text. To test for this possible confounding effect, we took the absolute value of 0.5 (the mean of the exploitation–exploration ratio scale) less the exploitation–exploration ratio and correlated it with the number of characters appearing in a letter. This process effectively tests whether fewer characters result in extreme exploitation–exploration ratios. This robustness check produced a non-significant relationship ($r = 0.010, p > .1$); therefore, the length of the letters had no significant effect on the distilled exploitation–exploration ratio.

**Control variables**

We included several variables in the analyses to control for possible confounding effects. We used the autoregressive component ($y_{t-1}$) to control for past firm performance. We included time dummies (for every quarter) to prevent contemporaneous correlation, the most likely form of cross-individual correlation (Roodman, 2009a). R&D spending is likely to influence firm
performance positively in times of economic upheaval (Hoang and Rothaermel, 2010; Srinivasan et al., 2011; Steenkamp and Fang, 2011). As such, we used the standardized value of R&D spending as a percentage of sales (‘R&D expenditure’). However, not all companies reported their R&D spending; therefore, we coded the firms that did not report R&D expenses as 0 (effectively replacing the missing value with the sample’s mean) and coded a dummy variable (‘R&D missing dummy’) as 1 (see Cohen et al., 2003; Uotila et al., 2009). Furthermore, larger firms may be better able to mitigate the effects of economic recessions and recoveries because of their large amount of resources (Lee and Makhija, 2009; Steenkamp and Fang, 2011). Therefore, we controlled for firm size, measured by calculating the standardized value of the number of employees (‘firm size’). Older firms are also likely to be more inert and thus less able to adapt to changing environmental circumstances (Steenkamp and Fang, 2011). Therefore, we included firm age in terms of the standardized value of the number of days since initial public offering. Finally, we incorporated geographic location by coding and including a dummy variable for U.S.- versus European-based firms (‘U.S. location dummy’) and also controlled for industry subsector by coding and including two dummy variables (‘GICS 4510 dummy’ and ‘GICS 4520 dummy’).

Analysis

A longitudinal research design can draw on sophisticated econometrical methods to control for endogeneity and unobserved heterogeneity (Blundell and Bond, 1998; Roodman, 2009a; Uotila et al., 2009). In this respect, simple dynamic panel models estimated with standard GMM estimators have often produced unsatisfactory results (see Blundell and Bond, 2000) arising from a weak instrument problem if the dynamic panel autoregressive coefficient is highly persistent, which causes large finite-sample biases (i.e., downward and imprecise) (Blundell and Bond,
1998). As such, testing the hypotheses with the data at hand required the use of system GMM estimation (Arellano and Bover, 1995).

Use of system GMM estimation has become increasingly popular because of its ability to allow for a short panel, a lack of good external instruments, fixed effects, and a first-order autoregressive error term (Arellano and Bover, 1995; Blundell and Bond, 1998; Roodman, 2009a). This method makes the endogenous variables predetermined and, therefore, not correlated with the error term, which prevents endogeneity problems. Moreover, system GMM estimation controls for (unobserved) heterogeneity (Roodman, 2009a). Thus, many studies have begun applying this method (see Roodman, 2009b).

Roodman (2009b) recommends putting all regressors (and their lags) into the instrument matrix. Therefore, we treated almost all variables as predetermined (Uotila et al., 2009); exceptions were the time dummies, the ‘bear dummy,’ the industry dummies, and the ‘U.S. dummy,’ all of which we treated as exogenous variables. This approach, combined with the number of variables used in the analyses, resulted in a large number of instruments and, therefore, in over-identification. Although over-identification does not compromise the coefficient estimates, it does weaken the Sargan/Hansen test and, as such, raises the need for robustness tests (Roodman, 2009a). Therefore, we also tested the models by varying the number of instruments. These robustness tests demonstrated that the key coefficients mostly remained comparable, in terms of sign, effect size, and significance level, with those of the model used for hypotheses testing (for an overview of robustness tests, see the Appendix).

RESULTS
Table 1 presents the descriptive statistics and correlations for the variables used in this study. The variable EE ratio significantly correlates with R&D expenditure (0.223, \( p < .05 \)), suggesting that top management teams with a strategic agenda directed toward exploration also realize
higher R&D investment levels. This finding provides further support for the attention-based view approach in this study, which draws on content analysis of letters to shareholders to uncover the strategic direction set by top management (D’Aveni and MacMillan, 1990; Yadav et al., 2007).

