Technological knowledge, the growth and cyclicality of R&D investment, and exploitation via advertising

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Abstract

We examine the effects of knowledge capital, a stock of technological knowledge and innovations, on the cyclicality of firm-level R&D investment during sales expansion and contraction and the intertemporal substitution between R&D and advertising as forms of exploration and exploitation, respectively. Knowledge capital is proxied by three measures based on citation-weighted patents and stock market reactions to patent grants. Analyzing public U.S. manufacturing firms drawn from COMPUSTAT between 1975 and 2010, we find that *ceteris paribus*, R&D is procyclical. Growing knowledge capital curbs R&D growth and makes R&D less procyclical during expansion, but has no effect during contraction. This asymmetry renders firms with larger knowledge capital much less sensitive to positive shocks than negative shocks. R&D investment relative to advertising is acyclical during contraction but countercyclical during expansion, and growing knowledge capital turns R&D share procyclical during contraction and more countercyclical during expansion. We establish a feedback loop from accumulated innovations to subsequent R&D investment in the knowledge-creation process and its interaction with firm performance: knowledge capital steers cyclical adjustments of R&D investment. Albeit preliminary, our results support that temporal variations in R&D search coincide with the within-firm, intertemporal balancing between technical and market search and that technological innovations accelerate this across-unit trade-off: knowledge capital steers balancing between exploration and exploitation.

Keywords R&D, business cycle, technological innovation, patent, advertising

JEL classification D22, D25, E32, M30, O31, O32

1 Introduction

Setting the level of R&D investment is a strategic decision made by chief executive officers (CEOs) and top management teams because R&D ultimately drives firms' productivity, profitability, and competitiveness (Baker and Mueller 2002). A large literature demonstrates that R&D investments, and resulting innovative output, contribute to a firm's stock market value (Griliches 1981; Hall et al. 2005; Kogan et al. 2017). Despite its strategic significance as long-term growth-enhancing investment, corporate R&D investments exhibit nontrivial temporal variation. Frequently, R&D budgets are adjusted by broad gauges, such as past sales and profits, to fit within corporate financial boundaries (Hartmann et al. 2006). While R&D has higher adjustment costs than physical investments such that firms may strive to "smooth" their R&D spending over time, firms' R&D expenditures are shown to be sensitive to idiosyncratic or aggregate transitory shocks: i.e., R&D varies over the business cycle (Aghion et al. 2012; Hall 2002; Himmelberg and Petersen 1994). Accordingly, the cyclicality of R&D investment has received considerable attention in the economics and management literature.

Put simply, an investment is procyclical (countercyclical) if it rises (falls) with positive sales shocks but falls (rises) with negative shocks. This article aims to endogenize the cyclicality of firm-level R&D investment by recognizing a potential feedback loop from knowledge capital (Hall et al. 2005) to subsequent decisions on the level of innovative input, i.e., R&D investment. We conceptualize knowledge capital as a storehouse of technological knowledge and innovations (Garud and Nyyar 1994; Greve 2003) and operationalize it by patent statistics and stock market reactions to the news of patent grants (Hall et al. 2005; Kogan et al. 2017). We argue that not only does R&D contribute to the creation of knowledge capital, but also the "value" or "significance" of knowledge capital advises managers on how to adjust their R&D investment levels in the near term. Our notion is akin to performance feedback on investment decisions and risk-taking in the behavioral theory of the firm (BTOF) (Cyert and March 1963). With a pool of significant technological innovations at their disposal, firms would feel it less urgent to fund new risky initiatives whose payoffs are highly uncertain, but more imperative to develop and implement go-to-market strategies: i.e., how to commercialize innovations and hence redefine their product portfolios to the customers. Sequential allocation of attention from exploration to exploitation (Gupta et al. 2006; March 1991) spurred by growing knowledge capital has two important implications for subsequent R&D investment. First, firms would shift from exploratory R&D – discovering novel knowledge by venturing into broad and unfamiliar terrains that are distant from the current core knowledge base – to exploitative R&D – aimed at either refining the original innovation or turning current technological knowledge into new commercial products. Second, in an effort to reap R&D investment, firms would build up other exploitative or value appropriation units such as production and marketing to differentiate their offerings and extend the duration of competitive advantage (Mizik and Jacobson 2003). Hence, a large buffer of stored innovations not only reduces the need for R&D search in general but also elevates intertemporal balancing between organizational units, thereby exerting downward pressure on R&D spending (i.e., relatively larger cuts and smaller increases) along the business cycle.

Analyzing public U.S. manufacturing firms in COMPUSTAT, we obtain the following results. First, *ceteris paribus*, R&D investment is procyclical during both sales expansion and contraction, and there is no asymmetry in the extent between two cycle phases. Second, the growth of R&D investment is negatively associated with knowledge capital: successful recent R&D reduces the pace of subsequence technological search. Third, R&D becomes much less procyclical (proportionately smaller increases) during expansion as knowledge capital increases:

in other words, upward adjustments in R&D investment at times of improving sales conditions are more pronounced for firms in stronger need of new technological capabilities. Fourth, no moderating effect of knowledge capital is found during contraction. Fifth, due to the third and fourth, R&D investment behaves asymmetrically in degrees between expansion and contraction for firms with highly successful recent R&D: their R&D investments are cyclically much less sensitive to positive shocks than to negative ones so that increases in R&D at good times are proportionately smaller than cuts at bad times. Last, we find some evidence that the share of R&D expenditure relative to advertising expenditure is acyclical during contraction but countercyclical during expansion and that knowledge capital moderates the cyclicality of R&D share such that firms with larger knowledge capital raise the advertising share further.

We contribute to the literature on R&D growth and cyclicality by endogenizing them via a novel construct in innovation management – knowledge capital. Unlike previous work, we conceptually separate R&D from knowledge capital: the former represents an innovative input, not necessarily knowledge itself, that may not always come to fruition, whereas the latter captures innovative output such as solutions and patents. Regarding R&D as part of knowledge capital that precedes other components, previous studies have focused on the differential effect sizes of those components on firm value but ignored the potential for feedback from accumulated innovations and technological knowledge to the level of R&D investment in the knowledge-creation process. In contrast, we explicitly model such a feedback loop and demonstrate that larger or more valuable knowledge capital, which evinces R&D success, induces firms to "cool down" their R&D growth, especially when performance is improving or better than peers, a finding that runs counter to the proposition that "optimizing firms will increase their R&D in response to success" (Hall et al. 2005, p. 34).

By establishing knowledge capital as a "switch," we advance organizational learning research on exploration and exploitation (Gupta et al. 2006; March 1991; Gilsing and Noteboom 2005; Mudambi and Swift 2014) and the marketing literature on the interplay between value creation (R&D) and value appropriation (advertising) (Mizik and Jacobson 2003; Sridhar et al. 2014). Our results suggest that positive feedback from past innovative outcomes guides the within-firm, intertemporal balancing between technical and market search (Lavie and Rosenkopf 2006): this across-unit trade-off is a source of intertemporal balancing – i.e., cyclical adjustments – of R&D expenditure. Upon successful exploration that culminates in, say, a patent, companies should monetize superior technological innovations by playing up market search such as sales or advertising. This study finds preliminary evidence that advertising receives more institutional attention over the entire business cycle as knowledge capital grows. Thus, a wealth of stored innovations may well raise the opportunity cost of exploratory R&D during both expansion and contraction since demand conditions either enable or urge firms to generate economic rents immediately and quickly by marketing efforts.

