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The Role of CEO Ability in Determining R&D Investment Behavior among High Technology Firms in Korea*

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ABSTRACT

This study examines whether and how R&D management in high technology firms differs from that in non-high technology firms in Korea. More importantly, given that CEOs are responsible for R&D investment decision-making, we investigate whether more competent CEOs at high technology firms engage in different R&D management than those less competent. Using the cost stickiness model developed by Anderson et al. (2003), we find that high technology firms exhibit stickier behavior with respect to R&D costs compared to non-high technology firms, indicating that high technology firms are less likely to reduce R&D investment in declining-sales periods. We also find that R&D cost stickiness in high technology firms appears only when the firms are managed by more competent CEOs. This indicates that CEO ability is one of the most important factors explaining R&D management decisions in high technology firms.

Key words: R&D costs, Cost stickiness, Managerial ability, High technology firms

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I. INTRODUCTION

Spending money on research and development (R&D) is one of the most fundamental investment decisions of a firm. Because investment in developing new products, processes, or technologies creates future competitive advantage and productivity (Barney, 1991), how R&D resources are controlled determines a firm's long-term survival and growth. Despite the general consensus on the importance of R&D investment, little is known about how R&D resources are managed and whether or how R&D management is different by managers. Motivated by the fact, we undertake this study to investigate the role of managerial ability on the R&D management in firms in the high technology industry compared to that in non-high-technology firms.

We focus on high technology firms for the following reason. It is undeniable that for a high tech firm, R&D expenditures are a more critical resource for its survival and growth than for any other firms. To generate future profits and innovative outputs, a high technology firm must continuously invest a large amount of money on R&D to sustain its capabilities to innovate at the cutting edge of technology (Jelinek & Schoonhoven, 1993). Otherwise, its value and uniqueness of technological resources can swiftly be lost to competitors, as they operate in a very competitive and dynamic business environment. Despite this need for R&D investment, such innovative activities are inherently risky, leading to a greater variability of outcomes and a greater probability of failure (Graves & Langowitz, 1993; Balkin et al., 2000). Moreover, because innovation requires long-term investment in R&D projects, high tech firms may need to bear a negative impact on immediate financial statements (Hoskisson et al., 1993). Under the resource-based theory, which suggests that sustainable competitive advantage of firms can be achieved by the resources they control (Barney, 1991), we presume that how competent managers exercise their control over the strategic resource (R&D) will be critical for the success of high tech firms, especially.

We examine the association of CEO ability with R&D cost behavior in high technology firms. CEOs make the strategic decisions in their firms. They make, influence, or are ultimately responsible for, critical resource allocations pertaining to investments in new products and technologies. How R&D costs are managed, we conjecture, varies with CEO ability. Indeed, this is consistent with the upper-echelon perspective suggested by Hambrick & Mason (1984), which argues that organization outcomes can be viewed as reflections of the values and cognitive bases of top managers in organizations. Adopting this perspective, we consider how R&D management varies with CEO ability. More importantly, the influence of CEO ability is more pronounced for firms in the high technology industry. R&D-intensive firms operate in what Hambrick & Finkelstein (1987) defined as a high-discretion context. In this context, managers enjoy their discretionary power and face a wide latitude of choices when making strategic decisions. As resources devoted to innovation increase, the potential impact of the CEO on a firm's relative success or failure also increases. Given that CEOs in high technology firms are provided with discretionary power on strategic costs like R&D, we draw an inference that there can be a substantial difference, in terms of R&D management, between a competent manager and a less competent one.

To examine how R&D costs are managed, we adopt the cost-stickiness model developed by Anderson et al. (2003). While several studies have investigated the differential level of R&D spending by industry (e.g. Scherer, 1984), we address our research question by analyzing asymmetric cost behavior of R&D. Indeed, the cost stickiness model allows us to capture how R&D costs are adjusted in response to a short-term shock, such as a decline in sales. According to the cost stickiness literature, costs are considered 'sticky' if they decrease less when sales fall than they increase when sales rise by an equivalent amount, the argument being that sticky costs occur because managers deliberately adjust resources. Recent literature documents the asymmetric cost behavior of R&D costs (e.g. Ahn et al., 2015; Kwon et al., 2018; Kim, 2019). For example, Ahn et al. (2015) showed that family-run firms exhibit greater R&D cost stickiness because they tend to run their businesses in more long-term perspective. Kwon et al. (2018) investigated the R&D cost behavior of chaebol firms and provided evidence that chaebol firms exhibit stickier R&D cost behavior compared to non-chaebol firms. Kim (2019) exclusively focused the IT industry and showed that firms in IT industry, compared to those in other industries, tended to maintain R&D costs in periods of declining sales.[2]

[2] This study compares the cost behavior of high tech firms versus non-high technology firms. Our definition of high tech firms partially includes IT companies defined in Kim (2019) but has substantially different sample. For example, while the professional services industry (KSIC 2-digit=71) is classified as high tech firms in our sample, it is defined as non-IT industry in Kim (2019).

We extend this line of literature by documenting the cost behavior of the high technology industry.

Using a sample of Korean firms for the period 2000–2016, we document that about 28% are classified as high tech firms, while the remaining 72% are non-high tech firms. We examine whether CEO ability affects the R&D cost behavior in high technology and non-high technology firms. Demerjian et al. (2013) believed that superior managers were more knowledgeable about their firms and industry, and that they produced superior prospective information. Under the assumption that more competent managers make more rational decisions on strategic costs such as R&D costs, we expect R&D cost behavior to vary with managerial ability within the high technology industry. However, we expect inconsistent results if the variation in CEO ability does not significantly explain the differential cost behavior within the industry. To measure CEO ability, we use the managerial ability score developed by Demerjian et al. (2012). We find that R&D cost stickiness is observed only for high tech firms run by high-ability managers. On the other hand, when R&D costs are controlled by relatively inferior managers, no asymmetric adjustment in R&D costs occurs in response to changes in sales revenue. Consequently, we provide evidence on the role of CEO ability is determining R&D management in high technology firms.

Our study makes several contributions to the literature. First, it contributes to the growing literature on asymmetric cost behavior. Banker et al. (2018) suggest that changes in R&D investment following a change in sales may be different from changes in SG&A costs. They argue that some workers in R&D or advertising departments are crucial for restoring future sales and, therefore, the standard "cost stickiness" theory cannot be applied; that is, there is a trade-off between "the current costs" and "the future benefits" of current R&D investment (Banker et al., 2018). Our findings suggest a breakpoint that determines whether benefits of maintaining R&D resources exceed costs. Second, our study provides important insights into the high technology industry by examining how R&D costs are managed, which are a crucial strategic resource for long-term value creation. While some prior studies suggest how high tech firms are different from other firms (e.g., Kwon & Yin (2006)), ours is the first study to provide evidence on their R&D management. Finally, we provide evidence that CEO ability is an important determinant of R&D cost behavior in the high technology industry; a CEO plays an important role in the development of the vision of a firm and the strategies to attain that vision. Overall, the findings of this study suggest the importance of the competence of top management team in the management of strategic resources such as R&D activities in high technology firms.

The remainder of the paper is organized as follows. Section II reviews the related literature and develops the hypotheses. Section III describes the data and sample and discusses the research design. Section IV reports the empirical results, followed by Section V which concludes.

