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R&D SPENDING AND STOCK RETURNS: EVIDENCE FROM SOUTH KOREA

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🆔 **Young Sik Kim¹**
🆔 **Keun Jae Park²⁺**

¹School of Management, Kyung Hee University, Republic of Korea.
Email: kys997@khu.ac.kr Tel: 82-2-961-0676

²Department of Business and Economics, Washington and Jefferson College, Washington, PA, USA.
Email: kpark@washjeff.edu Tel: 1-724-503-1001ext. 3466

(+ Corresponding author)

ABSTRACT

This study examined how research and development (R&D) spending affects stock returns. Three strands of research make different predictions about how R&D affects stock prices. The agency theory, presented by Jensen (1986) argues that managers do not make a corporate decision on behalf of shareholders and rather pursue their personal benefits by undertaking value-reducing projects such as R&Ds. The overconfidence theory suggests that overconfident managers tend to invest more in R&D because they overvalue their ability and they are excessively optimistic about future success of the R&D investment. These two theories predict that firms that invest more in R&D earn lower returns than those that invest less. In contrast, the signaling theory predicts that high-quality firms use R&D spending as a means of communicating with the stock market to mitigate information asymmetry problem, resulting in higher returns of the firms. Using data from Korean firms listed from January 1992 to December 2015 we showed that portfolios that invested heavily in R&D earn consistently high abnormal returns and that, consequently, spending on R&D is an effective explanatory factor for stock returns. We also found that the impact R&D expenditures has on stock value was long-term, as well as short-term. Overall, these results are consistent with the signaling theory in that R&D spending is an important channel through which firms improve their values by communicating with the stock market.

Contribution/ Originality: This paper contributes to the existing literature on the effect of R&D spending on stock returns. To our knowledge, this study provides the first evidence for the Korean stock market that Korean firms make R&D investment decisions to convey a positive signal to the market regarding a future success of the firms.

1. INTRODUCTION

With the recent attention given to the value that intangible assets hold for firms, investments made into such assets has naturally become a subject of much attention. Korean firms provide an ideal case study in exploring the impact of these investments in that Korea ranks first among developing countries in terms of the scale of investments made into research and development (hereafter R&D), which is considered to be the most representative example of an intangible asset. In 2015, R&D investments made by Korean firms reached 57.3 billion USD and grew 3.5% the following year, placing the country sixth worldwide in terms of investment scale. The

study of R&D investments holds a great deal of importance, as investment activity is a significant factor in determining firm value. However, although R&D activity has the potential to strengthen firm competitiveness by developing new products and improving process efficiency, financial gains are not immediate, and R&D investments are thus considered to be high-risk.

The question of what impact R&D activity has on firm value is not new and nor has it offered any consensus of evidence. There have been opposing views regarding a firm's R&D investment decisions. First, the signaling theory argues that firms have incentives to communicate with the capital market in order to reduce information asymmetry between inside managers and outside investors because firms that suffer from high information asymmetry are likely to be undervalued in the capital market (Ang & Cheng, 2011). Therefore, high-quality firms may make certain corporate decisions that their competitors cannot imitate and attempt to convey information that market participants are able to distinguish these firms from poor-quality firms. R&D investments tend to have a high uncertainty on the expected cash flows from the investments and the R&D investments are likely to suffer from more information asymmetry problems between investors and insiders of the company than any other investments. Due to these reasons, investors require a higher expected return for bearing the higher risk from the R&D investments, resulting in undervaluation of the firm's stock (Cohen, Diether, & Malloy, 2013).

While R&D investments may decrease short-term earnings and has a negative impact on a firm's financial statement, it allows the manager to convey investors a positive signal regarding future profits and investment opportunities because R&D is considered a key to a long-term success of a firm (Qian, Zhong, & Zhong, 2012). Evidence of the following studies support the signaling theory.

Grabowksi and Mueller (1978) examined the impact of R&D expenditures on a firm's profitability and find that firms that invest more in R&D investments tend to have a higher profitability. Chan, Martin, and Kensinger (1990) showed that the stock market, on average, positively responds to a firm's announcements of an increase in R&D spending whereas the same announcements for low-technology firms receive a negative response from the market. They conclude that R&D expenditures have a heterogeneous effect across industries.

Sougiannis (1994) argued that a firm value is determined by its present book value of its future residual income, a position that supports the view that a firm's future residual income is determined by its R&D investments. The author argues that the difference between a firm's book value and its market value can be interpreted by its advertising expenses and R&D effectiveness, proving the validity of the capitalization of both expenses. Generally, as the book-to-market value indicates a firm's potential for future growth, research that uses both ratios as dependent variables finds a positive correlation that shows that R&D investments convey a positive signal regarding a firm's future growth.

Therefore, based on the signaling theory, we predicted that firms that invest heavily in R&D spending earn a higher return than those that invest less. However, the agency theory states that R&D investments can generate a lower return. Due to conflicts of interests between shareholders and managers, managers may make corporate decisions to pursue personal benefits rather than maximizing shareholders' wealth. Jensen (1986) argued that entrenched managers may have incentives to use their firms' free cash flows to undertake value-destroying projects for their own benefits. Therefore, it is likely that entrenched managers inefficiently spend on R&D projects. As a result, the firms' competitiveness over time decrease and it will lower the firms' future returns.