Our research relates to the literature on strategic business cyclical management, which typically prescribes preemptive and somewhat aggressive investments as the firm alternates between favorable and unfavorable demand conditions (Navarro et al. 2010). Prior studies tend to view firm's heterogenous behaviors along the cycle as stemming from managerial skill, choice, orientation, or foresight – drivers somewhat exogenous to the state of the firm that could enable or restrict its actions. In our study, technologically advanced firms are just as procyclical during contraction and less procyclical during expansion than their less advanced peers: with sufficient technological assets, firms are poised to decelerate technological search, even with more internal funds freed up by increased sales. Instead, (proportionately) larger increases in

R&D are found among firms with smaller or less valuable knowledge capital, ones that must be more concerned with their ability to generate immediate or near-term profits. Thus, a more nuanced approach is required to prescribe R&D investment over the business cycle because it may well be dictated by a firm's endogenous technological position.

2 Theory and hypotheses

2.1 The cyclicality of R&D expenditure

At the firm level, the cyclicality of investment is measured by the reaction of its growth to the firm's sales growth or idiosyncratic shocks (Aghion et al. 2012). Two economic arguments lead to conflicting predictions about the cyclicality of R&D investment. On the one hand, the opportunity cost hypothesis argues for countercyclical R&D due to intertemporal substitution between productivity-enhancing activities and direct production activities. Recessions provide an incentive to make long-term innovation investments because the opportunity cost of R&D in terms of foregone output is lower during contraction (Aghion and Saint-Paul 1998). On the other hand, the cash flow argument postulates that the predominant source of firm R&D is internal funds, which tend to be procyclical, and thus cash-sensitive investments such as R&D should be procyclical to the extent that firms are credit-constrained (Aghion et al. 2005). In anticipation or presence of such constraints, firms would concentrate their R&D activities in booms instead, as their earnings and cash positions improve. Empirical results are contradictory. Whereas aggregated data at the sectoral or national level consistently substantiate procyclical R&D (Fatas 2000; Kim 2021; Ouyang 2011; Rafferty 2003), evidence from firm-level data is mixed (Aghion et al. 2012; Barlevy 2007; Beneito et al. 2015; Kabukcuoglu 2019).

Since two of our research hypotheses relate to moderating effects of knowledge capital on R&D cyclicality, our thesis on R&D cyclicality should be stated explicitly. Firm-level R&D in the U.S. is likely to be procyclical for two interrelated reasons: the accounting treatment of R&D and strong stock market pressure. US GAAP requires that R&D expenditure be expensed rather than capitalized so that pre-tax operating income fluctuates dollar-for-dollar with R&D spending, creating managerial incentives for discretionary adjustments to R&D budgets. To the extent that investors give heavy weight to reported earnings, managers have reason to inflate current earnings by cutting R&D at bad times and feel more comfortable shifting some surplus to authorize the full R&D budget or build extra R&D resources at good times (Bange and De Bondt 1998). Thus, earnings management could contribute to procyclical R&D above and beyond the effects of procyclical profits. It is argued that the U.S. stock market encourages short-termism and exerts strong earnings pressure (Hall and Oriani 2006). R&D could fall victim to short-sightedness since cuts in R&D immediately increase profits, yet potential benefits only materialize several years later. Furthermore, short-termism weakens the incentive to engage in intertemporal substitution, which is pivotal to the opportunity cost argument. Provided that profits are sufficiently procyclical, managers who discount longer-term benefits would concentrate their R&D during expansion in anticipation of higher present values of expected profits upon successful innovation launching (Barlevy 2007; Saint-Paul 1993).

2.2 Knowledge capital and R&D growth

The first hypothesis concerns how the level of knowledge capital affects a firm's ensuing R&D decisions: would recent R&D success accelerate or decelerate R&D investment? R&D is crucial to a firm's knowledge-creation process as the commitment of resources to innovation, and its output is an intangible asset that can be termed knowledge capital, which contributes to the firm's future net cash flows (Hall et al. 2005). A large literature shows that the stock market reacts favorably to various proxies for knowledge capital, e.g., patent counts and forward citations (Griliches 1981; Hall et al. 2005; Kogan et al. 2017). Knowledge capital embodies the effectiveness of past R&D activities, to the extent that it involves "significant" or "valuable" technological innovations. Essentially, knowledge capital is a pool of cumulative knowledge and stored solutions, a necessary condition for launching innovations later when firms strive to exploit new business opportunities and redefine a product portfolio for sustainable competitive advantages (Garud and Nyyar 1994; Greve 2003).

According to the BTOF, success (failure) decreases (increases) problemistic search (Cyert and March 1963; March 1994). Problemistic search is triggered when organizational performance falls short of the aspiration. Managers increase R&D when they believe upgrading their technology and product portfolio could solve performance problems, and added resources could be channeled into R&D projects near completion to reconcile the need to solve an urgent organizational problem and the long lead time common in R&D (Greve 2003). The value of a firm's knowledge asset is by no means directly or obviously translated into organizational performance. Nonetheless, stored innovations that could quickly morph into superior commercial solutions may well allow an educated guess about future financial performance, particularly when valued highly by investors. It is therefore logical that the accumulation of significant technological innovations should be framed by managers as a gain or success situation. Moreover, insofar as R&D is deemed discretionary, managers are under constant pressure to cut back on R&D for short-term earnings targets. The more knowledge amassed through the completion of research projects, the less urgent the need to initiate new projects, channel more dollars into existing ones, or accelerate what are near completion. As internal competition for scarce financial resources urges managers to distribute resources over areas of varying strategic importance, some of money earmarked for R&D could be freed up for investments of other kinds, without undermining the firm's current technological position. Consequently,

Hypothesis 1: Larger knowledge capital leads to smaller growth of R&D investment.

2.3. The moderating effect of knowledge capital on R&D cyclicality

Our next two hypotheses concern the relationship between knowledge capital and the procyclicality of R&D investment. Would successful recent R&D that adds to knowledge capital turn R&D investment more or less procyclical? While R&D achievements, evidenced by growing knowledge capital, certainly boost the morale of executives and R&D units, technological knowledge is not the end result sought after and must therefore be put to use: inventions and solutions embodied in the present pool should be transformed into commercial products of superior value to the target market. Hence, further down the line should distinct, deliberate, and directed efforts be expended to appropriate innovations generated by what came to fruition: firms would find it imperative to shift the focus of attention from exploration to exploitation over time (Gupta et al. 2006; March 1991; Gilsing and Noteboom 2005; Mudambi and Swift 2014; Lavie and Rosenkopf 2006; Ocasio 1997). Since exploration and exploitation are two fundamentally different yet essential approaches to organizational learning that compete for scarce resources, companies must make implicit and explicit choices between the two, often by stressing exploration at one point in time and then consciously shifting toward exploitation (Gupta et al. 2006; March 1991).

Firms cycle through exploration and exploitation within the R&D domain. In exploratory R&D, firms navigate distant, broad, and inexperienced domains to develop novel knowledge and capabilities, whereas in exploitative R&D, firms prioritize local, narrow, and familiar domains to leverage the current knowledge base and maximize its returns (March 1991; Ahn et al. 2021). Essentially, managers shall not repeat the same line of R&D tasks once they reach the exploitation phase, which entails less risk-taking and experimentation than does exploration (March 1991). A transition between exploration and exploitation within the R&D unit would give rise to a major overhaul of the firm's R&D portfolio and thus involve a significant change in R&D spending. Evidence shows that for a single project, early-stage activities – primarily exploratory – require higher spending than late-stage work – chiefly exploitative – and exploratory R&D accounts for the bulk of total R&D expenditure in the development cycle (Clark et al. 1987; DiMasi et al. 2003). Indeed, Mudambi and Swift (2014) demonstrate that a move toward exploitation (exploration) is associated with a considerable decrease (increase) in R&D spending.