Table 2 presents the results of the system GMM regression analyses. To test for the (assumed) inverted U-shaped relationship, we included the squared term of the independent variable under investigation (EE ratio) in the model (Aiken and West, 1991). As such, Model 1 introduces the ‘EE ratio,’ the ‘EE ratio squared,’ and the ‘bear dummy.’ Model 2 examines the moderating effect of the phase of the business cycle (bear dummy) on the relationship between the EE ratio and firm performance by including the interaction terms (Aiken and West, 1991).

Model 2 has a significantly better overall model fit than Model 1 ($p < .001$); therefore, we discuss only Model 2. The autoregressive component—that is, the relative Tobin’s $q_{t-1}$—is highly persistent ($b_6 = 0.885, p < .001$), which justifies the use of system GMM estimation (Blundell and Bond, 1998). Furthermore, both R&D expenditure ($b_7 = 0.025, p < .01$) and firm age ($b_{10} = -0.027, p < .01$) significantly influence the dependent variable. That is, the more R&D investments are made during times of economic upheaval and/or the younger the firm, the better is its performance.

Model 2 reveals a curvilinear relationship between the EE ratio and firm performance in both bear and bull markets. That is, the required coefficients are statistically significant and have the correct signs: EE ratio ($b_1 = 0.826, p < .01$), EE ratio squared ($b_2 = -0.633, p < .01$), EE ratio

\[ \text{INSERT TABLE 1 ABOUT HERE} \]

\[ \text{INSERT TABLE 2 ABOUT HERE} \]
bear dummy interaction ($b_4 = -0.627, p < .05$), and EE ratio squared × bear dummy interaction ($b_5 = 0.438, p < .05$). The vertexes are located within the theoretically plausible exploitation–exploration range (0.65 for the bear market, and 0.51 for the bull market), providing evidence that the relationships are non-monotonic. This implies that firms directed toward a more balanced exploitation–exploration ratio achieve better performance than their ‘non-balanced’ competitors, in both bear and bull markets. This result extends the findings of Uotila et al. (2009) to a context of strong economic upheaval.

Moreover, the bear dummy is statistically significant with the expected sign ($b_3 = 0.368, p < .001$). This indicates that in terms of absolute performance outcomes, a given exploitation–exploration ratio has a more positive effect on firm performance in a bull market than in a bear market. This provides support for hypothesis 1.

Figure 4 suggests that a deviation from the optimal exploitation–exploration ratio in a bear market has greater differential performance implications than the same deviation in a bull market. That is, the graph for the bear market is steeper than the graph for the bull market. The figure also suggests that the vertex, or optimal exploitation–exploration ratio, decreases when moving from a bear to a bull market (i.e., toward more exploitation). In this respect, Figure 4 shows a visual indication of the nature of the interaction effect, which provides face validity for hypotheses 2 and 3.

However, this visual interpretation in itself cannot demonstrate that the two graphs in Figure 4 are significantly different (Aiken and West, 1991; Dawson and Richter, 2006). To test hypotheses 2 and 3, we therefore needed to test whether a structural break (i.e., parameter
instability) occurs between the bear and the bull market. Thus, we analyzed whether \( n \) additional
observations (i.e., the bull market) confirm or change the regression with the first sample of \( m \) observations (i.e., the bear market). The nonlinear nature of this investigation in the context of
the GMM approach requires applying the sup-Wald statistic (Andrews, 1993), which is
statistically significant at quarter 9 (\( \text{sub } W_t = 63.66, p < .001 \)). As such, the transition from bear
to bull market constitutes a structural break, and therefore the two phases are characterized by
significantly different regression coefficients. From here, we can assess hypotheses 2 and 3.
More specifically, we use equation 1 to estimate Model 2 (\( X \) denotes the EE ratio and \( Z \) the bear
dummy):

\[
\hat{Y} = b_{1}X + b_{2}X^2 + b_{3}Z + b_{4}XZ + b_{5}X^2Z + b_{6} + [b_{6} \ldots b_{27}]. \quad (1)
\]

Because \( Z \) is either 0 or 1, it follows that

\[
\hat{Y}_{bull} = b_{1}X + b_{2}X^2 + b_{0} + [b_{6} \ldots b_{27}] \quad (as \ Z = 0), \quad (2)
\]

\[
\hat{Y}_{bear} = (b_{1} + b_{4})X + (b_{2} + b_{5})X^2 + b_{3} + b_{0} + [b_{6} \ldots b_{27}] \quad (as \ Z = 1). \quad (3)
\]

As such, the difference between the bear and the bull market equals

\[
\hat{Y}_{bear} - \hat{Y}_{bull} = b_{5}X^2 + b_{4}X + b_{3}. \quad (4)
\]

Differentiating function 4 helps capture the difference in the x-coordinate of the vertex:

\[
X_{df} = \frac{-b_{4}}{2b_{5}}. \quad (5)
\]