In addition, behavioral finance literature can also predict a relation between a firm's R&D spending and stock returns. It is possible that managers' psychological aspects affect their firms' R&D investment decisions. Literature on managerial overconfidence has examined whether managerial overconfidence affects a firm's decisions and economic consequences of the decisions. Overconfident managers tend to overvalue their ability and have more optimistic expectations about their future success. Malmendier and Tate (2005); Malmendier and Tate (2008); Malmendier, Tate, and Yan (2011) showed that managerial overconfidence affects a firm's investment, mergers and acquisitions, and financial policies. Related to long-term investment decisions, Hirshleifer, Low, and Teoh (2012)

found that overconfident managers spend more in R&D expenditures. Thus, overconfident managers are likely to overspend on their R&D projects. The overspent R&D projects are likely to be negative net present value (NPV) projects which, in turn, reduces a firm value. Therefore, if the sample firms' R&D investment decisions are made by overconfident mangers, the overconfidence theory predicts that R&D spending and a firm's stock returns are negatively related to each other.

In our analysis of the impact a firm's R&D expenditures have on stock returns, we measured the monthly returns of Korean firms between January 1992 and December 2015. We formed quintile portfolios based on the size of R&D expenditures and then analyzed the portfolios' abnormal returns which were estimated using multiple asset pricing models. Portfolio analysis showed that a portfolio of firms that invest heavily in R&D expenditure earn significant and positive abnormal returns (0.78% monthly based on Fama and French three-factor model) and a long-short portfolio generates positive abnormal returns (0.85% monthly).

The findings of the portfolios analysis were similar to our cross-sectional analysis which used the Fama and MacBeth (1973) method. Our results of outperforming portfolios investing more in R&D expenditure were robust when we used an alternative method of constructing quintile portfolios and computing abnormal returns and when long-term cumulative abnormal returns are used. Lastly, the results remain unchanged when we excluded periods of financial crises from the sample period. The evidence that firms that spend more on R&D investment earn higher risk-adjusted returns than those that spend less is consistent with the signaling theory in that high-quality firms use R&D investments to convey information to the market as a signaling tool.

The remainder of this article is organized as follows: Section 2 describes the sample, data collection, and methodology. Section 3 discusses empirical results for portfolio analysis, cross-sectional analysis, and robustness tests. Concluding marks are addressed in Section 4.

2. METHODOLOGY

2.1. Sample and Portfolio

To select the sample of our study, we started with the 1,071 stocks listed in the Korea Composite Stock Price Index (KOSPI) as of December 2016. We dropped financial firms and firms with no expenditures in R&D from the sample. As a result, the final sample included 571 firms.

Since risk-adjusted returns for portfolio analysis were estimated and the process of sorting firms into quintile portfolios and calculating monthly returns was important. The details of the process were as follows.

First, following Fama and French (1993) we first calculated the previous year's R&D expenditure ratios (R&D expenditures/sales) and then formed five portfolios according to the size of R&D/sales. We next calculated the monthly returns from July of that year to June of the following year. For example, for an R&D/sales at the end of 2000, the portfolio was formed for June 2001, and the monthly return was computed for the period between July 2001 and June 2002. As our sample period was from January 1992 to December 2015, the sample included 288 months in total.

2.2. Portfolio Construction

In this study, we used both equally-weighted and value-weighted returns for our analysis. The stock returns (in logarithm) were calculated as follows. We calculated the equally-weighted returns under the assumption that the stock of each firm in each portfolio was invested in at the same weight. For the value-weighted return, we first calculated the previous month's aggregated market value of listed stocks and computed the weight of each stock. Then the previously calculated log difference return was multiplied and calculated. We winsorized the returns at the 1st and 99th percentiles. We used the market model, Fama and French (1993) three-factor model (FF3), Carhart (1997) four-factor model to estimate the risk-adjusted abnormal returns.

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SIZE, which indicates a firm's size, was calculated by multiplying the price of an ordinary share of firm *i* with the firm's number of shares outstanding of an ordinary share. In this paper, the market capitalization of an ordinary share at the end of June was used for *t*. Second, *BM*, which indicates value, was calculated by dividing the book value of equity by market value. Third, *MOM*, which indicates momentum strategy, was computed by calculating average returns over the previous 11 months, following Carhart (1997).

We followed Fama and French (1993) to construct factor-mimicking portfolios. The 2 x 3 risk factors were composed of the market factor (*MKT*), size factor (*SMB*), value factor (*HML*), and momentum factor (*UMD*). The market factor, *MKT*, was calculated by subtracting the risk-free rate of return from the market portfolio return. In our paper, we used the one-year monetary stabilization bond yields from the Economic Statistic System (ECOS) in the Bank of Korea as the risk-free rate. For the size factor, *SMB*, based on the market capitalization at the end of June in year *t*, the sample firms were divided into the top 50% and bottom 50% to form the Big portfolio (*B*) and Small portfolio (*S*), respectively.

For the *BM* portfolio, the sample firms were divided into the top 30%, middle 40%, or low 30% based on their *BM* at the end of December in year *t-1* and placed in the High portfolio (*H*), Neutral portfolio (*N*), or Low portfolio, respectively. The size and BM portfolios were crossed to form size-BM (*SH, SN, SL, BH, BN, BL*) 2 × 3 portfolios.