The transition from exploration to exploitation also involves trade-offs between R&D and "exploitative" units such as production, sales, and marketing (Gupta et al. 2006; Lavie and Rosenkopf 2006). Activities aimed at commercialization and marketing are natural next steps to morph inventions and solutions into new products or processes of superior value and technological advantage. These functional units tend to be differentiated and loosely connected such that it is not impossible for firms to simultaneously engage in high degrees of both exploratory R&D and exploitation in complementary domains; nonetheless, insofar as exploration and exploitation compete for finite and scarce organizational resources, more resources allocated to one imply fewer resources left over for the other (Gupta et al. 2006). Thus, exploitative units or market search (e.g., advertising and sales) will become more salient and receive increasing material support and managerial attention in transition.

Because a growing stock of valuable innovations relaxes the requirement for further cash injection into R&D projects but entails a stimulus to market search, firms will be granted more leeway in adjusting R&D spending – larger cuts or smaller increases – to cope with fluctuating demands or cash flows over the business cycle. Facing tighter financial constraints during contraction, firms may cope with the trade-off between exploration and exploitation by decreasing R&D investment proportionately more than exploitative activities. Conversely, when confronted with improving market conditions during expansion, firms may prioritize exploitation by increasing investments in R&D functions proportionately less than in exploitative functions. Hence, attention shifted to harnessing current technologies from developing new capabilities will cause firms with larger knowledge capital to engage in more procyclical adjustments (larger decreases) of R&D investment during contraction, but less procyclical adjustments (smaller increases) during expansion than those which initiate or re-engage in technological exploration due to the absence or exhaustion of technological capabilities (Lavie and Rosenkopf 2006).

Hypothesis 2: Larger knowledge capital leads to less procyclical responses (smaller increases) in R&D investment during expansion.

Hypothesis 3: Larger knowledge capital leads to more procyclical responses (larger decreases) in R&D investment during contraction.

Figure 1 depicts our theoretical framework.

[Figure 1 about here]

3 Method and data

3.1 Empirical strategy

For hypothesis testing, we fit the equation similar to (Aghion et al. 2012) by the within (fixed-effects) estimator:

$$
\begin{aligned}
\Delta \ln R_{it} = {} & \upsilon_i + \tau_t + \xi Q_{i,t-1} + \sum_{j=1}^{2} \left(\alpha_j^H \Delta s_{i,t-j}^H + \alpha_j^L \Delta s_{i,t-j}^L\right) \\
& + X_{i,t-1}\left[\theta_X + \sum_{j=1}^{2} \left(\beta_j^H \Delta s_{i,t-j}^H + \beta_j^L \Delta s_{i,t-j}^L\right)\right] \\
& + Y_{i,t-1}\left[\theta_Y + \sum_{j=1}^{2} \left(\gamma_j^H \Delta s_{i,t-j}^H + \gamma_j^L \Delta s_{i,t-j}^L\right)\right] \\
& + Z_{i,t-1}\left[\theta_Z + \sum_{j=1}^{2} \left(\delta_j^H \Delta s_{i,t-j}^H + \delta_j^L \Delta s_{i,t-j}^L\right)\right] + \varepsilon_{it}.
\end{aligned}
$$

The subscripts *i* and *t* index firms and years, respectively, and ε_{it} is an error term. As is conventional, R&D investment is measured by a stock to reflect its dynamic and cumulative nature. Specifically, R&D stock, R_{it}, is computed using a declining balance formula with a 15% depreciation rate and a constant growth rate of 8% to obtain the initial stock of a given firm (Hall et al. 2005; Hall and Oriani 2006). A firm's knowledge capital, Z_{it}, is constructed identically. The dependent variable is the annual growth of the R&D stock. We include firm (υ_i) and time (τ_t) fixed-effects to account for persistent firm differences and idiosyncratic time variation. Q is the market-to-book ratio (MTB) to control for the firm's investment opportunity. The sales growth is denoted by $\Delta s_{i,t-j} = \ln S_{i,t-j} - \ln S_{i,t-j-1}$, where S denotes the firm's net sales ($). The firm is assumed to be in expansion (i.e., $\mathbb{I}_{i,t}^H = 1$) if $\Delta s_{i,t-j}$ is greater than the industry mean growth (over time). Using this indicator, we define expansion and contraction sales growth by $\Delta s_{i,t-j}^H = \mathbb{I}_{i,t}^H \cdot \Delta s_{i,t-j}$ and $\Delta s_{i,t-j}^L = \left(1 - \mathbb{I}_{i,t}^H\right) \cdot \Delta s_{i,t-j}$ such that $\Delta s_{i,t-j} = \Delta s_{i,t-j}^H + \Delta s_{i,t-j}^L$. The two controls *X* and *Y* are the firm's financial constraints and CEO optimism.

Since the equation couple the growth rate of the R&D stock with the growth rate of sales, we can interpret the coefficients α_j^H's and α_j^L's as *comovement elasticities*. Specifically, $\sum\alpha_j^H$ and $\sum\alpha_j^L$ are defined as "marginal" expansion and contraction comovement elasticities, respectively, controlling for other factors (Aghion et al. 2012). Positive (negative) comovement, $\sum\alpha_j^H > 0$ (< 0), indicates procyclical (countercyclical) R&D during expansion. The contraction cyclicality is determined likewise by $\sum\alpha_j^L$. The moderating effects of knowledge capital on comovement are represented by $Z\sum\delta_j^H$ and $Z\sum\delta_j^L$ during expansion and contraction, respectively. The interaction effects of financial constraints and CEO optimism are estimated similarly. Hypothesis 1 requires $\theta_Z < 0$. Hypothesis 2 stipulates $\delta_1^H < 0$, $\delta_2^H < 0$, and $\sum\delta_j^H < 0$. Hypothesis 3 specifies $\delta_1^L > 0$, $\delta_2^L > 0$, and $\sum\delta_j^L > 0$. All β's are expected be positive since financially more constrained firms should display a greater sensitivity of R&D investment to internal funds. If optimistic managers tend to take more risks, their R&D investments must display more procyclical R&D (larger increases) during expansion – $\gamma_1^H > 0$, $\gamma_2^H > 0$, and $\sum\gamma_j^H > 0$ – yet less procyclical R&D (smaller decreases) during contraction – $\gamma_1^L < 0$, $\gamma_2^L < 0$, and $\sum\gamma_j^L < 0$.

3.2 Data and measures

We collect annual accounting and R&D expenditure data from COMPUSTAT for publicly traded U.S. manufacturing companies (SIC codes 2000-3999) for the period 1975-2010. We retain firms reporting positive R&D expenditure and net sales; additionally, firms should have complete data for at least seven consecutive years. Each 3-digit SIC code is defined as a unique industry. To operationalize knowledge capital, we utilize Kogan et al. (2017)'s data, which cover all U.S. patents granted from 1926 to 2010. Patents have long been recognized as a rich source for studying innovation: patents catalog inventions that firms can appropriate, and forward citations convey the technological and economic value of a patent (Hall et al. 2005). We adopt Kogan et al. (2017)'s two measures as proxies. The first is a firm's citation-weighted patent count, representing the scientific value of patents; the second is abnormal stock returns following the announcement of a patent grant, quantifying the economic (dollar) value of a new innovation. Since asset prices are forward-looking, the second captures the private return to the patent holder based on *ex ante* information, the value that need not coincide with the scientific significance of the patent (Kogan et al. 2017). Both measures are scaled by book assets to account for size effects, but not weighted by any industry benchmarks. Next, following Mudambi and Swift (2014) we calculate ourselves the third proxy: the product of the number of patents granted for firm-year and their total forward citations received divided by the industry mean citations per patent in each industry-year. This "fixed-effects" approach has merit because information on citations is meaningful only when benchmarked against the industry and the time (Hall et al. 2001). We transform the three measures into stocks again using a declining balance formula, but set the initial stocks to the first observations of the respective flows because the series are long enough, dating back to as early as 1926. For stylistic brevity, we refer to the knowledge stocks as *Scientific Value*, *Economic Value*, and *Firm Knowledge* (Kogan et al. 2017; Mudambi and Swift 2014). The last stock is further scaled down by book assets, and then we apply a "log plus one" transformation.[2] Several controls are included: log book assets for firm size, MTB for investment opportunities, the Herfindahl index, cash holdings for financial constraints, and a measure of CEO optimism (Campbell et al. 2011). Dollar-metric variables are

[2] Book assets are available beginning 1975 in our sample. To fully utilize the very long time series of patents and citations, we apply the scaling in each firm-year after computing the *Firm Knowledge* stock.

deflated by the CPI, and all variables are winsorized at the 1% and 99% levels using annual breakpoints. The final sample comprises 2,022 firms and 28,040 firm-years.