Equation 4 follows a quadratic relationship (parabola). This indicates that \( b_{5} \) determines the
difference in steepness of the parabola (in this case, an inverted U shape) between the bear and
the bull market. The significant and positive \( b_{5} \) coefficient (\( b_{5} = 0.438, p < .05 \)) therefore
provides support for hypothesis 2: the differential performance effects of the EE ratio are greater
in a bear than a bull market.
Equation 5 must be significantly different from zero to confirm hypothesis 3. Because both $b_4 (b_4 = -0.627, p < .05)$ and $b_5 (b_5 = 0.438, p < .05)$ are significantly different from zero, $X_{\text{dif}}$ must also be different from zero. Therefore, we conclude that the bear and bull market graphs have a significantly different vertex x-coordinate. The most profitable exploitation–exploration ratio for the bear market equals 0.65, whereas this optimum is 0.51 for the bull market. Thus, the optimal exploitation–exploration ratio is significantly lower in a bull than a bear market, in support of hypothesis 3.

**DISCUSSION AND CONCLUSIONS**

The performance implications of managing exploitation and exploration are becoming increasingly understood (e.g., He and Wong, 2004; Jansen et al., 2006; Uotila et al., 2009). That is, environmental characteristics that vary mainly between different industries require a specific exploitation–exploration strategy for optimal performance. However, no research has attempted to empirically uncover whether the exploitation–exploration implications and management requirements change within a given industry over time (Raisch et al., 2009). As such, in this article, we investigated how the exploitation–exploration ratio implications and management requirements change over the course of a recession and recovery, within a given industry.

Our study focused on one particular R&D-intensive industry, the IT industry, during the recent global economic recession and recovery. Our results suggest that in times of strong economic upheaval, the performance implications of the exploitation–exploration ratio within the same industrial and competitive context strongly depend on the phase of the business cycle (i.e., recession or recovery). The assumption that the role and importance of exploitation–exploration do not change may be valid in less turbulent economic times, but our study clearly shows that this assumption is not valid in situations of very turbulent recession and recovery periods. This
finding constitutes our main theoretical contribution and extends previous (cross-sectional) studies, conducted across multiple industries (e.g., He and Wong, 2004; Uotila et al., 2009).

First, we find that the relationship between the exploitation–exploration ratio and firm performance has an inverted U shape—in both bear and bull markets. Here, our findings extend the work of Uotila et al. (2009), who test this curvilinear relationship on a cross-sectional sample consisting of both traditional manufacturing and IT firms. The findings provide new evidence for the ‘ambidexterity hypothesis’ arising from March’s (1991) original argument, but within the context of economic contraction and recovery. Moreover, we showed that a given exploitation–exploration ratio has a more positive effect on firm performance in a bull market than in a bear market, which we theoretically ascribe to differing levels of munificence.

Second, we observed distinct differential performance effects of managerial attention to exploitation and exploration over time. Previous work in this area has not explicitly considered this dimension (Raisch et al., 2009). By analyzing the influence of the bear and bull phases of the most recently completed recession/recovery cycle, we find that managerial failure to achieve a profitable exploitation–exploration ratio has far greater negative performance implications in a bear than a bull market. That is, the differential effects of the exploitation–exploration ratio on firm performance are significantly higher in the bear than the bull market. We argued that this is due to the decreased level of munificence, which makes for a severe external selection regime. This finding resonates with studies of organizational decline that show that especially times of deterioration provide extraordinary opportunities for firm revitalization and progress (Porter and Harrigan, 1983; Rosenblatt et al., 1993).

Third, we find that the managerial attention to exploitation–exploration requires adjustment when the context changes from a bear to a bull market. More specifically, we demonstrated that
to outperform competitors, firms must put stronger emphasis on exploration in a bear market than in a bull market. In this respect, managing recessions rather than recoveries requires the ability to face decreasing amounts of firm growth opportunities that demand relatively greater amounts of explorative investments (Block, 1979; Steenkamp and Fang, 2011). As such, in economic recessions, the benefits from extra attention to explorative activities seem to outweigh the benefits from extra attention to exploitative activities (Grewal and Tansuhaj, 2001). In the subsequent period of recovery, characterized by increasingly levels of munificence, management needs to shift attention back to more exploitation (i.e., to bring performance back to prerecession levels).

Our findings resonate with prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992), which suggests that top management teams, faced with environmental imperatives that undermine their organizations’ strategic positions, embrace risk taking and, thus, exploration. During a recovery, however, the theory proposes that managers who lack compelling motivation (e.g., firm performance decrease) are unlikely to risk disruptions to profitable operations. The most successful IT firms in our sample seemed to shift the balance of attention to explorative activities in a bear market, where it conflicts less with the pressure on current business operations (due to the decrease in demand), and to wait until economic conditions improved before shifting attention back to exploiting current operations (e.g., Barlevy, 2007). In the long run, the company that engages more in exploration in a bear market is likely to have new offerings ‘shelf ready’ in the bull market (Steenkamp and Fang, 2011).