The factor-mimicking portfolios were divided into two major categories. Small-minus-big (*SMB*) was the difference between the log average returns of the small portfolios (*SH, SN, SL*) and those of the big portfolios (*BH, BN, BL*). Next, *HML* was calculated as we subtracted the log average returns of *BL* and *SL* from those of *BH* and *SH*. Finally, a mimicking portfolio for *UMD* (up-minus-down) was calculated by first calculating the log average returns between *t-1* and *t-11* of the stocks, dividing them into the top 30%, middle 40%, and low 30%, and then subtracting the monthly log average returns of the bottom 30% group (*DOWN*) from those of the top 30% group (*UP*).

2.3. Empirical Models

In this study, we used the following three asset pricing models to compute the abnormal return, α.

$$E[r_i] - r_f = \alpha_i + b_i E[MKT] \tag{1}$$

$$E[r_i] - r_f = \alpha_i + b_i E[MKT] + S_i E[SMB] + h_i E[HML] \tag{2}$$

$$E[r_i] - r_f = \alpha_i + b_i E[MKT] + S_i E[SMB] + h_i E[HML] + m_i E[UMD] \tag{3}$$

Equation 1 is the market model where $E[r_i]$ - r_f represents the expected excess return of stock *i*. In this model, we estimated the abnormal return, α, by adjusting returns for the stock *i*'s market risk. Fama-French three-factor (FF3) model was implemented using Equation 2 where the abnormal returns, α, were calculated by incorporating three risk factors: market risk, size, and BM. Finally, Carhart's four-factor model Equation 3 used the Fama-French three factors plus the momentum risk factor to compute the abnormal returns. The slopes b_i, s_i, h_i and m_i are the exposures to the factors. The standard errors and *t*-statistics were adjusted for serial correlation using the Newey and West (1987) procedure (Davidson & Mackinnon, 1993).

2.4. Cross-Sectional Analysis

For our baseline cross-sectional analysis model, we used Fama and MacBeth (1973) two-stage model to see how a firm's R&D expenditures affect its return. The sample period, as with the analyzed models, covered a total of

288 months – from January 1992 to December 2015. Using data from this period, the slope coefficients were estimated for each month and we conducted a t-test using the average of the monthly estimated coefficients.

We included R&D spending as another explanatory variable in the Fama-French three-factor model and examined whether R&D spending has a significant marginal power to explain stock returns. To test the marginal effect of R&D spending across stocks, we used the following Equation 4.

$$r_{it} = a_t + \beta'_t RD_{it} + v'_{it} X_{it} + \epsilon_{it} \tag{4}$$

In the regression model (4), *t*, which is a subscript to the independent variable, was shown to be a variable that was created in the past period *t-1*. The stock return r_{it} was the estimated monthly log returns of firm *i* at time *t*. RD_{it} was the estimated ratio of R&D expenditures to sales of firm *i* at time *t*. The *X* vector represents a set of control variables: market factor (β), size factor (*SIZE*), value factor (*BM*). The market factor β was estimated using the monthly returns of each stock over the past three years and the KOSPI log returns as the market return. *SIZE*, the size factor, was calculated by multiplying the price of each stock in the portfolio at the end of June of each year by the number of issued stocks in the previous year and then multiplying the calculated log value of the market weight of each stock by the weight of the portfolio. Lastly, for *BM*, the value factor, the book value of equity of each stock at the end of December of year *t-1* was divided by the market capitalization of the same stock in December of year *t-1*, and we used a natural log of the ratio for the analysis.

To address potential omitted variable bias, we included variables that have been reported to explain stock returns. We added momentum (*CRETURN*), trading volume (*TURN*), and turnover ratio (*TCV*) to our model. For the momentum variable, the sum of the log return over six months (excluding the previous month) was used. For the trading volume, the volume of the previous month was used in the form of natural log. The turnover ratio was calculated by dividing the trading volume of the previous month of each firm by the number of shares outstanding at the end of the previous year. All the variables except firm size and value factor were estimated monthly.

3. EMPIRICAL RESULTS

3.1. Descriptive Statistics

Descriptive statistics of the sample firm are presented in Table 1. Panel A reports the summary statistics of the variables used in the portfolio analysis. In the case of value-weight returns, P1 (−0.38%), the portfolio of firms with the lowest R&D expenditures, showed the lowest risk-adjusted return, and P4 and P5 experienced returns of 0.36% and 0.32% respectively. This result shows that portfolios with high expenditures in R&D have higher returns than those with low expenditures in R&D. A long-short portfolio (buy P1 and sell/short P5) generates a risk-adjusted return of 0.70% monthly and the return is statistically significant at the 10 percent level. The equally-weighted returns were overall lower than the weighted-value returns, and standard deviations were lower. P1 had the lowest return (-0.22%) whereas P4 (0.23%) had the highest return (0.23%). A long-short portfolio (P5–P1) had a risk-adjusted return of 0.36% and it was statistically significant at the 10 percent level.

During the sample period, *MKT*, the market excess return was −0.18%.[1] *SMB* portfolio had a negative return (-0.05%), indicating that large firms have a higher return than small firms during the sample period. *HML* portfolio earned 0.87% return, suggesting that high *BM* portfolios earn a higher return than low *BM* portfolios. *UMD* portfolios earned 0.68% return during the sample period, indicating that past winner portfolios earn a higher return than past loser portfolios.