4 Results

4.1 Descriptive statistics

Table 1 contains descriptive statistics. The mean R&D growth is slightly higher than the mean sales growth (8.30% vs. 7.31%); the latter is about 3.5 times more volatile than the former. MTB is clearly right-skewed. Approximately 16% of the firm-years are classified as optimistic, and roughly 42% of the observations are in sales expansion. Two knowledge stocks – *Scientific Value* and *Economic Value* – are highly right skewed, reinforcing prior findings of extreme skewness of the technical and economic values of patents (Hall et al. 2001, 2005). Due to the log transformation, *Firm Knowledge* is much less skewed than the other two proxies.[3] Column Within Variance reveals substantial within-firm variation in the data; hence, the within estimator would fare well. Table 2 lists Pearson correlations. The R&D growth correlates positively with the sales growth, hinting at positive comovement (procyclical R&D); it correlates negatively with firm size but positively with MTB. Cash holdings, CEO optimism, and cyclical expansion are each positively associated with the R&D growth, whereas all knowledge stocks are negatively related to the R&D growth. *Firm Knowledge* exhibits moderate correlations with the other two proxies, and *Scientific Value* correlates positively, but weakly, with *Economic Value*.[4] In sum, we find no warning signs for collinearity in regression.

[Table 1 about here]

[3] Before the transformation, *Firm Knowledge* displays an extreme skewness of 15.08.

[4] The log transformation appears to inflate correlations. Without it, the correlations are .331 and .407 with *Scientific Value* and *Economic Value*, respectively.

[Table 2 about here]

4.2 Hypothesis testing

Table 3 shows the regression results. Standard errors are clustered by firm to account for potential across-firm heteroskedasticity and within-firm serial correlation. Cash holdings are multiplied by -1 such that the higher, the more constrained. Model 1 incorporates only controls and sales growth. Model 2 adds the measure of financial constraints and its interactions with sales growth. Model 3 similarly adds optimism. Models 4 through 6 incorporate knowledge capital and its interactions with sales growth. *Firm Knowledge* has a slightly higher explanatory power (3.5%-4.2% points) than *Scientific Value* or *Economic Value*. The significantly positive coefficients on all sales growth variables in Model 1 confirm procyclical R&D regardless of the cycle phase. Model 2 indicates that the financial constraint reduces R&D growth and makes R&D more procyclical; these findings are consistent with the well-established relationship between financial constraints and investment-cash flow sensitivity in finance (Fee et al. 2009).[5] Model 3 shows that optimism leads to larger R&D growth and that optimistic managers tend to increase their R&D proportionately more than their less optimistic peers during expansion; but optimism has no effects on the R&D procyclicality during contraction. In Models 4-6, the coefficients on the knowledge stocks are all significantly negative: Hypothesis 1 is supported. All expansion interaction terms are significantly negative: Hypothesis 2 is supported. However, none of the contraction interactions are significant: Hypothesis 3 is not supported. Tests of joint significance of interactions corroborate that knowledge capital matters only for expansion: the expansion interactions are jointly significant at the 1% level ($F_{2,1976}$=15.22, $F_{2,2021}$=4.96, and

[5] We find a correlation of .937 between log sales and log cash flow (income before extraordinary items plus depreciation and amortization).

$F_{2,2021}$=5.37), whereas the contraction interactions are not ($F_{2,1976}$=2.39, $F_{2,2021}$=.97, and $F_{2,2021}$=.15). Several extra analyses assure that the primary results in Table 3 are robust to alternative specifications and assumptions.[6]

[Table 3 about here]

4.3 Estimates of comovement elasticity

Table 4 displays the estimated comovement elasticities from Models 4-6. To illustrate the effects of financial constraints and knowledge capital, we calculate differences in the slopes between the sample 90th and 10th percentiles (hereafter P90 and P10). For optimism, we compute differences in the slope between optimism being 1 and 0. First, we find no significant differences between the marginal expansion and contraction elasticities. Absent any other effects, the comovement of the R&D stock with sales is symmetric between expansion and contraction both in the direction and extent: difference (1)–(2). The comovement elasticity is estimated to range from 10% to 12% per 100% change in sales. Second, more constrained firms are about twice as procyclical as less constrained firms: differences (3)–(4) and (5)–(6). This variation is more pronounced in the expansion elasticity. However, there is no clear evidence, at either end of the financial constraint, of asymmetry between expansion and contraction: differences (3)–(5) and (4)–(6). Third, whereas no significant differences exist in the contraction elasticity (difference (8)–(2)), the expansion elasticity for optimistic firms is 3.5-4.5% points higher than that for less optimistic ones (difference (7)–(1)); these differences amount to be about 1/3 of the latter. Optimistic firms have about twice as large the expansion elasticity as the contraction elasticity: difference (7)–(8). Last, the table documents significant dampening effects of knowledge capital

[6] The results of robustness checks are available upon request.

on the expansion comovement. The expansion elasticity at P90 of *Firm Knowledge* is about half what it is at P10, though the P90-P10 difference is smaller for the other two measures, with the P90-P10 ratios being .89 and .85 for *Scientific* and *Economic Value*, respectively: difference (9)–(10). Conversely, we find no effects of knowledge capital on the contraction elasticity, with the P90-P10 differences being small and insignificant: difference (11)–(12). The expansion-contraction ratios at P90 are .56, .90, and .91 for *Firm Knowledge*, *Scientific Value*, and *Economic Value*, respectively. Only *Firm Knowledge* posts a significant difference at P90 (difference (9)–(11)), whereas the expansion-contraction differences at P10 are all insignificant (difference (10)–(12)).

Since the knowledge stocks are highly skewed, we repeat the analysis using the 99th percentile. As expected, the differences multiply, and the expansion-contraction difference (9)–(11) becomes significant for *Economic Value* (d=–.0853, p=.042) as well. With the sharper contrast, we find stronger evidence of the dampening effects of knowledge capital on the expansion comovement. Contrary to optimistic firms, which more than offset their lost R&D in response to positive demand signals, during expansion firms with large knowledge capital do not attempt to increase their R&D large enough to make up all of their lost R&D during contraction.

[Table 4 about here]

4.4 R&D relative to advertising

We argue earlier that growing knowledge capital facilitates shifts in managerial attention from exploration to exploitation, thereby decreasing strategic emphasis on R&D such that the sequential trade-off between the two processes lessens (grows) the need to raise (reduce) exploratory R&D at times of rising (falling) demands. Though we cannot test the within-R&D

shift due to data limitations, we can test the across-unit trade-off between R&D and exploitative units: if our theorizing holds true, the relative size of R&D investment among discretionary expenses must move cyclically and respond to knowledge capital. To this end, we investigate the cyclicality of R&D expense relative to advertising, which is considered an exploitative activity (Gupta et al. 2006; Vissa et al. 2010) or value appropriation (Mizik and Jacobson 2003). We construct the expense share – R&D expense divided by combined R&D and advertising expenses – and analogously the stock share. The advertising stock is constructed the same way as the R&D stock except with a 40% depreciation rate (Srinivasan et al. 2011). Missing advertising expenses are replaced with zeros. For simplicity, we estimate fixed-effects linear regression, and the results appear in Table 5.