This finding is also in line with recent observations from the corporate turnaround literature (e.g., Schmitt, 2010). Of note, firms facing swift organizational decline (e.g., due to a recession) were typically advised to adopt a sequential approach of retrenchment and repositioning (e.g.,
Robbins and Pearce, 1992). Retrenchment involves a focus on cost reduction and efficiency and therefore can be highly similar to exploitation; conversely, repositioning is about firm growth by way of exploring new products and/or markets (e.g., Bibeault, 1982; Robbins and Pearce, 1992). However, subsequent studies of corporate turnaround have acknowledged that swift organizational decline should be fought with retrenchment in combination with repositioning (e.g., Schmitt, 2010). Our empirical findings suggest a highly similar strategy during recessionary times.

**Implications for practice**

The past decade has witnessed several periods of economic upheaval, and the proportion of time firms spend in such contexts has been as high as 35 percent (Claessens et al., 2009; Grewal and Tansuhaj, 2001; Terrones, Scott, and Kannan, 2009). As such, there is a need to understand the strategies that lead to superior or inferior performance, in both bear and bull markets (e.g., Rosenblatt et al., 1993; Schmitt, 2010). Recessions and recoveries possess radically different macroeconomic indicators (e.g., in terms of supply and demand), and therefore management requirements vary significantly between these two phases.

Our study has important implications for top managers confronted with bear and subsequent bull markets. To effectively respond to the opportunities arising from a bull market, top management should attend and allocate resources to both exploration and exploitation. Our results suggest that an ‘ambidextrous’ strategy is likely to help firms remain profitable. Furthermore, our findings reveal that in recessions in particular, firms have the most to gain or lose. Moreover, exploration is more critical in periods of economic contraction than economic expansion. Considering that many executives actually shift their attention to exploitation in a
recession, proactively emphasizing exploration in the context of economic and organizational
decline is a counterintuitive strategy for most (Srinivasan et al., 2011; Walrave et al., 2011).

Particularly in recessions, many firms adopt a retrenchment approach in an attempt to
maintain liquidity (in contrast with prospect theory) (Robbins and Pearce, 1992; Srinivasan et al.,
2011; Steenkamp and Fang, 2011). Top managers then frequently avoid attending to long-term
challenges and problems because of short-term resource constraints and threat-rigidity responses
(D’Aveni and MacMillan, 1990; Levinthal and March, 1993; Staw, Sandelands, and Dutton,
1981). In addition, shareholders tend to press managers toward exploitation in an effort to
(quickly) compensate for the swiftly declining performance (Walrave et al., 2011; Wiersema,
2002). Compared with engaging in exploration, such a risk-adverse strategy is likely to generate
more certain (short-term) outcomes (Repenning, 2001). However, our results suggest that firms
adopting such a strategy are likely to emerge from a recession in a rather vulnerable position,
relative to competitors that have proactively invested in exploration during the recession. Thus, a
proactive focus on exploration demands non-traditional and courageous CEOs, who can sustain a
truly ambidextrous strategy in the face of shareholder pressure on how publicly owned firms
manage their costs, investments, and performance (Walrave et al., 2011).

Limitations

A limitation of this study arises from the nature of the sample. The results are grounded in a data
set of large (relatively resource-rich) firms in the IT industry, based in the United States and
Europe. This focus helped uncover whether the exploitation–exploration implications and
management requirements change within a given industry over time. Therefore, our findings may
be limited to (large companies within) the IT industry and the U.S. and European capital market
regimes. Future work could test whether our findings can be generalized to other industries and smaller firms.

We selected the IT industry because the performance implications arising from different exploitation–exploration ratios are likely to be observed more clearly and within a shorter time span than in other industries. That is, the actual set of exploitation and exploration activities in an IT firm is likely to follow and adapt to changes in managerial attention to exploitation–exploration quite quickly. In other industries, however, the lead times of major exploration (e.g., R&D) efforts are extremely long; for example, firms in the consumer electronics or pharmaceutical industry engage in R&D projects that can take 10 to 15 years (or longer) from first idea or patent to market introduction. These firms tend to engage in exploitation–exploration strategies that are long-term oriented and less likely to be adapted along the way, even when a global economic recession occurs. This raises the need for further research.