II. PRIOR STUDIES AND HYPOTHESIS DEVELOPMENT

1. Cost stickiness

It is widely assumed that there is a linear relationship between a cost driver and costs. However, more recent studies suggest that managerial decisions are important elements of costs and can explain the cost behavior of a firm (Anderson et al., 2003; Banker et al., 2018). In a seminal study, Anderson et al. (2003) first introduce the notion that managerial decisions were important cost drivers; they suggested that the amount by which costs decreased for a given sales volume decrease x is smaller than that by which the costs increased when the sales volume increases by the same amount x, i.e., “cost stickiness”.[3] They suggested that managerial decisions on cost stickiness occurred because of three reasons: adjustment costs, managers’ future expectation of future sales, and managerial entrenchment. Since this study, many scholars have attempted to answer the question: What are the determinants of cost stickiness?

Adjustment costs may be incurred when sales are restored. For example, the investment cost for a program to train new machine operators arises when old machines are sold due to volume decreases and new machines are purchased when volume is restored. Prior studies use employee intensity or employment protection laws as proxies for the adjustment costs (Anderson et al., 2003; Banker et al., 2013).

[3] In Korea, Ahn et al. (2004) first show the cost stickiness of Korean manufacturing firms. They show that the stickiness pattern exists in both SG&A costs and manufacturing costs for Korean manufacturing firms.

Banker et al. (2013) show that the cost stickiness in firms in a specific country becomes stronger when the employment protection laws of the country become stronger.

Managers' expectation of future sales is also an important determinant of cost stickiness. When managers have an optimistic view of future sales, that is, that demand will rebound, they will attempt to maintain current resources, despite diminishing sales volumes. GDP growth and consecutive sales decreases are generally used in cost stickiness research to capture managerial expectation (Anderson et al., 2003). Furthermore, several studies have found a positive association between managerial overconfidence and cost stickiness (Chen et al., 2015). In these studies, managerial overconfidence is interpreted as managers' expectation of future sales.

Several researchers extend the subject of cost behavior by studying the components of SG&A costs. Dierynck et al. (2012) used Belgian private firms and investigated labor costs behavior. Using the sample of Korean firms, Hwang et al. (2017) examined whether labor costs are affected by managers' incentive to avoid losses. Gu et al. (2016) examined how state ownership in China affected labor costs. Hall (2016) studied the effect of ownership structure on labor cost stickiness. However, only a few studies have focused on the cost behavior of R&D costs (Ahn et al., 2015; Kwon et al., 2018; Kim, 2019). For instance, Ahn et al. (2015) studied the relationship between family ownership and R&D costs stickiness. They predict and find that the R&D cost stickiness is greater for family-run firms.

Other studies consider cost stickiness by industry. For example, Subramaniam & Weidenmier (2003) found that, because of high fixed costs, firms in the manufacturing industry exhibited greater cost stickiness, while firms in the retail industry had less sticky cost behavior as they faced higher competition and pressure to increase earnings. Several studies use proprietary industry-specific data. Cannon (2014) uses data for the airline industry and found significant stickiness in airlines' capacity costs. He also documents that airlines add physical capacity when sales revenue increased and retained idle capacity when sales revenue decreases. Balakrishnan et al. (2004) examine the health care sector and find cost stickiness in physical therapy clinics, while the cost behavior in hospitals is examined by Balakrishnan & Gruca (2008), Balakrishnan & Soderstrom (2009), and Holzhacker et al. (2015). Regarding Korean data, Lee et al. (2004) are the first to investigate the differential cost behavior across industries. This study divides the sample into manufacturing, retail, construction, and service industries and examined their cost behavior; however, R&D costs are not analyzed. Cheung et al. (2014) examine whether industry characteristics such as the degree of competition, entry costs, and industry concentration affect asymmetric cost behavior. Despite the extensive literature on cost stickiness across different industries, high-technology firms have not been thoroughly examined, particularly with regards to R&D expenditures.

2. The importance of R&D investments

R&D investment ensures firms' future growth and long-term survival. Through R&D, firms can develop new products or technology, create a new market, or achieve dominance over their competition. Furthermore, R&D investment spurs firms to acquire outside knowledge (Cohen & Levinthal, 1989; Cho & Park, 2013). R&D projects produce long-term gains for the firm (Chan et al., 2001; Eberhart et al., 2004).

Previous studies have investigated various factors affecting R&D investments. Baber et al. (1991) show that firms are more likely to lower R&D expenditure to report positive earnings. De Waegenaere et al. (2012) investigate how the tax rate of a domestic country affected the R&D expenditures of multinational companies. Bushee (1998) finds that firms with higher institutional ownership are less likely to adjust R&D investment to reverse earnings decline. Cheng (2004) suggests that changes in R&D expenditures are positively associated with changes in the value of CEO stock option grants. Nuens et al. (2012) studied European Union and show that R&D investments have positive impacts on the survival and growth of high tech firms compared to non-high tech firms.

Nonetheless, these studies implicitly assume that the relationship between the factors and R&D costs is linear. To our knowledge, only a few studies modeled R&D costs as non-linear. One exception is Brown & Petersen (2011), who argue that young firms utilize cash holdings to reduce the volatility of R&D investment. When it comes to the literature of asymmetric cost behavior, which considers costs reacts to sales in a non-linear way, most studies examined SG&A costs or operating costs, which are the upper category, and R&D costs has been rarely separately examined. Exceptionally, Ahn et al. (2015) argue that investment in R&D is asymmetrically affected by family ownership. Kwon et al. (2018) examined the asymmetry of R&D cost of chaebol firms. Lastly, Kim (2019) focused on R&D costs and compared R&D cost behavior between IT industry and non-IT industry. He showed that firms in IT industry exhibited higher cost stickiness than those in other industries. However, since high tech firms are not limited to IT industry[4], still little is known about R&D cost management in high tech firms in general.

3. The role of managerial ability

Top managers' ability has a significant impact on their firms' activities. This view stems from the upper-echelon perspective suggested by Hambrick & Mason (1984), which argues that the values and cognitive bases of top managers in an organization are reflected in the outcomes of the organization. Managers oversee important strategic decision-making and operational planning throughout the firm (Bertrand & Schoar, 2003). One stream of literature that focuses on manager-specific effects investigates whether and how managerial ability influences a wide range of corporate decisions. Accounting literature has largely been focused on whether managerial ability is related to financial reporting by investigating earnings quality (Demerjian et al., 2013), income smoothing (Baik et al., 2017), tax avoidance (Koester et al., 2016), and management forecasts (Baik et al., 2011). In terms of managers' operational decisions, Holcomb et al. (2009) demonstrate the importance of managerial ability in value creation through better utilization of resources. Chen et al. (2015) find a positive association between managerial ability and corporate innovative output, measured by the number of patents and citations, and further find that the market perceives patents generated by high ability managers to be more valuable than those generated by low ability managers.