Models 1-3 use the expense share. Among the sales growth variables, only the lagged expansion growth is significant. *Ceteris paribus*, while acyclical during contraction, the expense share is countercyclical during expansion: advertising commands a higher share during expansion presumably because the opportunity cost of exploration increases with the better prospect of extracting profits. Knowledge capital has no direct effect on the expense share: the size of knowledge capital *in vacuo* does not alter the relative merits of R&D and advertising. Whereas we find no moderating effects of *Firm Knowledge* and *Scientific Value,* we do find *Economic Value* to amplify the countercyclical R&D share during expansion. This result is evidence that knowledge capital adds to the opportunity cost of exploration during expansion, further increasing the relative allocation to advertising.

Models 4-6 use the stock share. Though evidence of the countercyclical R&D share is stronger as both lagged and twice lagged expansion growth are significantly negative, and knowledge capital yields a different pattern of moderating effects. While the expansion-period interactions are all insignificant and do not augment the cyclicality of the R&D share, Model 6 registers significant contraction-period moderating effects (one with p<.10) of *Economic Value* that turn the R&D stock share procyclical: i.e., the R&D share decreases as sales decrease when knowledge capital is large. Emboldened by technological innovations at hand, firms place relatively less emphasis on R&D vis-à-vis advertising, even when unfavorable demand conditions foster R&D due to low opportunity costs of exploration. Taken together, both results point to the dampening effect of knowledge capital: firms direct relatively more resources into advertising (exploitation) at the expense of R&D (exploration) regardless of sales performance. Finally, it is noteworthy that only *Economic Value* is at work in the share equations. Contrary to the other two, *Economic Value* is based on *ex ante* asset prices. Managers appear to factor in investor reactions while pondering the right mix of exploration and exploitation, and the allocation of resources and attention between R&D and advertising seems to be more sensitive to expected private rents to a patent than its intrinsic scientific or technical advantage (Kogan et al. 2017)

[Table 5 about here]

5 Discussion

5.1 Theoretical implications

We introduce knowledge capital as a novel determinant of R&D cyclicality and examine its impact; reveals its association with the growth of R&D investment; demonstrates its moderating effect that operates asymmetrically between sales expansion and contraction; and provides evidence that balancing between R&D and advertising bears on this moderating effect. This study examines the impact of knowledge capital – a manifestation of successful R&D – on the growth of R&D investment through the theoretical lens of the BTOF, which posits a negative relationship between positive performance and subsequent R&D search intensity. We expand the BTOF literature by demonstrating that search intensity (R&D growth) may also rely on granular, unit-level performance metric (patents and technological innovations) as a signal of subsequent firm-level financial performance such that technological search might rest on a complex interplay between feedbacks from both the respective unit (technological innovations) and the whole organization (sales growth).

Our research deepens insights and prescriptions from the business cycle management literature (Navarro et al. 2010; Srinivasan et al. 2011; Steenkamp and Fang 2011). In our study, technologically more advanced firms are just as procyclical during contraction and less procyclical during expansion than their less advanced peers. Even if increasing sales free up more internal funds, firms with sufficient innovations can slow down the pace of technological search without running the risk of technological obsolescence. In contrast, those with the urgency to rejuvenate their R&D portfolios cannot help but assume more risk and accelerate the rate of R&D growth on signs of improving market conditions, which also raise the opportunity cost of R&D. Accordingly, it might be elusive to judge whether certain directions and extents of cyclical adjustments of R&D investment are desirable in and of themselves, and such temporal spending variability needs to be scrutinized in conjunction with firm-specific technological stocks. It follows that prescriptions for R&D cyclicality and temporal variability had better grow more nuanced and contextualized because heterogenous R&D behaviors along the business cycle are driven by the firm’s technological position as much as they may stem from managerial choice or resolution to move ahead of the competition.

We advance the important idea that the business cycle or an idiosyncratic demand shock provides a context in which managerial attention is allocated between exploration and exploitation. Furthermore, this study indicates that internal capabilities and intangible assets, as well as the organizational structure or environmental embeddedness, could regulate a selective focus of attention by rendering exploitative activities more salient: notably, the evolution of knowledge capital moderates the dynamic interplay between R&D and marketing. Valuable innovations, especially when cross-checked by investors, could signal for managers to increase their strategic emphasis on exploitation versus exploration by heightening the relative allocation to marketing. When decreasing performance tightens financial constraints, firms may cope with the trade-off between exploration and exploitation via a larger cut in R&D than marketing; with more internal funds freed up by increasing performance, firms may deal with the trade-off via a larger lift in marketing than R&D. Thus, while a firm-level performance indicator – e.g., sales, firm value, and ROA – may well set the stage for dynamic balancing between R&D (exploration) and marketing (exploitation), such balancing could also rest on managers' interpretation of granular metrics for technological assets. What's more, a stronger emphasis on advertising triggered by knowledge capital reflects that the larger the stock of stored technological innovations, the higher the opportunity cost of exploration and the stronger the longing for marketing that creates market and get the innovation to the right customers at the right time (Yohn 2019).

Furthermore, our research has implications for the interplay among organizational search of different kinds. Prior research mostly focuses on a single search domain (e.g., R&D) and how its intensity depends on contextual factors and slack resources; or firms are assumed to make a discrete choice among search types, a choice that relies largely on stable firm characteristics (e.g., Vissa *et al.*, 2010). Resource allocation over multiple search domains is a complex decision that requires close examination of conflicts and complementarity among them, as their roles are distributed disproportionately over exploration and exploitation. We tackle directly the substitution between technical (R&D) and market search (advertising) and reveal that the relative salience of technical search vis-à-vis market search fluctuates cyclically and, more significantly, to dynamically changing technological knowledge base and solutions that can be deployed and launched. More broadly, our research suggests that a mixture of diverse search activities adapts to the dynamics of firm performance, internal technological capability, and very likely other intangible marketing assets (e.g., brand equity or customer relationships). Intriguingly, the blending of technological and market search is sensitive to stock market valuation of an innovation rather than an assessment of its intrinsic scientific significance, implying that managers avail themselves of investor reactions as a decision heuristic to simplify organizational adaptation (Levinthal and March 1993).

5.2 Managerial implications

Most U.S. manufacturing firms – heavy R&D users – seem to invest in R&D procyclically. Though countercyclical R&D might be desirable especially from a competitive viewpoint, it seems that managers come under pressure for quick cyclical adjustments to R&D investment: it would be hard to defy the conventional wisdom. Thus, managers should understand that because of the common expectation, selling a countercyclical R&D investment strategy requires well-crafted messaging to assuage employees, stakeholders, and investors.

While procyclical R&D is widespread, firms differ in the extent of procyclicality for multiple reasons such as competition, cash flow, financial constraints, and confidence. A firm's stance is endogenously determined by yet another factor, a stock of technological knowledge and innovations. In other words, firms' R&D strategies are predicated on not just managerial intention but also internal assets and capabilities. Thus, a mere attempt to achieve spending parity (e.g., the percentage-of-sales method) with industry peers is ill-advised because it ignores substantial heterogeneity in the ability to bring a new innovation to the market. Instead of mimicking a customary heuristic for R&D spending, firms had better craft their R&D investment level by comparatively assessing their technological advantages. On the one hand, smaller (even no) increases in R&D than competitors during sales expansion is not so bad as previously prescribed in the business cycle literature, insofar as firms have accumulated valuable and abundant innovations that can quickly debut on the market. On the other hand, if a firm is technologically behind, increasing R&D more than the competition or even countercyclically is not a choice any more but a *sine qua non* because the goal is not so much to preempt the competition as to catch up with technology leaders. Herding, in this sense, would be detrimental, further exacerbating the firm's weak technological and competitive positions. Consequently, competitive intelligence should look above and beyond the surface because competitors' R&D investments are enabled or impelled by their internal resources and capabilities perhaps more than by managerial attitude, confidence, and desire.