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[1] The negative market excess return occurs because of the financial crisis in 1998. During the crisis, the market return was lower than a risk-free rate. The market excess returns become positive since 2000.

Panel B presents the descriptive statistics for the variables used in the cross-sectional analysis. First, during the sample period, β was 0.71 and the natural log of market capitalization was 11.49. *BM* was 0.234 and *CRETURN*, cumulative returns, was 1.3%. *TURN*, the natural log of the trading volume over the previous month, was 10.68 and *TCV*, turnover ratio, was -0.28. Lastly, *RD*, R&D expenditures divided by sales, was 2.2%.

Table-1. Descriptive Statistics.

Panel A: Portfolio analysis
Value-Weighted Return (%)

Variable	Mean	Std. Dev.	Min	Max	N
P1	-0.378	7.339	-22.652	17.253	
P2	-0.207	7.575	-30.939	25.606	
P3	-0.110	8.539	-28.188	36.848	288
P4	0.358	8.419	-26.501	28.673	
P5	0.323	8.894	-32.970	31.585	
P5-P1	0.701 (1.54)				

Equally Weighted Return (%)

Variable	Mean	Std. Dev.	Min	Max	N
P1	-0.219	6.867	-21.078	18.346	
P2	0.126	5.467	-19.001	13.098	
P3	0.042	4.937	-16.299	14.373	288
P4	0.234	4.632	-16.959	10.659	
P5	0.136	4.889	-18.560	13.883	
P5-P1	0.355* (1.81)				

Control Variable

Variable	Mean	Std. Dev.	Min	Max	N
MKT	-0.181	8.055	-32.814	39.911	
SMB	-0.049	0.518	-1.850	2.576	288
HML	0.873	5.637	-32.235	26.454	
UMD	0.678	5.556	-24.466	21.083	

Panel B: Cross-section analysis

Variable	Mean	Std. Dev.	Min	Max	N
RET	0.216	16.402	-195.499	217.14	151,006
β	0.709	0.361	-1.543	5.357	151,023
SIZE	11.485	1.739	5.298	19.204	148,694
BM	0.234	0.880	-7.586	5.966	147,808
CRETURN	0.013	0.400	-3.770	3.479	148,576
TURN	10.682	2.194	0.000	20.670	150,771
CVT	-0.237	0.456	-1.792	8.491	150,466
RD	0.022	0.041	-0.012	1.845	87,338

Note: ***, ** and * indicate that the coefficient is significantly different from zero at the 1, 5 and 10% levels, respectively.

Figure 1 illustrates the cumulate abnormal returns (value-weighted returns) during the sample period. Throughout the sample period, P4 earned the highest return among the five portfolios and was consistently higher than *MKT*. The difference in long-term cumulative abnormal returns between P4 and P1 or P2 became larger. In the periods of financial crises (i.e., the Korean financial crisis in 1998 and the global financial crisis in 2008), the returns showed drastic fluctuations. One of the implications of Figure 1 is that investing in firms that invest more heavily in R&D leads to higher long-term returns than those that invest less.
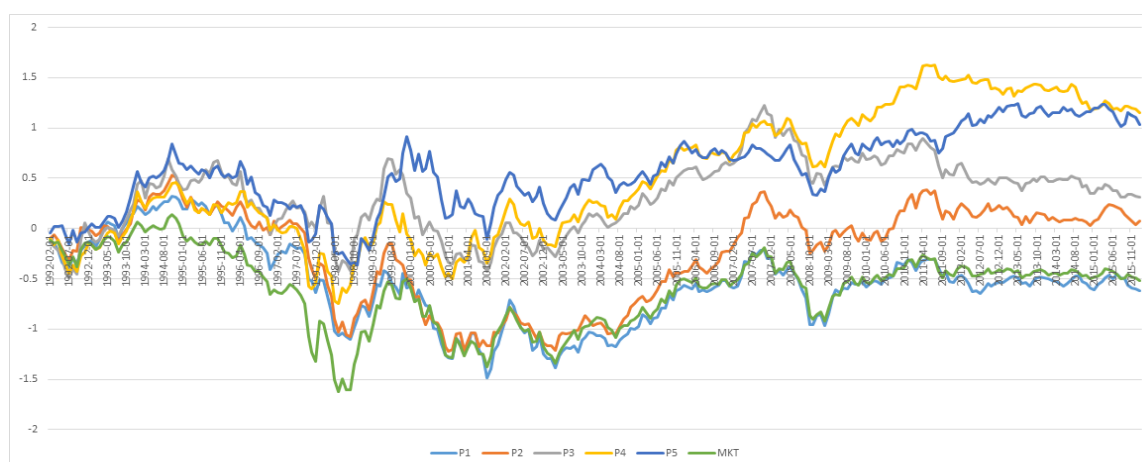
Figure-1. CARs during periods of 1992-2015.