Managerial ability matters to high tech firms. More competent managers can effectively promote innovation, which is key to successful business for high tech firms. Product innovation requires top managers' technical literacy, involvement in the planning and execution of technological activities, and commitment to risk-taking (Cooper & Kleinschmidt, 1995). Product development in the high tech sector

[4] For instance, the professional services industry (KSIC 2-digit=71), which is classified as high tech firms in our sample while defined as non-IT industry in Kim (2019), constitute 37% of our sample of high tech firms.

typically requires funds and resources, which cannot be procured without top management support. Therefore, investment choices depend on managerial ability. For example, Andreou et al. (2017) demonstrate that low-ability managers suffered underinvestment problems more severely during the financial crisis period around 2008 than high-ability managers. In addition, previous studies show that managerial skills affect technological investment activities and outcomes. For instance, Bertrand & Schoar (2003) observe that managers' styles affect R&D activity. Wu (2007) report that managers' ability plays a vital role in enhancing start-up capabilities and performance for high tech firms.

4. Hypothesis development

Observing high tech firms provides a great setting to understand R&D investment decisions due to their high R&D intensity. Firms' R&D leans on highly educated scientists or engineers. Laying these people off leads to a huge loss to R&D, requiring high adjustment costs. Therefore, firms prefer to smooth R&D investments to avoid laying off these R&D workers (Hall et al., 1986; Hall, 2012). Banker et al. (2018) stated: "*R&D and marketing resources often constitute a strategic long-term investment to generate future revenue … the researcher should modify the theory to incorporate the trade-off [sic] between the current costs and the future benefits of strategic investment in R&D and marketing resources, with a careful consideration of how this trade-off [sic] changes during sales decreases*." Consistent with this argument, prior research provides an evidence that the benefits to maintaining R&D expenditure when sales decrease are greater for IT-industry than for non-IT industry (Kim, 2019), which may be expandable for high tech firms versus non-high tech firms. We argue that high tech firms are suitable for use in identifying the impact of managerial ability on the "… tradeoff [sic] between the current costs and the future benefits of strategic investment in R&D …", because managers' attitude towards investment in R&D is crucial for high tech firms' growth.

To better understand why high-technology firms exhibit higher cost stickiness, we focus on high-technology firms and consider how R&D management varies with CEO ability. We expect that CEO ability will influence R&D spending in high technology firms because product development and innovation activities are bigger concerns for top managers in the high tech industry than in other industries. Hambrick & Finkelstein (1987) suggest that managers of R&D-intensive firms have high discretion in strategic decision making. Since CEOs in high technology firms enjoy discretionary power in respect of strategic costs, R&D expenditure is largely affected by the choice of CEO. Therefore, we infer a substantial variation in terms of R&D management according to managers' competence levels.

We argue that high-ability CEOs will not reduce R&D expenditures during declining sales periods, as opposed to low-ability CEOs. More competent managers understand the importance of maintaining resources related to R&D activities even when sales decline; this is because internally-generated intangible assets may be lost if R&D-related resources are diminished, and such assets cannot be easily restored when sales increase. R&D spending undercuts can delay development processes and cost firms' growth opportunities. As Andreou et al. (2017) observe, managerial ability mitigates underinvestment problems during economic crises; thus, we conjecture that high-ability CEOs will pursue consistent R&D investments despite temporary sales declines. Competent managers who understand the value of maintaining R&D resources choose stickier R&D investment behavior when sale decrease.[5] Thus, our second hypothesis:

H1: *CEO ability is associated with a greater degree of R&D cost stickiness in high technology firms.*

III. RESEARCH DESIGN

1. Model specification

We employ the cost stickiness model developed by Anderson et al. (2003) as follows:

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[5] There is an alternative postulate. Able managers utilize resources more effectively (Holcomb et al., 2009). Hence, firms with high ability managers may eliminate more resources when sales decrease because able managers can generate good innovate output with reduced resources, leading to an opposite prediction to ours in H2. However, able managers can produce more outputs with more resources. Therefore, firms with able managers do not need to eliminate R&D investment when there is a decrease in sales.

$$\begin{aligned}\Delta RD_{i,t} = \beta_0 &+ \beta_1 \Delta SALE_{i,t} + \beta_2 \Delta SALE_{i,t} * DEC_{i,t} \\ &+ \beta_3 \Delta SALE_{i,t} * DEC_{i,t} * ASSET\_INT_{i,t} + \beta_4 \Delta SALE_{i,t} * DEC_{i,t} * EMP\_INT_{i,t} \\ &+ \beta_5 \Delta SALE_{i,t} * DEC_{i,t} * SDEC_{i,t} + \beta_6 \Delta SALE_{i,t} * DEC_{i,t} * GDP_{i,t} \\ &+ \beta_7 DEC_{i,t} + \beta_8 ASSET\_INT_{i,t} + \beta_9 EMP\_INT_{i,t} + \beta_{10} SDEC_{i,t} + \beta_{11} GDP_{i,t} \\ &+ \text{Year FE} + \text{Industry FE} + \varepsilon_{i,t} \qquad (1)\end{aligned}$$

where,

$RD_{i,t}$	research and development (R&D) expenditures for firm *i* in year *t*;
$SALE_{i,t}$	Sales revenue for firm *i* in year *t*;
$\Delta RD_{i,t}$	log-change in research and development (R&D) expenditures;
$\Delta SALE_{i,t}$	log-change in sales revenue;
$DEC_{i,t}$	a dummy variable, which equals 1 when sales in year *t* are smaller than sales in year *t-1*, and 0 otherwise;
$ASSET\_INT_{i,t}$	logarithm of the ratio of total assets to sales revenue;
$EMP\_INT_{i,t}$	logarithm of the ratio of number of employees to sales revenue;
$SDEC_{i,t}$	a dummy variable, which equals 1 when sales have decreased in two consecutive years (i.e. $SALE_{i,t-2} > SALE_{i,t-1} > SALE_{i,t}$);
$GDP_{i,t}$	the percentage growth in real GDP during year *t*;
Year *FE*	year dummies;
Industry *FE*	industry dummies (using KSIC two-digit industry classification).

In Model (1), the slope coefficient β_1 measures the increase in R&D costs for a sales increase, while $\beta_1 + \beta_2$ measures the decrease in R&D costs for a sales decrease. If R&D costs are sticky, the slope for a sales decrease should be smaller than the slope for a sales increase. Thus, conditional on $\beta_1 > 0$, $\beta_2 < 0$ is expected.

Following previous studies on cost behavior, we control for the economic determinants of cost asymmetry (Anderson et al., 2003). First, we control for adjustment costs. They are measured by asset intensity (*ASSET_INT*) and employee intensity (*EMP_INT*), because adjustment costs are likely to be higher for firms that rely more on assets owned for R&D activities and for firms that use more employees to support a given volume of sales. Second, when firms experience consecutive sales declines, managers are more likely to form pessimistic expectations of future demand that, in turn, result in less sticky behavior. Thus, we control for the incidence of consecutive sales declines as measured by *SDEC*.

Managers also consider macroeconomic situations in their R&D adjustment decisions; thus, we include GDP growth (*GDP*) as a control. The effects of theses determinants on cost stickiness are controlled for, as well as their direct effects on R&D costs changes. Last, we include industry and year dummies to address the variations in cost behavior across industry and year.