Innovation is one thing, and commercialization is another thing. Innovations induce firms to shift their attention to exploitative or value appropriating activities including production, marketing, and sales. Firms' abilities to profit from innovations are as heterogenous as their abilities to create innovations. Since both value creation and value appropriation capabilities are required for achieving long-term competitive advantages (Mizik and Jacobson 2003), even firms with advanced technologies should not let their guard down because great products may not sell themselves. While technology leaders build their shares of voice (i.e., advertising) to capture advantages generated by successful R&D, followers should strive to counterbalance the competitive force by matching advertising dollars. Such a tit-for-tat seems quite necessary to decelerate the diffusion of a new product or the encroachment on the core clientele. In other words, swift actions to say "not so fast" could buy followers some time as they strive to either expedite their own technological innovations or imitate the leaders rather quickly.

5.3 Limitations and future research

More complete and nuanced understanding of R&D cyclicality requires analysis of comprehensive global data in a consistent econometric framework that allows for rich between-nation as well as within-firm idiosyncrasies. We ignore unobserved firm heterogeneity; future research could fit more sophisticated models to estimate firm-level comovement elasticities and their distribution within industry. Due to data limitations, we cannot distinguish between exploratory and exploitative R&D; thus, researchers could model within-R&D trade-off and advance further insights into how the within trade-off evolves with the growth of knowledge capital. Models for problemistic search that delve into investment decisions could be augmented with knowledge capital because a buffer of stored innovations that can quickly translate into solutions may diminish the need for increased R&D to develop brand new solutions. In addition, models for organizational search can be expanded to simultaneously include multiple search domains, and one can examine how attainment discrepancy, technological capability, and organizational slack interact to govern the relative intensities of divergent search activities. We examine advertising expense as a kind of surrogate for marketing endeavor because marketing expenses are not readily available in COMPUSTAT. A direct measure of total marketing investment is required to provide a comprehensive coverage of activities geared toward exploitation and value appropriation. Various metrics of marketing investments and assets could shed more light on firms' intertemporal decisions on attention allocation in response to the business cycle and financial performance. Among others, intangible marketing assets merit investigation as they could affect an incentive for technological search.

Ethics declarations

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Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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Fig. 1 Theoretical framework

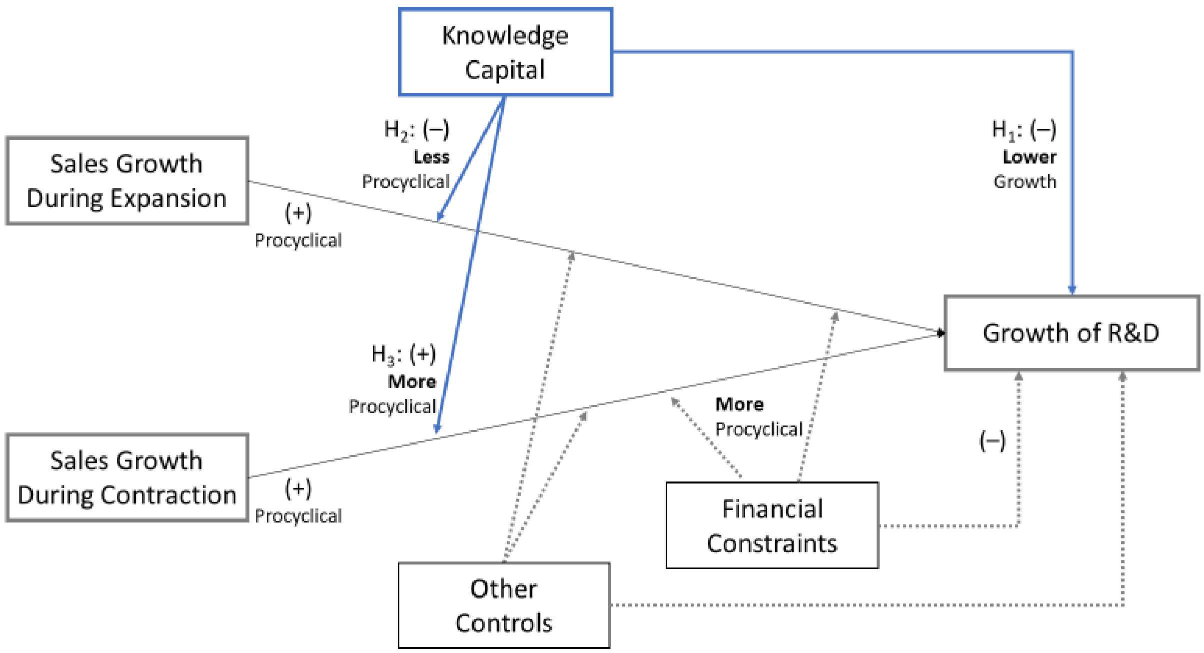

Table 1 Descriptive statistics

Variable	Mean	SD	Within Variance	P1	P99	Skew
Growth of R&D stock	.0830	.1248	68.3%	-.1259	.5274	1.55
Sales growth	.0731	.4381	90.6%	-1.2351	1.7327	1.40
Log book assets	4.6143	2.1023	10.0%	.5124	9.8135	.35
MTB	2.0115	2.2733	52.6%	.3752	12.1375	4.34
Herfindahl index	.1753	.1402	16.2%	.0378	.7692	2.31
Cash holdings	.2188	.2414	25.4%	.0016	.9290	1.36
Optimism	.1614	.3679	69.3%	0	1	1.84
Expansion	.4181	.4933	89.4%	0	1	.33
Firm Knowledge	.8749	1.0991	22.2%	.0008	4.5954	1.74
Scientific Value	.6376	1.2513	28.6%	0	6.8577	4.34
Economic Value	.4958	1.1155	38.3%	0	6.1430	4.76

All variables are lagged by one year except growth of R&D stock.
SD = standard deviation. P = percentile.
Column Within Variance shows the percentage of within-firm variance in the sample variance.
Dollar-metric variables are deflated by the CPI, and all variables are winsorized at the 1% and 99% levels using annual breakpoints.
Log book assets = the natural logarithm of book assets; MTB = market capitalization at the fiscal year-end plus book value of debt divided by book assets; Herfindahl index = computed in each year-industry; Cash holdings = cash plus marketable securities divided by book assets; Optimism = a dummy taking on 1 (optimistic CEO) if the firm's capital expenditure belongs to the top quintile in the industry for two consecutive years and 0 otherwise.