3.2. Portfolio Analysis Results

Table 2 presents the results of the portfolio analysis of the R&D expenditures. We used the three asset pricing models to compute abnormal returns. First, in the model in which the value-weighted returns were calculated using the market model, P4 (0.55%) earned the highest abnormal returns, which was statistically significant at the 5 percent level. P5, the portfolio with the highest percentage of R&D expenditures, earned 0.52% abnormal returns, which was statistically significant at the 10 percent level. When using the FF3 factor model, the portfolio with the highest abnormal returns was P5 (0.78%), which was statistically significant at the 10 percent level. A long-short portfolio (P5-P1) generated an abnormal return of 0.85% monthly, which was also statistically significant at the 5 percent level. When using the Carhart four-factor model, P5 earned 0.67% abnormal returns and a long-short portfolio (P5-P1) generated an abnormal return of 0.76% monthly, which was statistically significant at the 10 percent level. However, for the weighted-value returns, even though portfolios with relatively more expenditures in R&D (P4 and P5) showed relatively higher returns than other portfolios, the abnormal returns were not statistically significant at the 10 percent level regardless of an asset pricing model being used. A long-short portfolio generated positive abnormal returns across all asset pricing models, but the returns were statistically significant at the 10 percent level. Results in Table 2 suggests that firms that spend more on R&D perform better than those that spend less in the stock market. Therefore, the evidence in Table 2 is consistent with prior studies that show that R&D expenditures lead to a higher firm value (Aboody & Lev, 1998; Callimaci & Landry, 2004; Han & Manry, 2004; Lev & Sougiannis, 1996).

Table-2. Portfolio analysis.

Return	Model	P1 (Low)	P2	P3	P4	P5 (High)	H-L	N
Value weighted return	CAPM	-0.069 (-0.28)	0.171 (0.69)	0.265 (0.88)	0.554** (2.18)	0.515* (1.77)	0.584 (1.48)	288
	FF3	-0.074 (-0.30)	0.029 (0.12)	0.216 (0.71)	0.500* (1.94)	0.778** (2.79)	0.853** (2.20)	
	FF4	-0.09 (0.36)	0.03 (0.12)	0.186 (0.60)	0.451 (0.36)	0.667** (2.42)	0.756* (1.95)	
Equally weighted return	CAPM	0.095 (0.39)	0.073 (0.33)	0.122 (0.56)	0.236 (1.10)	0.143 (0.66)	0.047 (0.31)	
	FF3	-0.021 (-0.08)	-0.066 (-0.30)	-0.025 (-0.12)	0.114 (0.53)	0.093 (0.42)	0.114 (0.74)	
	FF4	0.070 (0.28)	0.016 (0.07)	0.012 (0.06)	0.177 (0.83)	0.119 (0.54)	0.049 (0.32)	

Note: ***, ** and * indicate that the coefficient is significantly different from zero at the 1, 5 and 10% levels, respectively.

In addition, these findings also offer implications regarding how investors understand firms' R&D investment decisions. Rather than considering these expenditures to be a manager's discretionary expense for pursuing

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personal benefits (agency theory) and managerial overconfident decisions (overconfident theory), they consider them investments for the sake of a signaling tool that these firms are high-quality firms. In conclusion, the evidence in Table 2 is consistent with the signaling theory. These findings also offer some investment strategies regarding R&D expenditures. According to the analysis results, investors can see that they can raise their risk-adjusted returns by investing in firms that make considerable R&D expenditures. It also shows that buying portfolios with high R&D expenditures and selling portfolios with low R&D expenditures is a valid and effective investment strategy. This shows that investment information regarding R&D expenditures is still not sufficiently impounded in stock price.

3.3. Cross Section Analysis Results

Model (1) shows the results of the univariate regression analysis. According to the analysis results, a coefficient of R&D spending was positive and statistically significant at the 1 percent level, indicating that R&D expenses were shown to be a factor explaining the stock returns. Model (2) includes control variables of the Fama and MacBeth (1973) model. In this model, a coefficient of R&D spending was also positive and statistically significant at the 1 percent level. In model (3), we included additional control variables to address potential omitted variable bias problems. Similarly, a coefficient of R&D spending was positive and statistically significant at the 1% level.

The results in Table 3 were consistent with those of the portfolio analysis, and R&D spending had a positive impact on stock returns, which implies that R&D spending has an explanatory power for stock returns. However, model (4) included all control variables along with a change in R&D spending as a main independent variable. A coefficient of a change in R&D spending was positive but statistically insignificant at the 10 percent level.

In models (5), (6), and (7), instead of using the returns at $t+1$, we used the contemporaneous returns as a dependent variable. Across all models, a coefficient of R&D spending was positive and statistically significant at the 1 percent level. The results in Table 3 imply that R&D expenses have a considerable positive impact on stock prices, which is consistent with the signaling hypothesis.

Table-3. Cross section results.

Returns	R_{t+1}				R_t		
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RD_t	0.105*** (4.43)	0.125*** (5.25)	0.121*** (5.19)		0.130*** (5.55)	0.168*** (7.07)	0.158*** (6.73)
ΔRD_t				0.101 (0.58)			
β_t		-1.101** (-2.30)	-0.141 (-0.32)	-0.154 (-0.35)		-0.923* (-1.87)	0.415 (-0.90)
$SIZE_t$		-0.78 (-0.72)	-0.034 (-0.31)	-0.393 (-0.35)		-0.112 (-1.04)	-0.068 (-0.63)
$\ln(BM)_t$		-0.198** (-2.39)	-0.227** (-2.57)	-0.212** (-2.41)		-0.299*** (-3.49)	-0.348*** (-3.72)
$CRETURN_t$			0.424 (1.01)	0.223 (0.59)			0.258 (0.63)
$\ln(TURN)_t$			-0.297*** (-4.12)	-0.286*** (-3.93)			-0.439*** (-5.64)
$\ln(CTV)_t$			0.248 (1.33)	0.275 (1.44)			-0.364 (-0.34)
$ADJ\ \overline{R^2}$	0.007	0.074	0.113	0.113	0.007	0.078	0.121
Month	288	288	288	287	288	288	288
N	86,920	83,973	83,348	82,734	87,338	84,383	83,754

Note: ***, ** and * indicate that the coefficient is significantly different from zero at the 1, 5 and 10% levels, respectively.