To examine our presumption on the strategic importance of R&D cost management in high tech industries, we investigate whether the degree of R&D cost stickiness is different for high tech and non-high tech industries as a baseline test. To test this, we divide the sample into high tech and non-high tech industries, and estimate Model (1) separately for each group. In doing so, we compare managers' R&D management (i.e., expansion or reduction) in high tech and non-high tech companies in the context of both sales increases and decreases. Additionally, the subgroup analysis allows us to vary the effects of the economic determinants on cost stickiness by each group, considering that high technology firms have distinct characteristics. For instance, high tech firms may have to bear greater adjustment costs than compared to that in non-high tech firms. We expect β_2, which captures the degree of R&D cost stickiness, to be significantly more negative for high tech firms.

Given the importance of managerial contribution in high technology firms, we examine the effect of managerial ability on R&D cost behavior. Hypothesis 1 examines whether greater cost stickiness in high tech firms is more prevalent when the firm is managed by high ability managers. Our measure of managerial ability (*CEOABILITY*) comes from Demerjian et al. (2012).[6] We divide the sample of firms in high tech industries into two, based on the sample median of *CEOABILITY*, and run Model (1) separately for each group. We expect β_2 to be smaller (i.e. stickier) when the CEO of the high tech firm has high ability. While we do not have expectations on whether high-ability CEOs of non-high technology firms have an impact on R&D cost stickiness, we run the same regression model for the sample of non-high technology firms to allow for a comparison of results.

2. Measurement of managerial ability

Managers are in charge of important strategic decision-making and operational

[6] See Section 3.2 for detailed information on its measurement.

planning throughout the firm (Bertrand & Schoar, 2003). The impact of managerial contribution on firm value is important; therefore, economics, finance, accounting, and management research attempt to identify and quantify manager-specific features, particularly managerial ability. In this regard, previous studies have attempted to measure managerial ability using prior firm performance (industry-adjusted stock returns or industry-adjusted return-on-assets), prior media citations, pay level, and pay-for-performance sensitivities (Fee & Hadlock, 2003; Milbourn, 2003; Rajgopal et al., 2006; Terviö, 2008; Carter et al., 2010). However, these studies have acknowledged that the existing ability measures are noisy and difficult to attribute solely to managers, and that the measures instead represent significant aspects of firms.

Recently, Demerjian et al. (2012) introduced a better proxy to capture managers' talent by means of a data envelopment analysis (DEA) methodology. Researchers have used the DEA methodology widely to measure firm efficiency (Thore et al., 1994; Murthi et al., 1996; Murthi et al., 1997; Berk & Green, 2004; Berk & Stanton, 2007; Leverty & Grace, 2012). As a first step to estimate managerial ability, Demerjian et al. (2012) estimate relative firm efficiency within an industry using financial data. They use sales revenue as the main output at firm level and consider an array of revenue-generating input variables: cost of inventory, general and administrative expenses, R&D expenditures, tangible assets, including operating leases, and intangible assets. We primarily follow their method; however, we also refer to Park et al. (2016), who were the first to measure firm efficiency and managerial ability in Korean listed firms. We use sales revenue as the output variable as in Demerjian et al. (2012); however, our input variables must be restricted to four variables, as in Park et al. (2016), due to the data availability in the Korean data domain: cost of inventory, SG&A (selling, general, and administrative) expenses, net PP&E (property, plant, and equipment), and intangible assets.[7]

$$\max \theta = \frac{\text{Sales}}{v_1 \text{CoGS} + v_2 \text{SG\&A} + v_3 \text{PPE} + v_4 \text{Intang}} \tag{2}$$

[7] Variable definitions: *Sales* = sales revenue; *CoGS* = cost of goods sold; *SG&A* = selling, general and administrative; *PPE* = tangible assets; *Intang* = intangible assets.

After obtaining the efficiency score ($\max\theta = \frac{\text{Sales}}{v_1 \text{CoGS} + v_2 \text{SG\&A} + v_3 \text{PPE} + v_4 \text{Intang}}$) for each firm-year observation, we regress it on firm-specific factors. As aforementioned, we define managerial ability as the unexplained portion of the total firm efficiency—the residual term in Equation (3) below.

$$FIRM\ EFFICIENCY_{i,t} = \gamma_0 + \gamma_1 SIZE_{i,t} + \gamma_2 MSHARE_{i,t} + \gamma_3 FCF_{i,t} + \gamma_3 FIRMAGE_{i,t} + \gamma_4 BIZSEG_{i,} + \gamma_5 FOREIGNG_{i,t} + \text{Year FE} + \varepsilon_{i,t} \qquad (3)$$

We include firm characteristics of firm size (*SIZE*), market share (*MSHARE)*, free cash flow indicator (*FCF*), firm age (*FIRMAGE*), business segmentation (*BIZSEG*), and foreign currency translation accounts (*FOREIGNG*), following the literature, and year fixed effects.[8] The variable definitions in this study are slightly modified due to data availability and Korean accounting standards (Park et al., 2016). We denote the residual of the Tobit regression as *CEOABILITY*.[9]

An advantage of this two-stage approach to measure managerial ability is in that the method does not confound ability with observable firm characteristics. The second-stage regression removes the impacts of observable firm characteristics that determine firm efficiency from the residuals. In other words, the regression residuals are not correlated with the known factors of firm performance. Thus, the measurement of managerial ability rather purely captures managerial ability.[10]

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[8] Variable definitions: firm size = the natural logarithm of total assets at the end of year t; market share = the percentage of revenues earned by the firm within its two-digit KSIC in year t; free cash flow indicator = 1 if free cash flow (net income before depreciation – change in operating capital – capital expenditure) > 0 , = 0 otherwise; firm age = the natural logarithm of the number of years the firm has been listed on the Korean Stock Exchange; business segmentation = the number of product sales ratio that exceeds 10%; foreign currency translation accounts = the absolute magnitude of foreign currency translation accounts (foreign currency gain, foreign currency transactions, loss on foreign currency transactions) divided by total sales revenue.

[9] The measure of managerial ability is attributable to the ability of the management team, although we focus on the CEO and refer this measure as *CEOABILITY* throughout our analyses, under the assumption that CEO is the most powerful manager and, thus, on average, the most likely to influence the most of outcomes (Fee & Hadlock, 2003; Demerjian et al., 2012).

[10] Since the measure of managerial ability is independent of firm characteristics, such as firm size and cash holdings, that might affect fund availability in R&D activities, it lowers a concern that those firm characteristics might affect R&D investments directly. We thank our referee for this point.

IV. SAMPLE STATISTICS AND EMPIRICAL RESULTS

1. Sample selection

We obtain firm-specific accounting information data from *DataGudie Pro* and *TS2000*, while GDP growth is obtained from The Bank of Korea (http://www.bok.or.kr) for the sample period from 2000 to 2016.[11]

Consistent with prior literature, we exclude firms in the financial service industries and regulated industries. We drop firm-years with non-December fiscal year end to align recognition timing of accounting items across firms, since only a very small fraction of companies in Korea have fiscal year ends in months other than December. We drop observations with zero or missing data on R&D expenditures and sales revenue for the current year and the previous year. We further drop observations with missing data on economic variables (i.e., *ASSET_INT*, *EMP_INT*, *SDEC*). Following this sample selection procedure, our sample consists of 6,132 firm-year observations, which used to test overall R&D cost behavior of high tech firms versus non-high tech firms as a baseline test. In this sample, about 28% (1,695 firm-years) are classified as high tech firms and the remaining 72% (4,437 firm-years) as non-high tech firms. After excluding the observations that do not have enough information to calculate managerial ability score, it leaves 1,114 firm-year observations in high tech industries and 2,460 observations in non-high tech industries[12], We used the final sample of 1,114 observations in high tech industries to test our H1. The sample selection procedure is presented in <Table 1>.