Table 2 Correlation matrix

Variable	1	2	3	4	5	6	7	8	9	10
1. Growth of R&D stock										
2. Sales growth	.199									
3. Log book assets	-.051	-.078								
4. MTB	.253	.206	-.264							
5. Herfindahl index	-.068	-.026	.075	-.143						
6. Cash holdings	.197	.125	-.311	.417	-.279					
7. Optimism	.141	.031	.049	.035	.019	-.121				
8. Expansion	.204	.054	-.068	.174	-.001	.084	.055			
9. Firm Knowledge	-.146	-.009	.261	.088	-.064	.046	.049	-.058		
10. Scientific Value	-.067	.020	-.252	.248	-.051	.181	.003	.067	.504	
11. Economic Value	-.042	-.009	.319	.192	-.148	.148	.006	-.012	.620	.339

For N=25,478, correlations of .012 and .016 yield two-sided p<.05 and p<.01, respectively

Table 3 Innovation and cyclicality of R&D stock

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Measure of knowledge capital				*Firm Knowledge*	*Scientific Value*	*Economic Value*
Constant	**-.0794*****	**-.1497*****	**-.1381*****	.0166	**-.1239*****	**-.1609*****
	(.0122)	(.0148)	(.0153)	(.0198)	(.0160)	(.0148)
Log book assets	**.0336*****	**.0310*****	**.0311*****	**.0244*****	**.0293*****	**.0372*****
	(.0025)	(.0024)	(.0024)	(.0023)	(.0024)	(.0023)
MTB	**.0120*****	**.0108*****	**.0105*****	**.0106*****	**.0107*****	**.0117*****
	(.0009)	(.0009)	(.0009)	(.0008)	(.0008)	(.0008)
Herfindahl index	.0245	.0213	.0194	.0276*	.0244	.0213
	(.0186)	(.0182)	(.0179)	(.0166)	(.0175)	(.0175)
Expansion sales growth(t-1): $\Delta s_{i,t-1}^{H}$	**.0300*****	**.0731*****	**.0640*****	**.0666*****	**.0688*****	**.0666*****
	(.0038)	(.0072)	(.0075)	(.0084)	(.0079)	(.0074)
Contraction sales growth(t-1): $\Delta s_{i,t-1}^{L}$	**.0244*****	**.0466*****	**.0496*****	**.0473*****	**.0522*****	**.0422*****
	(.0040)	(.0069)	(.0069)	(.0072)	(.0074)	(.0071)
Expansion sales growth(t-2): $\Delta s_{i,t-2}^{H}$	**.0209*****	**.0490*****	**.0429*****	**.0442*****	**.0446*****	**.0463*****
	(.0029)	(.0057)	(.0057)	(.0063)	(.0060)	(.0057)
Contraction sales growth(t-2): $\Delta s_{i,t-2}^{L}$	**.0306*****	**.0682*****	**.0668*****	**.0587*****	**.0659*****	**.0598*****
	(.0041)	(.0071)	(.0075)	(.0071)	(.0075)	(.0073)
Cash holdings		**-.1007*****	**-.1020*****	**-.0815*****	**-.1006*****	**-.1043*****
		(.0102)	(.0102)	(.0095)	(.0102)	(.0097)
Cash holdings × $\Delta s_{i,t-1}^{H}$		**.0840*****	**.0755*****	**.0555*****	**.0718*****	**.0734*****
		(.0102)	(.0105)	(.0110)	(.0106)	(.0102)
Cash holdings × $\Delta s_{i,t-1}^{L}$		**.0338*****	**.0366*****	**.0439*****	**.0338*****	**.0273****
		(.0108)	(.0107)	(.0102)	(.0108)	(.0107)
Cash holdings × $\Delta s_{i,t-2}^{H}$		**.0564*****	**.0504*****	**.0439*****	**.0487*****	**.0517*****
		(.0080)	(.0079)	(.0076)	(.0079)	(.0076)
Cash holdings × $\Delta s_{i,t-2}^{L}$		**.0643*****	**.0617*****	**.0516*****	**.0591*****	**.0565*****
		(.0106)	(.0109)	(.0096)	(.0109)	(.0104)
Optimism			**.0156*****	**.0116*****	**.0160*****	**.0149*****
			(.0032)	(.0029)	(.0031)	(.0030)
Optimism × $\Delta s_{i,t-1}^{H}$			**.0300****	**.0269****	**.0317*****	**.0258****
			(.0122)	(.0111)	(.0118)	(.0113)
Optimism × $\Delta s_{i,t-1}^{L}$			-.0312*	-.0191	-.0306*	-.0289*
			(.0171)	(.0174)	(.0174)	(.0168)
Optimism × $\Delta s_{i,t-2}^{H}$			.0139*	.0078	.0135*	**.0147****
			(.0076)	(.0070)	(.0073)	(.0071)
Optimism × $\Delta s_{i,t-2}^{L}$			-.0057	-.0102	-.0011	-.0108
			(.0203)	(.0216)	(.0198)	(.0199)
Knowledge capital				**-.0358*****	**-.0131*****	**-.0201*****
				(.0027)	(.0025)	(.0025)
Knowledge capital × $\Delta s_{i,t-1}^{H}$				**-.0153*****	**-.0054*****	**-.0077*****
				(.0028)	(.0017)	(.0028)
Knowledge capital × $\Delta s_{i,t-1}^{L}$				.0010	-.0024	.0012
				(.0025)	(.0017)	(.0026)
Knowledge capital × $\Delta s_{i,t-2}^{H}$				**-.0068*****	**-.0026****	**-.0056*****
				(.0023)	(.0013)	(.0019)
Knowledge capital × $\Delta s_{i,t-2}^{L}$				-.0038	-.0013	.0012
				(.0026)	(.0017)	(.0022)
#Firms	2,022	2,022	2,022	1,977	2,022	2,022
#Firm-years	28,040	28,040	28,040	25,478	28,040	28,040
Overall R^2	.4696	.4834	.4877	.5359	.4938	.5017
Within R^2	.1852	.2063	.2130	.2557	.2223	.2345

***, **, and * for p<.01, p<.05, and p<.10, respectively. Time fixed-effects are included in the within estimation. Standard errors are clustered by firm and displayed in parentheses. Cash holdings are multiplied by -1 such that the higher, the more constrained. Overall R^2 is obtained by least square dummy variable estimation.

Table 4 Estimates of comovement elasticity

Elasticity (ε) and difference	Symbol	Model 4 *Firm Knowledge*	Model 5 *Scientific Value*	Model 6 *Economic Value*
Marginal (ceteris paribus)				
(1) Expansion ε	$\sum\alpha_j^H$	**.1108*****	**.1134*****	**.1128*****
(2) Contraction ε	$\sum\alpha_j^L$	**.1060*****	**.1180*****	**.1021*****
(1) – (2)		.0048	-.0047	.0108
Cash holdings (X)				
(3) Expansion ε at P90	$\sum\alpha_j^H + X_{(90)}\sum\beta_j^H$	**.1095*****	**.1118*****	**.1112*****
(4) Expansion ε at P10	$\sum\alpha_j^H + X_{(10)}\sum\beta_j^H$	**.0494*****	**.0390*****	**.0356*****
(3) – (4)		**.0600*****	**.0728*****	**.0756*****
(5) Contraction ε at P90	$\sum\alpha_j^L + X_{(90)}\sum\beta_j^L$	**.1048*****	**.1168*****	**.1010*****
(6) Contraction ε at P10	$\sum\alpha_j^L + X_{(10)}\sum\beta_j^L$	**.0471*****	**.0607*****	**.0504*****
(5) – (6)		**.0577*****	**.0561*****	**.0506*****
(3) – (5): Exp-Con at P90		.0047	-.0050	.0102
(4) – (6): Exp-Con at P10		.0024	-.0217*	-.0148
Optimism (Y)				
(7) Expansion ε at *Y*=1	$\sum\alpha_j^H + \sum\gamma_j^H$	**.1455*****	**.1586*****	**.1533*****
(8) Contraction ε at *Y*=1	$\sum\alpha_j^L + \sum\gamma_j^L$	**.0767****	**.0863*****	**.0623****
(7) – (1): Expansion *Y*=1 vs. *Y*=0		**.0347****	**.0452*****	**.0405*****
(8) – (2): Contraction *Y*=1 vs. *Y*=0		-.0293	-.0318	-.0397
(7) – (8): Exp-Con at *Y*=1		**.0687****	**.0723****	**.0910*****
Knowledge capital (Z)				
(9) Expansion ε at P90	$\sum\alpha_j^H + Z_{(90)}\sum\delta_j^H$	**.0557*****	**.1004*****	**.0959*****
(10) Expansion ε at P10	$\sum\alpha_j^H + Z_{(10)}\sum\delta_j^H$	**.1104*****	**.1134*****	**.1128*****
(9) – (10): Expansion P90 vs. P10		**-.0547*****	**-.0129*****	**-.0170*****
(11) Contraction ε at P90	$\sum\alpha_j^L + Z_{(90)}\sum\delta_j^L$	**.0990*****	**.1121*****	**.1051*****
(12) Contraction ε at P10	$\sum\alpha_j^L + Z_{(10)}\sum\delta_j^L$	**.1060*****	**.1180*****	**.1021*****
(11) – (12): Contraction P90 vs. P10		-.0069	-.0059	.0030
(9) – (11): Exp-Con at P90		**-.0433****	-.0117	-.0092
(10) – (12): Exp-Con at P10		.0044	-.0047	.0108
P99 vs. P01				
(9) – (10): Expansion P99 vs. P01		**-.1012*****	**-.0548*****	**-.0816*****
(11) – (12): Contraction P99 vs. P01		-.0128	-.0252	.0144
(9) – (11): Exp-Con at P99		**-.0836*****	-.0343	**-.0853****
(10) – (12): Exp-Con at P01		.0047	-.0047	.0108