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3.4. Robustness

3.4.1. Conversion of Portfolio Construction Methods

The portfolios examined in our study were formed once a year, and the scaled R&D expenses were assumed to be unchanged throughout the year (Fama & French, 1993; Gompers, Ishii, & Metrick, 2003). In this section, we examined the impact of R&D spending on stock returns using an alternative portfolio construction method. Instead of scaling R&D spending by sales, we scaled R&D spending by a firm's market capitalization because the market capitalization value is what the market participants currently value the firm. For this reason, R&D was calculated on an annual basis whereas market capitalization was calculated monthly. We then divided the sample firms into quintile portfolios based on the ratio of R&D to market capitalization. We then rebalanced the quintile portfolios every month.

Table 4 presents the analysis results after changing the portfolio construction method as described above. The results were similar to those of Table 2. Portfolios with high R&D expenditures ed higher abnormal returns than those with low R&D expenditures. A zero-net investment strategy (H-L) earned significant positive abnormal returns ranging from 0.75% to 0.96% across all asset pricing models. The results remained similar when equal-weighted returns were used instead of value-weighted returns.

Table-4. Robustness: Alternative portfolio formation analysis.

Return	Model	P1 (LOW)	P2	P3	P4	P5 (HIGH)	H-L
Value-weighted return (N=288)	CAPM	−0.260 (−0.86)	−0.069 (−0.26)	0.048 (0.17)	0.511* (1.76)	0.486 (1.58)	0.745* (1.70)
	FF3	−0.310 (−1.01)	−0.175 (−0.66)	0.003 (0.01)	0.485 (1.65)	0.653** (2.14)	0.962** (2.20)
	FF4	−0.267 (−0.36)	−0.224 (−0.84)	−0.045 (−0.16)	0.421 (1.42)	0.654** (2.13)	0.921** (2.09)
Equally-weighted return (N=288)	CAPM	−0.111 (−0.38)	0.221 (1.06)	0.131 (0.75)	0.315* (1.83)	0.224 (1.28)	0.334* (1.78)
	FF3	−0.201 (−0.68)	0.105 (0.51)	0.001 (0.01)	0.225 (1.31)	0.138 (0.79)	0.339* (1.77)
	FF4	−0.074 (−0.26)	0.155 (0.75)	0.037 (0.22)	0.251 (1.46)	0.174 (0.99)	0.248 (1.32)

Note: ***, ** and * indicate that the coefficient is significantly different from zero at the 1, 5 and 10% levels, respectively.

3.4.2. R&D and Long-Term Returns

The existing literature has examined whether R&D expenditures improve future profits and firm value (e.g. Lev and Sougiannis (1996)). In this section, we explored more specifically the long-term impact of these R&D expenditures. As a measure of long-term impact, we computed cumulative abnormal returns for each portfolio. The cumulative abnormal returns were calculated using Equation 5.

$$CAR_{p,k} = \sum_{t=1}^{k} AR_{p,t} \tag{5}$$

Here, $CAR_{p,k}$ represents the cumulative abnormal returns of the portfolios during the holding period and K represents 12 months, 36 months, 60 months, and 120 months. AR is abnormal returns after deducting the risk-free rate from the portfolio's rate of returns.

The analysis results are presented in Table 5. The results showed that portfolios of firms that invest more in R&D earned higher cumulative abnormal returns than those that invest less regardless of investment horizons. A long-short portfolio earned from 6.76% (12 months) to 49.26% (120 months) and these cumulative abnormal

returns were statistically significant at the 1 percent level.[2] We found similar results when equal-weighted returns were used. A long-short portfolio did not earn significant positive cumulative abnormal returns for 12 months horizon but it earned positive cumulative abnormal returns for 36 months (1.89%) and 60 months (2.83%) and these cumulative abnormal returns were statistically significant at the 10 percent level.

Table-5. Portfolio analysis using long-term CARs.

Return	Model	P1 (LOW)	P2	P3	P4	P5 (HIGH)	P5-P1
Value weighted return	T12 (N=276)	-0.636 (-0.36)	1.991 (1.02)	3.257* (1.75)	6.738*** (3.95)	6.128*** (3.57)	6.763* (5.32)
	T36 (N=252)	-7.504** (-2.57)	0.147 (0.04)	4.992* (1.74)	18.195*** (6.88)	13.809*** (8.77)	21.313*** (10.11)
	T60 (N=228)	-14.113*** (-3.48)	1.024 (0.20)	7.023* (1.96)	33.311*** (9.69)	19.644*** (8.63)	33.757*** (11.07)
	T120 (N=168)	-0.721 (-0.21)	35.331*** (4.75)	38.227*** (10.43)	93.628*** (19.60)	48.534*** (18.54)	49.255*** (12.18)
Equally weighted return	T12 (N=276)	0.857 (0.59)	0.923 (0.62)	1.262 (0.91)	2.572* (1.74)	1.107 (0.81)	0.249 (0.47)
	T36 (N=252)	-3.678 (-1.39)	-3.125 (-1.41)	-0.251 (-0.10)	1.976 (0.85)	-1.784 (-0.81)	1.893* (1.76)
	T60 (N=228)	-9.312** (-2.42)	-8.582** (-2.87)	-1.766 (-0.48)	1.766 (0.55)	-6.483** (-2.16)	2.829* (1.79)
	T120 (N=168)	-0.921 (-0.17)	-0.852 (-0.21)	14.645** (2.79)	25.720*** (6.08)	-8.169* (-1.78)	-7.247*** (-4.62)