This study draws on letters to shareholders to capture the CEOs’ attentional focus on exploitation and exploration. Some researchers have criticized the use of letters to shareholders, particularly because they are largely written for ‘impression management’ purposes (Yadav et al., 2007). That is, letters to shareholders can be deliberately crafted to manipulate the perceptions of external audiences, rather than being a governance and procedural channel that adequately reflects organizational attention on firm strategy. However, a substantial body of research has confirmed that the content of these letters has a systematic effect on firm action and also has demonstrated that these letters effectively reflect the attentional focus of CEOs (e.g., D’Aveni and MacMillan, 1990; Noble, Sinha, and Kumar, 2002; Tetlock, Saar-Tsechansky, and Macskassy, 2008; Yadav et al., 2007). Nevertheless, the results should be interpreted with care.
Furthermore, bear and bull markets can occur at any period within a business cycle (e.g., outside an economic recession and recovery context). In this article, however, the terms ‘bear’ and ‘bull’ explicitly refer to periods of recession and recovery associated with a context of substantial economic turmoil.

CONCLUSION

The recent recession constitutes an exogenous shock and thus can be treated as a natural experiment. Natural experiments are useful because of their external origin and the unforeseen severity of abrupt shifts—in this case, an industry’s economic conditions—that are similar for all firms within that industry. As such, these shifts can provide unique insights into firm characteristics related to success or failure in dire times. Our study demonstrates that bear and bull markets provide distinct settings for managing the impact of the exploitation–exploration ratio on firm performance. That is, the exploitation–exploration implications and management requirements change within a given industry over time. Our findings also have important implications for how to ‘fight the bear’ and ‘ride the bull’ in times of extreme economic upheaval. In particular, shifting the balance of attention to exploration in a bear market is counterintuitive and highly different from what many managers actually do in a recession.

REFERENCES


An exploitation–exploration ratio of 0 implies a complete focus on exploitation, while a ratio of 1 implies an exclusive focus on exploration.

Figure 1. Illustration of hypothesis 1

Figure 2. Illustration of hypothesis 2
Figure 3. Illustration of hypothesis 3

Figure 4. The differences between the exploitation–exploration performance implications and management requirements in bear and bull markets
### Table 1. Means, standard deviations, and correlations* ($t_1$–$t_{16}$)

<table>
<thead>
<tr>
<th></th>
<th>M</th>
<th>SD</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Tobin’s q</td>
<td>.776</td>
<td>.321</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Tobin’s q$_{t-1}$</td>
<td>.779</td>
<td>.319</td>
<td>.871</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>EE ratio</td>
<td>.677</td>
<td>.172</td>
<td>.087</td>
<td>.109</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>(EE ratio)$^2$</td>
<td>.487</td>
<td>.222</td>
<td>.072</td>
<td>.092</td>
<td>.984</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Bear dummy</td>
<td>.477</td>
<td>.500</td>
<td>-.332</td>
<td>-.433</td>
<td>-.155</td>
<td>-.144</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>R&amp;D expenditure</td>
<td>.000</td>
<td>1.000</td>
<td>.123</td>
<td>.081</td>
<td>.223</td>
<td>.223</td>
<td>.034</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Firm size</td>
<td>.000</td>
<td>1.000</td>
<td>-.021</td>
<td>-.021</td>
<td>.026</td>
<td>.029</td>
<td>.016</td>
<td>-.242</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Firm age</td>
<td>.000</td>
<td>1.000</td>
<td>-.022</td>
<td>-.032</td>
<td>.104</td>
<td>.094</td>
<td>-.012</td>
<td>.074</td>
<td>-.288</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>R&amp;D missing dummy</td>
<td>.136</td>
<td>.343</td>
<td>-.013</td>
<td>-.025</td>
<td>.055</td>
<td>.049</td>
<td>.009</td>
<td>-.031</td>
<td>.002</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>GICS 4510 dummy</td>
<td>.412</td>
<td>.492</td>
<td>.011</td>
<td>.005</td>
<td>.187</td>
<td>.197</td>
<td>.021</td>
<td>-.016</td>
<td>.036</td>
<td>.235</td>
<td>.363</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>GICS 4520 dummy</td>
<td>.328</td>
<td>.470</td>
<td>-.085</td>
<td>-.078</td>
<td>-.145</td>
<td>-.009</td>
<td>-.265</td>
<td>.122</td>
<td>-.265</td>
<td>-.161</td>
<td>-.585</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>U.S. location dummy</td>
<td>.738</td>
<td>.440</td>
<td>-.029</td>
<td>.032</td>
<td>.042</td>
<td>.043</td>
<td>.001</td>
<td>.088</td>
<td>.102</td>
<td>-.132</td>
<td>-.097</td>
<td>.139</td>
</tr>
</tbody>
</table>

*Correlations are significant the .05 level. Significance levels reported are two-tailed.