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[11] Our initial sample starts with the year 1998, since the proxy for managers' future expectations measured by prior sales decreases (*SDEC*) requires sales information for the previous two years.

[12] While the required information for managerial ability calculation was missing in 34% of high tech firm observations (N=1,695), it was missing in 45% of non-high tech firm observations (N=4,437). Thus, our examination of high tech firms does not suffer a sample selection problem compared to other studies scoping all industries in general when testing the managerial ability score common in the literature.

<Table 1> Sample Selection Procedure

	N
Initial Sample: 1998-2016	18,522
Firms in non-regulated and non-financial industries	16,621
Firms in December fiscal year end	15,566
Firms with non-zero and non-missing data on sales revenue in current and prior years and R&D investment in current and prior years	6,231
Firms with non-missing financial data for measuring control variables	6,132
Sample for testing high-technology versus non-high-technology firms: 2000-2016	6,132
Firms in high tech industries	1,695
Firms in non-high technology industries	4,437
Sample for testing the effect of managerial ability: 2000-2016	3,574
Firms in high tech industries	1,114
Firms in non-high technology industries	2,460

This table presents our sample selection procedure. We extract financial information of Korean listed firms from DataGuide for the sample period 2000 to 2016. Continuous variables are winsorized at the top and bottom 1 percent. We obtained the sample for testing the effect of managerial ability by excluding the observations that do not have enough information to calculate managerial ability score from the sample for testing high-technology versus non-high-technology firms.

2. Sample composition of high tech industries

We follow Kile & Phillips (2009) and Kim & Sohn (2011) to identify high tech industries in Korean firms. Kile and Phillips (2009) developed procedures for selecting samples of high technology firms for the North American Industry Classification System (NAICS), Global Industry Classification (GICS), and Standardized Industry Classification (SIC) codes from analyses of detailed descriptions of firms' businesses from "Description of Business" and footnote disclosure (required in all 10-Ks and registration statements). Kim & Sohn (2011) then applied Kile & Phillips's (2009) industry classification to identify high tech industries in Korea. Thus, following Kim & Sohn (2011), we classify high tech industries as in <Table 2>. When we identify high tech firms according to the classification suggested, we find that firms related to professional services constitute the largest proportion (i.e. 10%) of our sample, followed by firms manufacturing electronic/electrical equipment and semiconductors.

<Table 2> Sample Composition

KSIC code	Industry description	*N*	%
High-tech Industries:		**1,695**	**27.6%**
261	Manufacturing of semiconductor	125	2.0%
262	Manufacturing of electronic components	237	3.9%
263	Manufacturing of computers and peripheral equipment	22	0.4%
264	Manufacturing of communication and broadcasting apparatuses	89	1.5%
265	Manufacturing of electronic video and audio equipment	38	0.6%
266	Manufacturing of magnetic and optical medium	0	0.0%
27	Manufacturing of medical, precision and optimal instruments etc.	55	0.9%
28	Manufacturing of electrical equipment	237	3.9%
60	Broadcasting activities	14	0.2%
61	Postal activities and telecommunications	70	1.1%
62	Computer programing, consultancy and related activities	73	1.2%
63	Information service activities	61	1.0%
70	Research and development	0	0.0%
71	Professional services	619	10.1%
72	Architectural, engineering and other scientific technical services	16	0.3%
73	Other professional, scientific and technical services	0	0.0%
74	Business facilities management and landscape services	0	0.0%
75	Business support services	39	0.6%
Non high-tech industries:		**4,437**	**72.4%**
Total		**6,132**	**100.0%**

3. Descriptive statistics

<Table 3> reports the descriptive statistics, <Table 4> compares the variables in the tests between the high technoloy and non-high technoloy industries, and <Table 5> reports Pearson correlations. *HIGH_TECH* is defined as a dummy variable, which equals 1 if a firm is classified as a high tech firm, and 0 otherwise. The mean value of *HIGH_TECH* is 0.276, indicating that about 28% of our sample are high tech firms. On average, sample firms have ₩ 2,313 billion (median = ₩ 266 billion) in net sales revenues and ₩ 54.59 billion in R&D expenditures (median = ₩ 2 billion). The ratio of R&D to sales revenue is 2.5% (median = 0.8%) on average. In the cost model presented in Equation (1), we use log-change of R&D costs (ΔRD) and sales revenue ($\Delta SALE$) to mitigate the skewness in the variables and thus improve the comparability of the variables across firms and alleviate heteroscedasticity (Davidson & MacKinnon, 1981). The average asset intensity is

0.14 (median = 0.11), while the average employee intensity is -13.37 (median = -13.20). Statistics on *SDEC* show that 14% of our sample firms have experienced successive declines in sales revenue. During the sample period, the average GDP growth was 4.34% (median = 3.90%). The mean value of the managerial ability measure (a residual from the firm efficiency measure) is -0.002 (median = 0.007).[13] Among the final sample of 6,132 observations, 60% (3,632 observations) have complete (non-missing) values for managerial ability.

<Table 3> Descriptive Statistics

variable	N	Mean	STD	P25	P50	P75
HIGH_TECH	6,132	0.276	0.447	0.000	0.000	1.000
SALE (Korean won in billion)	6,132	2,313.038	9,434.817	114.432	266.069	1,003.09
RD(Korean won in billion)	6,132	54.586	490.332	0.615	1.998	9.278
RD / SALE	6,132	0.025	0.434	0.003	0.008	0.023
Δ*RD*	6,132	0.079	0.642	-0.110	0.068	0.265
Δ*SALE*	6,132	0.065	0.238	-0.032	0.060	0.159
DEC	6,132	0.323	0.468	0.000	0.000	1.000
ASSET_INT	6,132	0.141	0.487	-0.169	0.113	0.422
EMP_INT	6,132	-13.372	1.112	-13.895	-13.202	-12.626
SDEC	6,132	0.139	0.346	0.000	0.000	0.000
GDP	6,132	4.337	2.040	2.800	3.900	5.500
CEOABILITY	3,574	-0.001	0.080	-0.036	0.009	0.040

This table presents the descriptive statistics of the variables used in the analyses. The definition of variables are as follows: *HIGH_TECH* is a dummy variable, which equals to 1 if the firm belongs to high-tech industries, and 0 otherwise. *SALE* is sales revenue and *RD* is research and development (R&D) expenditures that are both capitalized and expensed. *RD / SALE* is the ration of R&D expenditures to sales. Δ*RD* is the log-change in R&D expenditures. Δ*SALE* is the log-change in sales revenue. *DEC* is a dummy variable, which equals to 1 when sales in year *t* are smaller than in year *t-1*. *ASSET_INT* is the logarithm of the ratio of total assets to sales revenue. *EMP_INT* is the logarithm of the ratio of the number of employees to sales revenue. *SDEC* is a dummy variable, which equals to 1 when sales have decreased in two consecutive years (i.e. $SALE_{i,t-2} > SALE_{i,t-1} > SALE_{i,t}$). *GDP* is the percentage growth in real GDP during year *t*. *CEOABILITY* is the measure of managerial ability as developed in Demerjian et al. (2012). See Section 3.2 for detailed information.