***, **, and * for *p*<.01, *p*<.05, and *p*<.10, respectively. P = percentile. Subscripts in parentheses indicate percentiles: e.g., $X_{(90)}$ is the 90th percentile of *X*. Standard errors are clustered by firm. Cash holdings are multiplied by -1 such that the higher, the more constrained.

Table 5 Innovation and R&D relative to advertising

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Dependent variable		$100 * \frac{R\&D}{R\&D + Ad}$			$100 * \frac{R\&D\ Stock}{R\&D\ Stock + Ad\ Stock}$	
Measure of knowledge capital	*Firm Knowledge*	*Scientific Value*	*Economic Value*	*Firm Knowledge*	*Scientific Value*	*Economic Value*
Constant	**104.0497*****	**104.3216*****	**104.0615*****	**99.9271*****	**100.2519*****	**100.2690*****
	(2.6626)	(2.1353)	(2.0507)	(1.5200)	(1.2364)	(1.1931)
Log book assets	.1786	.1344	.1726	-.2210	-.2745	-.2735
	(.4292)	(.3846)	(.3773)	(.2571)	(.2401)	(.2360)
MTB	.0410	.0627	.0626	-.0068	.0194	.0169
	(.0648)	(.0577)	(.0559)	(.0429)	(.0387)	(.0373)
Herfindahl index	3.2891	3.4470	3.3429	5.2522	5.1565	5.1274
	(5.6808)	(5.3227)	(5.3242)	(4.0265)	(3.8046)	(3.8013)
Expansion sales growth$_{(t-1)}$: $\Delta s^H_{i,t-1}$	**-1.6691****	**-1.3087****	**-1.1497***	**-1.5498*****	**-1.2813*****	**-1.2199*****
	(.7375)	(.6218)	(.6112)	(.4003)	(.3808)	(.3743)
Contraction sales growth$_{(t-1)}$: $\Delta s^L_{i,t-1}$	-.5550	-.6548	-.8420	-.0421	-.1945	-.2737
	(.7762)	(.6656)	(.6381)	(.4456)	(.4120)	(.3987)
Expansion sales growth$_{(t-2)}$: $\Delta s^H_{i,t-2}$	-.7359	-.3271	-.1760	**-1.0026*****	**-.8240****	**-.7718****
	(.5524)	(.4486)	(.4577)	(.3497)	(.3270)	(.3248)
Contraction sales growth$_{(t-2)}$: $\Delta s^L_{i,t-2}$	-.0322	-.0100	-.1491	-.4576	-.4692	-.4745
	(.7860)	(.6971)	(.6757)	(.3864)	(.3725)	(.3664)
Cash holdings	-.3566	-.9808	-.9117	.1529	-.2916	-.2597
	(1.2503)	(1.0947)	(1.0992)	(.7224)	(.6517)	(.6558)
Cash holdings × $\Delta s^H_{i,t-1}$	**-2.4143*****	**-1.9145****	**-2.0053*****	**-2.2656*****	**-1.8838*****	**-1.9359*****
	(.8649)	(.7643)	(.7679)	(.4712)	(.4539)	(.4548)
Cash holdings × $\Delta s^L_{i,t-1}$	-.3478	-.6786	-.6826	.3774	-.1053	-.0710
	(.8853)	(.7902)	(.7964)	(.5250)	(.4877)	(.4904)
Cash holdings × $\Delta s^H_{i,t-2}$	-1.1785*	-.8307	-.8624	**-1.5104*****	**-1.3277*****	**-1.3260*****
	(.6316)	(.5610)	(.5566)	(.3957)	(.3741)	(.3755)
Cash holdings × $\Delta s^L_{i,t-2}$	-.2415	-.1726	-.0799	-.3589	-.5346	-.4882
	(.8796)	(.8280)	(.8440)	(.4597)	(.4659)	(.4695)
Optimism	**1.0588****	**.9895****	**.9761****	**.5601****	**.5397****	**.5385****
	(.4281)	(.4108)	(.4105)	(.2543)	(.2485)	(.2480)
Optimism × $\Delta s^H_{i,t-1}$	-.4813	-.2457	-.2081	-.0657	-.2426	-.2236
	(.7512)	(.6613)	(.6633)	(.4023)	(.3715)	(.3774)
Optimism × $\Delta s^L_{i,t-1}$	-.2067	-.2033	-.1893	-.8396	-.4344	-.4158
	(.9750)	(.8356)	(.8361)	(.6714)	(.5118)	(.5089)
Optimism × $\Delta s^H_{i,t-2}$	-.5644	-.5250	-.4291	-.3232	-.4626	-.4393
	(.4907)	(.4615)	(.4702)	(.3203)	(.3305)	(.3346)
Optimism × $\Delta s^L_{i,t-2}$	.0072	.0017	-.0157	.0118	.0649	.0414
	(.9961)	(.9435)	(.9398)	(.4850)	(.5261)	(.5305)
Knowledge capital	-.1050	-.2704	.0941	.3550	-.0591	.0854
	(.3900)	(.2449)	(.2833)	(.2586)	(.1428)	(.1942)
Knowledge capital × $\Delta s^H_{i,t-1}$	.0450	.0123	**-.2918****	.0043	.0024	-.1248
	(.1548)	(.0816)	(.1451)	(.0841)	(.0480)	(.0857)
Knowledge capital × $\Delta s^L_{i,t-1}$	-.0087	-.0539	.1536	.1728*	.0392	**.1912****
	(.1587)	(.0916)	(.1408)	(.1006)	(.0489)	(.0952)
Knowledge capital × $\Delta s^H_{i,t-2}$	.1428	-.0146	**-.2768****	.0406	-.0097	-.0866
	(.1342)	(.0877)	(.1248)	(.0838)	(.0543)	(.0915)
Knowledge capital × $\Delta s^L_{i,t-2}$	-.1437	-.0606	.0917	.1266	.0482	.1188*
	(.1583)	(.0740)	(.1268)	(.0781)	(.0404)	(.0708)
#Firms	1,977	2,022	2,022	1,977	2,022	2,022
#Firm-years	25,478	28,040	28,040	25,478	28,040	28,040
Overall R^2	.8426	.8386	.8386	.9032	.8985	.8986
Within R^2	.0875	.0860	.0861	.1629	.1609	.1611

***, **, and * for $p<.01$, $p<.05$, and $p<.10$, respectively. Time fixed-effects are included in the within estimation. Standard errors are clustered by firm and displayed in parentheses. Cash holdings are multiplied by -1 such that the higher, the more constrained. Overall R^2 is obtained by least square dummy variable estimation.