### Table 2. Results of the system GMM regression analysis (half the available lags used)

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Model 1:</th>
<th>Model 2:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relative Tobin’s q</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(b_1) – EE ratio</td>
<td>.396 (.196)**</td>
<td>.826 (.306)**</td>
</tr>
<tr>
<td>(b_2) – (EE ratio)$^2$</td>
<td>-.359 (.157)**</td>
<td>-.633 (.225)**</td>
</tr>
<tr>
<td>(b_3) – Bear dummy</td>
<td>.154 (.021)***</td>
<td>.368 (.099)***</td>
</tr>
<tr>
<td>(b_4) – EE ratio \times bear dummy</td>
<td>-.627 (.307)*</td>
<td></td>
</tr>
<tr>
<td>(b_5) – (EE ratio)$^2$ \times bear dummy</td>
<td>.438 (.233)*</td>
<td></td>
</tr>
<tr>
<td>(b_6) – Relative Tobin’s q$_{t-1}$</td>
<td>.885 (.020)***</td>
<td>.885 (.019)***</td>
</tr>
<tr>
<td>(b_7) – R&amp;D expenditure $^a$</td>
<td>.024 (.010)**</td>
<td>.025 (.010)**</td>
</tr>
<tr>
<td>(b_8) – R&amp;D missing dummy</td>
<td>-.012 (.035)</td>
<td>-.006 (.036)</td>
</tr>
<tr>
<td>(b_9) – Firm size $^a$</td>
<td>-.019 (.021)</td>
<td>-.013 (.018)</td>
</tr>
<tr>
<td>(b_{10}) – Firm age $^a$</td>
<td>-.029 (.011)**</td>
<td>-.027 (.011)**</td>
</tr>
<tr>
<td>(b_{11}) – U.S. location dummy</td>
<td>-.009 (.014)</td>
<td>-.010 (.014)</td>
</tr>
<tr>
<td>(b_{12}) – GICS 4510 dummy</td>
<td>.027 (.018)+</td>
<td>.022 (.017)</td>
</tr>
<tr>
<td>(b_{13}) – GICS 4520 dummy</td>
<td>.000 (.017)</td>
<td>.000 (.016)</td>
</tr>
<tr>
<td>(b_{14}) – Constant</td>
<td>-.146 (.063)**</td>
<td>-.305 (.098)**</td>
</tr>
<tr>
<td>Hansen test of overidentification</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Arellano Bond test for AR(1) $^c$</td>
<td>-6.40 ***</td>
<td>-6.35 ***</td>
</tr>
<tr>
<td>Arellano Bond test for AR(2) $^c$</td>
<td>-.23</td>
<td>-.27</td>
</tr>
<tr>
<td>Wald $\chi^2$ (df in parentheses)</td>
<td>7288.32 (24)***</td>
<td>8166.43 (26)***</td>
</tr>
<tr>
<td>$\Delta$Wald $\chi^2$ (df in parentheses)</td>
<td>878.11 (2)***</td>
<td></td>
</tr>
</tbody>
</table>
a Standardized value; b The standard errors are robust to heteroskedasticity and arbitrary patterns of autocorrelation within agents (Roodman, 2009a); c z values reported; + p < .10; * p < .05; ** p < .01; *** p < .001; time dummy variables were included in all models but are omitted from these results. One-tailed significance levels are reported.

APPENDIX

We assessed the robustness of key findings with a series of tests. Almost all tests confirmed the robustness of the results. The only notable exceptions were the models ran with one and two available lags, which decreased the significance of $b_1$ and $b_2$. This can be explained by the loss in efficiency resulting from the substantial decrease in the number of instruments available.