[13] The mean is not zero because the managerial ability measure is estimated using a Tobit regression. Unlike OLS residuals, which must sum to zero by definition, Tobit residuals need not. The mean value of managerial ability in Demerjian et al. (2012) is also statistically different from zero.

<Table 4> reports the univariate tests for the high tech and non-high tech firms for the variables used in the analyses. High technology firms have a higher ratio of R&D to sales and higher asset intensity. Possibly due to higher sales volatility in high tech businesses, high tech firms experience more incidents of sales decreases or successive sales decreases compared to non-high tech firms. In addition, CEO ability in the high tech firms is greater than that in the non-high tech firms; from this we infer the importance of managers' competence in innovative firms. Lower employee intensity in the high tech firms is counter-intuitive to our initial prediction; however, it is possible that the high tech firms may have a few highly skilled employees who generate high sales revenues, while the non-high tech firms have many employees with general expertise.

<Table 4> Descriptive Statistics: High-tech vs. Non high-tech firms

	HIGH_TECH=1		***HIGH_TECH=0***				
variable	**N**	**Mean**	**N**	**Mean**	**Diff**		***t*-stat**
RD / SALE	1,695	0.051	4,437	0.016	0.035	***	2.86
Δ*RD*	1,695	0.065	4,437	0.085	-0.020		-1.10
Δ*SALE*	1,695	0.058	4,437	0.067	-0.009		-1.31
DEC	1,695	0.351	4,437	0.312	0.039	***	2.89
ASSET_INT	1,695	0.196	4,437	0.119	0.077	***	5.56
EMP_INT	1,695	-13.490	4,437	-13.327	-0.163	***	-5.13
SDEC	1,695	0.159	4,437	0.132	0.027	***	2.77
GDP_GROWTH	1,695	4.286	4,437	4.357	-0.071		-1.22
CEOABILITY	1,114	0.000	2,460	-0.002	0.002		0.69

This table presents the univariate comparison of means of test variables between high tech and non-high tech industries. Variable definitions are presented in the footnote of Table 3. The t-statistic is for a difference of means test from high tech to non-high tech industries. *, **, *** indicated significance at the 10%, 5%, and 1% level, respectively (two-tailed test).

<Table 5> presents the Pearson correlations for the regression variables. The correlation between the log-change in R&D (Δ*RD*) and the log-change in sales revenue (Δ*SALE*) is 0.13 and statistically significant at the 1% level. This indicates that changes in R&D move with changes in sales; however, this correlation is lower

than that between changes in SG&A and changes in sales (0.49, p-value = 0.00; not tabulated).

<Table 5> Correlation

	HIGH _TECH	*RD / SALE*	*ΔRD*	*ΔSALE*	*DEC*	*ASSET _INT*	*EMP _INT*	*SDEC*	*GDP*	*CEO ABILITY*
HIGH_TECH	1.00									
RD / SALE	0.04	1.00								
	(0.00)									
ΔRD	-0.01	0.01	1.00							
	(0.27)	(0.64)								
ΔSALE	-0.02	-0.06	0.13	1.00						
	(0.19)	(0.00)	(0.00)							
DEC	0.04	0.02	-0.09	-0.64	1.00					
	(0.00)	(0.06)	(0.00)	(0.00)						
ASSET_INT	0.07	0.06	-0.03	-0.20	0.16	1.00				
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)					
EMP_INT	-0.07	0.03	0.01	-0.11	0.04	0.19	1.00			
	(0.00)	(0.01)	(0.36)	(0.00)	(0.00)	(0.00)				
SDEC	0.04	-0.00	-0.10	-0.39	0.58	0.15	0.02	1.00		
	(0.01)	(0.74)	(0.00)	(0.00)	(0.00)	(0.00)	(0.14)			
GDP	-0.02	-0.01	-0.01	0.15	-0.11	-0.02	0.21	-0.03	1.00	
	(0.22)	(0.27)	(0.65)	(0.00)	(0.00)	(0.05)	(0.00)	(0.04)		
CEOABILITY	0.03	-0.13	0.04	0.16	-0.11	-0.25	-0.08	-0.08	0.00	1.00
	(0.06)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.95)	

This table presents Pearson correlation among variables in the test. *P*-values are in the parentheses. Variable definitions are presented in the footnote of Table 3.

4. Comparing the R&D cost stickiness between high tech and non-high tech firms

<Table 6> shows the regression results for R&D cost stickiness separately for high tech and non-high tech firms as baseline. The coefficients and t-statistics are based on firm-clustered standard errors, which encounter heteroscedasticity and serial correlation within a firm in our panel data (Petersen, 2009).

First, we test whether R&D costs are sticky on average, using the full sample. We estimate Equation (1) and report the regression results in Column (1). We find that β_1 is significantly positive ($\beta_1 = 0.262$, t-statistics = 3.74) and β_2 is negative but insignificant (β_2 = -0.161, *t*-statistics = -0.27), indicating symmetric behavior in R&D investments. We next compare R&D cost stickiness between the high tech and non-high tech firms by estimating Equation (1) separately for each group. In Column (2), we report the R&D cost behavior for the high tech firms. We find that β_1 is significantly positive (β_1 = 0.255, *t*-statistics = 2.68) and β_2 is significantly negative (β_2 = -1.341, *t*-statistics = -2.12), supporting sticky cost behavior. This is consistent with our prediction that managers in the firms with high technology do not immediately cut R&D costs on observing falling demand; instead, they maintain a high level of R&D investment, which is an important source of innovation and incremental firm value. On the other hand, in Column (3), we find a lesser degree of cost stickiness for the non-high tech firms, evidenced by significantly positive β_1 (=0.284, *t*-statistics = 3.01) and positive β_2 with marginal significance (=1.741, *t*-statistics = 1.71). Thus, non-high tech firms exhibit anti-cost stickiness on average, and we infer from the result that managers in non-high tech firms deem R&D expenditures as expenses that can be reduced in response to sales declines rather than investments for the firm's long-term growth.

In terms of the effect of adjustment costs on cost behavior, *ASSET_INT* has negative coefficients in all the columns; however, statistical significance only appears in the sub-sample of non-high tech industries. *EMP_INT* has significant and negative coefficients in the subsample of high tech industries, indicating that the adjustment costs arising from human capital also contribute to greater cost stickiness. Regarding *SDEC*, the coefficients are positive in all the columns as in previous literature, but not significant. The coefficients on *GDP* are insignificant in our cost model.

In Column (4)-(7), we provide the results of robustness tests to verify whether our results are sensitive to alternative model specification, which includes the effects of the economic determinants during increasing sales periods. To the extent that there may be a correlated omitted variables problem, the model may be specified incorrectly. The regression outputs based on two modified specifications still show sticky behavior in R&D investments in high tech firms when the two-way interactions with the log-change in sales and economic determinants (i.e. *ASSET_INT*, *EMP_INT*, *GDP*) and/or the main effects of the economic determinants are included in the model.