Note: ***, ** and * indicate that the coefficient is significantly different from zero at the 1, 5 and 10% levels, respectively.

Figure 2 illustrates long-term value-weighted cumulative abnormal returns for quintile portfolios that are sorted based on R&D spending. It shows that portfolios of firms that invest more in R&D consistently beat those that invest less and the difference in cumulative abnormal returns between P5 and other portfolios became larger as the investment horizon got longer.
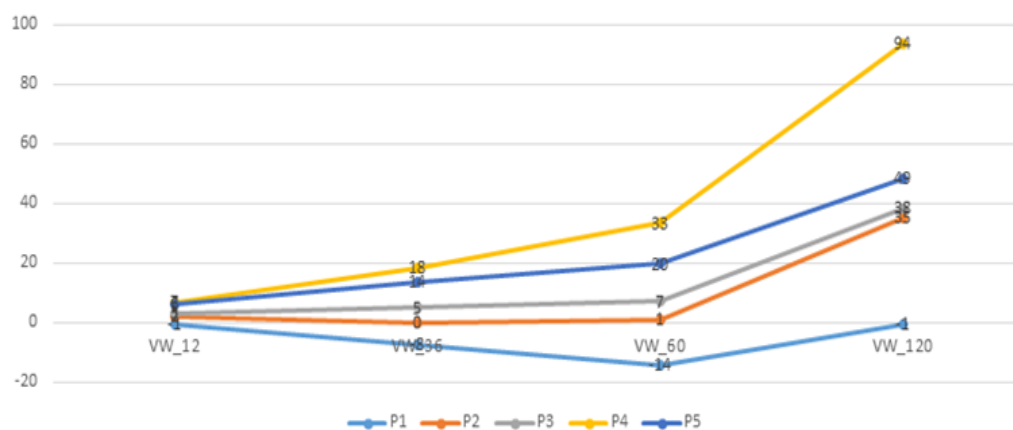

Figure-2. Portfolio analysis using long-term CARs.

Table 6 presents the cross-sectional analysis results using long-term cumulative abnormal returns. The long-term cumulative abnormal returns were computed at intervals of 12 months, 36 months, 60 months, and 120 months for the analysis. The regression results showed that a coefficient of R&D spending was positive and statistically significant across all investment intervals. The economic magnitude and statistical significance of the coefficient gradually increased as the interval increased, suggesting that there was no long-term return reversal.

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[2] For brevity, we only report the abnormal returns using Fama-French three-factor model. We find similar results when the market model and Carhart four-factor model are used.

The evidence from a cross-sectional analysis confirmed that R&D explains stock returns and R&D spending and stock returns were positively related to each other.

Table-6. Cross sectional analysis for R&D expenditures.

DV	R_{12}	R_{36}	R_{60}	R_{120}
Model	(1)	(2)	(3)	(4)
RD_t	0.067**	0.068*	0.092**	0.111**
	(2.42)	(1.72)	(2.00)	(2.85)
β_t	0.064	–0.36	0.29	–0.542
	(0.16)	(–0.90)	(0.66)	(–1.23)
$SIZE_t$	0.112	0.094	0.157	0.177
	(0.92)	(0.87)	(1.26)	(1.80)
$\ln(BM)_t$	0.118	–0.042	–0.066	–0.116
	(1.30)	-(0.32)	-(0.39)	-(0.76)
$CRETURN_t$	–0.422	–0.036	–0.401	–0.055
	-(1.19)	-(0.13)	-(1.23)	-(0.18)
$\ln(TURN)_t$	–0.243***	–0.188**	–0.152**	–0.09
	-(3.76)	-(2.59)	-(2.28)	-(1.28)
$\ln(CTV)_t$	0.003	0.019	–0.233	–0.046
	(0.02)	(0.09)	-(0.87)	-(0.18)
$ADJ\ \overline{R^2}$	0.090	0.074	0.113	0.113
Month	276	252	228	168
N	79,304	69,878	60,649	38,900

Note: ***, ** and * indicate that the coefficient is significantly different from zero at the 1, 5 and 10% levels, respectively.