<table>
<thead>
<tr>
<th>Dependent variable: Relative Tobin’s q</th>
<th>Extra observations (0–8 lags)</th>
<th>Tobin’s q divided by mean</th>
<th>Tobin’s q divided by median</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef. (SE) b</td>
<td>Coef. (SE) b</td>
<td>Coef. (SE) b</td>
</tr>
<tr>
<td>EE ratio, H1</td>
<td>.789 (.304)**</td>
<td>2.534 (.916)**</td>
<td>3.037 (1.100)**</td>
</tr>
<tr>
<td>(EE ratio)$^2$, H1</td>
<td>-.605 (.224)**</td>
<td>-1.837 (.650)**</td>
<td>-2.202 (.780)**</td>
</tr>
<tr>
<td>Bear dummy, H2</td>
<td>.358 (.098)***</td>
<td>.955 (.318)**</td>
<td>1.145 (.381)**</td>
</tr>
<tr>
<td>EE ratio × bear dummy, H2</td>
<td>-.593 (.305)*</td>
<td>-2.274 (.933)*</td>
<td>-2.725 (1.119)*</td>
</tr>
<tr>
<td>(EE ratio)$^2$ × bear dummy, H2</td>
<td>.413 (.232)*</td>
<td>1.616 (.667)*</td>
<td>1.937 (.7800)*</td>
</tr>
<tr>
<td>Relative Tobin’s q -1</td>
<td>.885 (.019)***</td>
<td>.882 (.017)***</td>
<td>.882 (.017)***</td>
</tr>
<tr>
<td>R&amp;D expenditure a</td>
<td>.026 (.010)**</td>
<td>.038 (.012)**</td>
<td>.046 (.015)**</td>
</tr>
<tr>
<td>R&amp;D missing dummy</td>
<td>-.005 (.035)</td>
<td>.008 (.044)</td>
<td>.010 (.053)</td>
</tr>
<tr>
<td>Firm size a</td>
<td>-.012 (.016)</td>
<td>-.011 (.027)</td>
<td>-.013 (.032)</td>
</tr>
<tr>
<td>Firm age a</td>
<td>-.027 (.011)**</td>
<td>.022 (.020)</td>
<td>.027 (.024)</td>
</tr>
<tr>
<td>U.S. location dummy</td>
<td>-.010 (.014)</td>
<td>.027 (.021)</td>
<td>.032 (.026)</td>
</tr>
<tr>
<td>GICS 4510 dummy</td>
<td>.021 (.017)</td>
<td>.008 (.022)</td>
<td>.010 (.027)</td>
</tr>
<tr>
<td>GICS 4520 dummy</td>
<td>.000 (.016)</td>
<td>.011 (.026)</td>
<td>.014 (.031)</td>
</tr>
<tr>
<td>Constant</td>
<td>-.294 (.097)**</td>
<td>-.924 (.313)**</td>
<td>-1.108 (.375)**</td>
</tr>
<tr>
<td>Hansen test of overidentification</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Arellano Bond AR(1)c</td>
<td>-6.38 ***</td>
<td>-4.52 ***</td>
<td>-4.52 ***</td>
</tr>
<tr>
<td>Arellano Bond AR(2)c</td>
<td>-.23</td>
<td>1.02</td>
<td>1.02</td>
</tr>
<tr>
<td>Dependent variable:</td>
<td>0–1 lag (min)</td>
<td>0–2 lags</td>
<td>0–4 lags</td>
</tr>
<tr>
<td>---------------------</td>
<td>---------------</td>
<td>----------</td>
<td>----------</td>
</tr>
<tr>
<td>Relative Tobin’s q</td>
<td>Ccoeff. (SE) ^b</td>
<td>Ccoeff. (SE) ^b</td>
<td>Ccoeff. (SE) ^b</td>
</tr>
<tr>
<td>EE ratio, H1</td>
<td>.654 (.546)</td>
<td>.487 (.354)+</td>
<td>.764 (.325)**</td>
</tr>
<tr>
<td>(EE ratio)^2, H1</td>
<td>-.512 (.400)+</td>
<td>-.396 (.263)+</td>
<td>-.571 (.239)**</td>
</tr>
<tr>
<td>Bear dummy, H2</td>
<td>.501 (.187)**</td>
<td>.406 (.129)**</td>
<td>.382 (.106)***</td>
</tr>
<tr>
<td>EE ratio × bear dummy, H2</td>
<td>-.1063 (.568)*</td>
<td>-.766 (.401)*</td>
<td>-.646 (.330)*</td>
</tr>
<tr>
<td>(EE ratio)^2 × bear dummy, H2</td>
<td>.768 (.416)*</td>
<td>.551 (.304)*</td>
<td>.435 (.250)*</td>
</tr>
<tr>
<td>Relative Tobin’s q_{-1}</td>
<td>.887 (.025)***</td>
<td>.887 (.023)***</td>
<td>.887 (.020)***</td>
</tr>
<tr>
<td>R&amp;D expenditure ^a</td>
<td>.022 (.011)+</td>
<td>.024 (.008)**</td>
<td>.021 (.009)**</td>
</tr>
<tr>
<td>R&amp;D missing dummy</td>
<td>.049 (.076)</td>
<td>.033 (.066)</td>
<td>.000 (.045)</td>
</tr>
<tr>
<td>Firm size ^a</td>