<Table 6> R&D Cost Stickiness: High-tech vs. Non high-tech industries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Full Sample	***HIGH _TECH=1***	***HIGH _TECH=0***	***HIGH _TECH=1***	***HIGH _TECH=0***	***HIGH _TECH=1***	***HIGH _TECH=0***
ΔSALE	**0.262*****	**0.255*****	**0.284*****	1.112***	1.858***	0.974**	2.154***
	(3.74)	**(2.68)**	**(3.01)**	(2.64)	(3.29)	(2.06)	(3.06)
ΔSALE*DEC	**-0.161**	**-1.341****	**1.741***	-2.795***	-0.337	-2.256***	-0.703
	(-0.27)	**(-2.12)**	**(1.71)**	(-4.06)	(-0.30)	(-2.77)	(-0.51)
*ΔSALE *DEC*	-0.064	0.113	-0.326*	0.203	-0.346	0.167	-0.372
**ASSET_INT*	(-0.54)	(0.82)	(-1.76)	(1.04)	(-1.62)	(0.68)	(-1.29)
*ΔSALE *DEC*	-0.039	-0.173**	0.237	-0.283***	0.015	-0.229**	-0.053
**EMP_INT*	(-0.47)	(-2.00)	(1.62)	(-3.20)	(0.09)	(-2.09)	(-0.27)
*ΔSALE *DEC*	0.167	0.169	0.222	0.471**	0.420*	0.160	0.209
**SDEC*	(0.82)	(0.63)	(0.81)	(2.37)	(1.90)	(0.60)	(0.75)
*ΔSALE *DEC*	0.043	0.089	0.000	0.211***	0.102	0.203**	0.116*
**GDP*	(1.21)	(1.53)	(0.00)	(2.67)	(1.58)	(2.57)	(1.76)
DEC	0.065**	0.069	0.054			0.080	0.071**
	(2.25)	(1.21)	(1.62)			(1.39)	(2.11)
ASSET_INT	-0.004	-0.011	0.001			-0.009	-0.005
	(-0.20)	(-0.38)	(0.05)			(-0.27)	(-0.14)
EMP_INT	0.023**	0.024	0.019			0.018	-0.012
	(2.00)	(1.64)	(1.10)			(1.07)	(-0.54)
SDEC	-0.095**	-0.137*	-0.072			-0.140*	-0.075
	(-2.35)	(-1.86)	(-1.48)			(-1.90)	(-1.52)
GDP	0.006	0.002	0.008			0.011	0.014
	(0.94)	(0.14)	(0.97)			(0.55)	(1.13)
*ΔSALE **				-0.049	0.043	-0.037	0.049
ASSET_INT				(-0.35)	(0.32)	(-0.22)	(0.28)
*ΔSALE **				0.068	0.182**	0.046	0.216**
EMP_INT				(1.38)	(2.38)	(0.83)	(2.24)
*ΔSALE * GDP*				-0.086**	-0.080**	-0.083**	-0.088**
				(-2.09)	(-2.32)	(-2.00)	(-2.47)
Constant	-0.083	0.128	-0.100	0.093	0.143**	0.092	-0.062
	(-0.81)	(1.29)	(-0.76)	(0.87)	(2.40)	(0.54)	(-0.34)
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering by	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Observations	6,132	1,695	4,437	1,695	4,437	1,695	4,437
Adjusted R^2	0.032	0.048	0.027	0.067	0.043	0.070	0.044

In this table, Column (1)-(3) reports the regression results of R&D investment behaviors of high tech firms and non-high tech firms using Equation (1). Additionally, this table reports the regression results of R&D investment behaviors of high tech firms and non-high tech firms using alternative model specification in Column (4)-(7). Variable definitions are presented in the footnote of Table 3. Continuous variables are winsorized at the top and bottom 1 percent. All specifications are estimated with robust standard errors clustered by firm and include year/industry fixed effects. The robust t-statistics are in parentheses. *, **, *** indicated significance at the 10%, 5%, and 1% level, respectively (two-tailed test).

5. Effect of Managerial Ability on the R&D cost stickiness of high tech firms

Hypothesis 1 predicts R&D cost stickiness in high technology firms to be more pronounced when a firm is run by high ability managers. <Table 7>, Column (1)-(2) shows the results. To test the hypothesis, we divide the sample of high tech firms into two groups based on *CEOABILITY*, which is the proxy for managerial ability developed by Demerjian et al. (2012), and run Equation (1) for each group. We find that R&D cost stickiness appears only in the high tech firms with high ability CEOs, consistent with our hypothesis. Specifically, when *CEOABILITY* is equal to or greater than its median value (Column 2 of Table 7), β_1 is significantly positive (β_1 = 0.430, *t*-statistics = 1.90) and β_2 is significantly negative (β_2 = -2.967, *t*-statistics = -2.80), indicating sticky behavior. The suggestion is that able managers of high tech firms understand the value of slack resources and thus choose stickier R&D investment behavior. On the other hand, when *CEOABILITY* is smaller than its median value (Column 1 of Table 7), both β_1 and β_2 are insignificant, showing that R&D adjustment in high tech firms with low ability managers does not relate to sales changes.

Although we do not hypothesize on whether high-ability CEOs of non-high technology firms have an impact on R&D cost stickiness, we show the regression results of non-high technology firms in Table 7, Column (3)-(4) to address a question. One may argue that high ability CEOs will maintain R&D costs in a sales decreasing period even in non-high tech firms because they understand the value of consistent investments in R&D activities. However, our results indicate that managerial ability does not have a significant impact on R&D cost stickiness of non-high tech firms. Specifically, β_2 is insignificant at the 10% level when *CEOABILITY* is equal to or greater than its median value (Column 4 of Table 7) (β_2 = -1.004, *t*-statistics = -0.71) and when *CEOABILITY* is smaller than its median value (Column 3 of Table 7) (β_2 = 1.271, *t*-statistics = 0.73). The results corroborate our assertion that R&D investments is the domain of strategic management only in high tech firms.

<Table 7> Effect of Managerial Ability on R&D Cost Stickiness among Firms in High Tech Industries and in Non-High Technology industries

	HIGH_TECH=1		*HIGH_TECH=0*	
	(1) Low Ability CEOs	**(2) High Ability CEOs**	**(3) Low Ability CEOs**	**(4) High Ability CEOs**
ΔSALE	**0.276**	**0.430***	**0.331****	**0.207**
	(1.44)	**(1.90)**	**(2.00)**	**(1.15)**
ΔSALE *DEC	**0.989**	**-2.967*****	**1.271**	**-1.004**
	(1.01)	**(-2.83)**	**(0.73)**	**(-0.71)**
Δ*SALE *DEC *ASSET_INT*	-0.007	0.311	-0.427	-0.042
	(-0.03)	(0.99)	(-1.00)	(-0.15)
Δ*SALE *DEC *EMP_INT*	0.221	-0.405***	0.187	-0.116
	(1.50)	(-3.75)	(0.72)	(-0.63)
Δ*SALE *DEC *SDEC*	0.100	0.475	0.155	0.409
	(0.24)	(1.03)	(0.29)	(1.08)
Δ*SALE *DEC *GDP*	0.178*	0.003	0.068	0.040
	(1.74)	(0.03)	(0.97)	(0.50)
DEC	0.098	0.010	0.001	0.058
	(0.98)	(0.10)	(0.02)	(1.10)
ASSET_INT	-0.035	0.077	0.016	0.023
	(-0.55)	(1.13)	(0.29)	(0.46)
EMP_INT	0.077**	-0.026	0.000	0.015
	(2.58)	(-1.23)	(0.00)	(0.51)
SDEC	-0.184*	-0.076	0.027	-0.163**
	(-1.68)	(-0.48)	(0.29)	(-1.98)
GDP	-0.003	-0.006	0.013	0.001
	(-0.16)	(-0.24)	(0.51)	(0.03)
Constant	0.489**	-0.147	0.033	0.299
	(2.56)	(-0.91)	(0.11)	(1.10)
Observations	553	561	1,225	1,235
Adjusted R-squared	0.068	0.054	0.060	0.043
Industry effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Firm Clustering	Yes	Yes	Yes	Yes