<td>-.029 (.049)</td>
<td>-.039 (.036)</td>
<td>-.012 (.018)</td>
</tr>
<tr>
<td>Firm age ^a</td>
<td>.014 (.028)</td>
<td>.008 (.021)</td>
<td>-.024 (.013)*</td>
</tr>
<tr>
<td>U.S. location dummy</td>
<td>.015 (.022)</td>
<td>.012 (.018)</td>
<td>-.008 (.014)</td>
</tr>
<tr>
<td>GICS 4510 dummy</td>
<td>-.004 (.026)</td>
<td>.008 (.024)</td>
<td>.016 (.016)</td>
</tr>
<tr>
<td>GICS 4520 dummy</td>
<td>.018 (.025)</td>
<td>.022 (.020)</td>
<td>-.003 (.016)</td>
</tr>
<tr>
<td>Constant</td>
<td>-.271 (.173)+</td>
<td>-.216 (.112)*</td>
<td>-.295 (.103)***</td>
</tr>
<tr>
<td>Hansen test of overidentification</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Arellano Bond AR(1) ^c</td>
<td>-6.43 ***</td>
<td>-6.51 ***</td>
<td>-6.36 ***</td>
</tr>
<tr>
<td>Arellano Bond AR(2) ^c</td>
<td>-.28</td>
<td>-.26</td>
<td>-.29</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>0–8 lags (reported)</th>
<th>0–16 lags (max)</th>
<th>All endogenous</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relative Tobin’s q</td>
<td>Ccoeff. (SE) ^b</td>
<td>Ccoeff. (SE) ^b</td>
<td>Ccoeff. (SE) ^b</td>
</tr>
<tr>
<td>EE ratio, H1</td>
<td>.826 (.306)***</td>
<td>.874 (.316)***</td>
<td>.743 (.299)***</td>
</tr>
<tr>
<td>(EE ratio)^2, H1</td>
<td>-.633 (.225)***</td>
<td>-.669 (.236)***</td>
<td>-.581 (.226)***</td>
</tr>
<tr>
<td>Bear dummy, H2</td>
<td>.368 (.099)***</td>
<td>.387 (.098)***</td>
<td>.326 (.099)***</td>
</tr>
<tr>
<td>EE ratio × bear dummy, H2</td>
<td>-.627 (.307)*</td>
<td>-.683 (.303)*</td>
<td>-.491 (.307)+</td>
</tr>
<tr>
<td>(EE ratio)^2 × bear dummy, H2</td>
<td>.438 (.233)*</td>
<td>.479 (.230)*</td>
<td>.334 (.236)+</td>
</tr>
<tr>
<td>Relative Tobin’s q_{-1}</td>
<td>.885 (.019)***</td>
<td>.882 (.019)***</td>
<td>.884 (.019)***</td>
</tr>
<tr>
<td>R&amp;D expenditure ^a</td>
<td>.025 (.010)***</td>
<td>.026 (.009)***</td>
<td>.032 (.010)***</td>
</tr>
<tr>
<td>R&amp;D missing dummy</td>
<td>-.006 (.036)</td>
<td>.008 (.031)</td>
<td>.014 (.030)</td>
</tr>
<tr>
<td>Firm size ^a</td>
<td>-.013 (.018)</td>
<td>-.009 (.016)</td>
<td>-.009 (.016)</td>
</tr>
<tr>
<td>Firm age ^a</td>
<td>-.027 (.011)***</td>
<td>-.022 (.012)*</td>
<td>-.014 (.013)</td>
</tr>
<tr>
<td>U.S. location dummy</td>
<td>-.010 (.014)</td>
<td>-.008 (.013)</td>
<td>-.004 (.013)</td>
</tr>
<tr>
<td>GICS 4510 dummy</td>
<td>.022 (.017)</td>
<td>.016 (.017)</td>
<td>.015 (.018)</td>
</tr>
<tr>
<td>GICS 4520 dummy</td>
<td>.000 (.016)</td>
<td>-.001 (.015)</td>
<td>.006 (.015)</td>
</tr>
<tr>
<td>Constant</td>
<td>-.305 (.098)**</td>
<td>-.320 (.099)**</td>
<td>-.280 (.095)***</td>
</tr>
<tr>
<td>Hansen test of overidentification</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Arellano Bond AR(1) ^c</td>
<td>-6.35 ***</td>
<td>-6.39 ***</td>
<td>-6.41 ***</td>
</tr>
<tr>
<td>Arellano Bond AR(2) ^c</td>
<td>-.27</td>
<td>-.27</td>
<td>-.24</td>
</tr>
</tbody>
</table>

^a Standardized value; ^b The standard errors are robust to heteroskedasticity and arbitrary patterns of autocorrelation within agents (Roodman 2009a); ^c z values larger than |4| were omitted from the analysis; + p < .10; * p < .05; ** p < .01; *** p < .001. Time dummy variables were included in all models but are omitted from these results. One-tailed significance levels are reported.