This table reports the regression results of R&D investment behaviors with respect to CEO ability in high tech firms and non-high technology firms, respectively. We divide the sample into two based on the median value (by year) of *CEOABILITY*. Variable definitions are presented in the footnote of Table 3. Continuous variables are winsorized at the top and bottom 1 percent. All specifications are estimated with robust standard errors clustered by firm and include year/industry fixed effects. The robust t-statistics are in parentheses. *, **, *** indicated significance at the 10%, 5%, and 1% level, respectively (two-tailed test).

6. Alternative Measure of High Technology Firms

In our main tests, we used industry-based approach of Kile & Phillips (2009) and Kim & Sohn (2011) to identify high tech industries in Korean firms[14]. Additionally, we applied another approach using firm characteristic to identify high tech firms for a robustness check. We used the R&D cost-to-sales ratio to redefine high tech firms using firm-specific characteristic. Intensive R&D investments is the distinctive characteristic of high tech firms compared to non-high tech firms (Nunes et al., 2012). Thus, we classified observations having the R&D cost-to-sales ratio equal or greater than the sample median into high tech firms and into non-high tech firms otherwise.

<Table 8> provides the results of Equation (1) using the alternative measure of high tech firms. To test whether R&D cost stickiness in high technology firms to be more pronounced when a firm is run by high ability managers, we divide the sample of high tech firms into two groups based on *CEOABILITY*. Similar to the results in Table 7 where used industry-based definition of high tech firms, we find that R&D cost stickiness appears only in the R&D-intensive firms with high ability CEOs, consistent with our hypothesis. Specifically, when *CEOABILITY* is equal to or greater than its median value (Column 2 of Table 8), β_1 is significantly positive (β_1 = 0.498, *t*-statistics = 2.97) and β_2 is significantly negative (β_2 = -2.551, *t*-statistics = -3.79), indicating sticky behavior. On the other hand, when CEOABILITY is smaller than its median value (Column 1 of Table 8), β_2 is insignificant. The results support our hypothesis that CEO ability is associated with a greater degree of R&D cost stickiness in high technology firms.

[14] Among each high tech industry of Table 2, the professional services industry (KSIC=71) alone has enough sample size to estimate the regressions of Table 7. Other industries individually have less than 100 observations per the subsamples based on managerial ability, so it is inappropriate to run regression individually due to the lack of the statistical power. For the professional services industry, we find that R&D cost stickiness appears only in the high tech firms with high ability CEOs, consistent of H1.

<Table 8> Alternative Measure of High Technology Firms

	R&D ratio ≥ sample median	
	(1) Low Ability CEOs	**(2) High Ability CEOs**
ΔSALE	**0.373****	**0.498*****
	(2.30)	**(2.97)**
ΔSALE *DEC	**1.066**	**-2.551*****
	(1.03)	**(-3.79)**
*ΔSALE *DEC *ASSET_INT*	-0.065	0.301
	(-0.32)	(1.47)
*ΔSALE *DEC *EMP_INT*	0.150	-0.302***
	(0.97)	(-3.32)
*ΔSALE *DEC *SDEC*	-0.099	0.599*
	(-0.29)	(1.95)
*ΔSALE *DEC *GDP*	0.072	0.033
	(0.97)	(0.58)
DEC	0.084	0.007
	(1.24)	(0.15)
ASSET_INT	0.004	0.065
	(0.09)	(1.15)
EMP_INT	-0.007	-0.019
	(-0.31)	(-0.70)
SDEC	-0.112	0.020
	(-1.37)	(0.28)
GDP	0.025	0.002
	(1.10)	(0.10)
Constant	-0.008	0.060
	(-0.04)	(0.31)
Observations	957	963
Adjusted R-squared	0.129	0.120
Industry effects	Yes	Yes
Year effects	Yes	Yes
Firm Clustering	Yes	Yes

This table reports the regression results of R&D investment behaviors with respect to managerial ability in high tech firms using alternative measure of high tech firms. We classified observations having R&D cost-to-sales ratio greater than the sample median as high tech firms. Variable definitions are presented in the footnote of Table 3. Continuous variables are winsorized at the top and bottom 1 percent. All specifications are estimated with robust standard errors clustered by firm and include year/industry fixed effects. The robust t-statistics are in parentheses. *, **, *** indicated significance at the 10%, 5%, and 1% level, respectively (two-tailed test).

V. CONCLUSION

This study investigates whether and how firms in the high technology industry manage R&D costs relative to firms in the non-high technology firms, using the asymmetric cost model developed by Anderson et al. (2003). Because investment in R&D is an important antecedent of a firm's innovation for a high technology firm, we expect the R&D to be managed differently relative to a non-high technology firm. To extend the analysis, we examine whether CEO ability matters in determining R&D cost behavior. Since a high tech firm is involved in a very competitive and dynamic business environment, it is important for the CEO to have a complete understating of their business and industry. Furthermore, since CEOs in high tech firms are more likely to have discretionary power (Hambrick & Finkelstein, 1987), their ability may influence R&D investment decisions. Therefore, we conjecture that R&D management may differ by the extent of managerial ability.

Using the cost stickiness model developed by Anderson et al. (2003), we document an evidence that R&D costs are stickier in high technology firms than in non-high technology firms, indicating that high technology firms are more likely to maintain R&D investments in declining sales periods. We find that the R&D cost stickiness observed on average in high tech firms is driven by the firms managed by more competent CEOs. This indicates that managerial ability significantly affects R&D management decisions in high technology firms.

While we believe that our conclusion on the impact of managerial ability on R&D cost management is generalizable, we admit that our approach to measure managerial ability following Demerjian et al. (2012) left at least 37 percent of the sample unexamined due to high requirement of information. Future research may develop a measure of managerial ability that can be applied to a bigger set of sample and re-examine our research question.

This study has several implications for the relevant literature. First, it contributes to the growing literature on asymmetric cost behavior. Banker et al. (2018) observed that a change in R&D investment following a change in sales may be different from the corresponding change in SG&A costs, and asserted the need to examine R&D investments in terms of sticky cost behavior. Our findings suggest that maintaining R&D resources in declining sales periods can be beneficial in the long run. Second, we provide insights into the strategic resource management of the high tech industry with respect to how R&D costs are managed. To our knowledge, this study is the first to provide evidence of asymmetric R&D cost behavior in high tech firms. Finally, we contribute to the literature on managerial ability and support the role of CEO in operating high technology firms.

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