3.4.3. Fama & French Five-Factor Model

As a further robustness test, we also used the Fama and French (2015) five-factor (FF5) model to compute risk-adjusted returns. The FF5 model includes additional risk factors of profitability and investments along with the market risk, size, and value factor. Fama and French (2015) showed that profitability and stock returns are positively related to each other and that internal investment in growth projects is negatively associated with stock returns. Following Fama and French (2015) we included profitability and capital investments as additional risk factors in the model when computing abnormal returns of stocks. Equation 6 was our regression model to compute the abnormal returns using the Fama-French five factors.

$$E[r_i] - r_f = \alpha_i + b_i E[MKT] + S_i E[SMB] + h_i E[HML] + r_i E[RMW] + c_i E[CMA] \quad (6)$$

In Equation 6 $E[r_i] - r_f$ is the expected excess return, *MKT* is the market excess return, *SMB* (small minus-big) is the difference between the returns on diversified portfolios of small and big stocks, *HML* (high-minus-low) is the difference between the returns on diversified portfolios of high and low book-to-market stocks, *RMW* (robust-minus-weak) is the difference between the returns on diversified portfolios of strong and weak profitability stocks, and *CMA* (conservative-minus aggressive) is the difference between the returns on diversified portfolios of low and high investment stocks. The slopes b_i, s_i, h_i, r_i and c_i are the exposures to the five factors.

Table 7 reports risk-adjusted returns using the FF5 model after sorting the sample firms into quintile portfolios based on a size of R&D spending. For value-weighted risk-adjusted returns, a portfolio of firms that invest the most in R&D (P5) earned the highest return (0.69%) and the returns were statistically significant at the 5 percent level. A long-short portfolio (buy P5 and short P1) generated abnormal returns of 0.76%, which was also

statistically significant at the 10 percent level. The evidence in Table 7 confirmed that the results were not sensitive to using an alternative asset pricing model to compute abnormal returns.

Table-7. Abnormal returns using Fama and French five-factor model.

Value-Weighted Return (N=288)					Equally-Weighted Return (N=288)				
P1(L)	P2	P3	P4	P5(H)	P1(L)	P2	P3	P4	P5(H)
−0.069	−0.015	0.250	0.483*	0.694**	0.096	0.030	0.075	0.185	0.163
(−0.28)	(−0.06)	(0.81)	(1.85)	(2.46)	(0.39)	(0.14)	(0.35)	(0.87)	(0.75)
P5(H)-P1(L)		0.764(1.95)*						0.067(0.44)	

Note: ***, ** and * indicate that the coefficient is significantly different from zero at the 1, 5 and 10% levels, respectively.

3.4.4. Exclusion of Financial Crisis Periods

During the sample period, the sample firms suffered from two major financial crises. One might argue that the finding of the positive relation between R&D spending and stock returns may be driven by period-specific factors that can be attributed to the two financial crises. We thus excluded the 1998 Foreign Exchange Crisis and the 2008 Financial Crisis from the sample period for our analysis. The analysis results are presented in Table 8.

Based on the value-weighted abnormal returns, a portfolio of firms that spend heavily on R&D (P5) consistently earned the highest abnormal returns across all asset pricing models. The abnormal returns were all statistically significant at the 5 percent level. A long-short portfolio also generated positive and statistically significant abnormal returns (except CAPM) at the 5 percent level. The results in Table 8 suggest that the finding of the positive impact of R&D spending on stock returns was not driven by period-specific factors and that rather R&D has a persistent impact on stock returns across the entire sample period.

Table-8. Excluding foreign exchange crisis and financial crisis.

Return	Model	P1(LOW)	P2	P3	P4	P5(HIGH)	H-L
Value-weighted return (N=266)	CAPM	0.032 (0.13)	0.266 (1.01)	0.282 (0.93)	0.484* (1.84)	0.655** (2.31)	0.622 (1.54)
	FF3	0.005 (0.02)	0.094 (0.36)	0.197 (0.64)	0.395 (1.49)	0.875*** (3.22)	0.870** (2.21)
	FF4	−0.006 (−0.02)	0.116 (0.44)	0.209 (0.67)	0.404 (1.51)	0.812** (2.99)	0.818** (2.07)
Equally-weighted return (N=266)	CAPM	0.199 -0.79	0.147 (0.65)	0.123 (0.54)	0.246 (1.11)	0.204 (0.91)	0.005 (0.03)
	FF3	0.078 (0.31)	0.002 (0.01)	−0.023 -(0.10)	0.130 (0.60)	0.163 (0.72)	0.085 (0.55)
	FF4	0.152 (0.61)	0.067 (0.31)	0.004 (0.02)	0.183 (0.84)	0.172 (0.75)	0.019 (0.13)

Note: ***, ** and * indicate that the coefficient is significantly different from zero at the 1, 5 and 10% levels, respectively.

4. CONCLUSION

Using the data of publicly listed Korean firms from January 1992 to December 2015, we examined the impact of R&D expenditures on stock returns. This study offered a comprehensive analysis of how R&D expenditures were perceived in the stock market.

We proposed three plausible hypotheses to predict a relation between R&D spending and stock returns. The signaling hypothesis asserts that high-quality firms may attempt to communicate with the market to reduce information asymmetry between insider managers and outside investors by spending more on R&D because R&D projects tend to have greater information asymmetry and because investors pay attention to a firm's R&D spending decision. The agency hypothesis predicts that entrenched managers inefficiently spend on R&D projects because they want to use free cash flows to seek their personal benefits rather than maximizing shareholders' wealth. The

overconfidence hypothesis argues that overconfident managers are likely to overspend on R&D projects because they believe that they have better ability than they actually have and these managers are optimistic about future success of the R&D projects.

Our portfolio analysis showed that portfolios of firms that spend heavily on R&D show consistent positive abnormal returns, indicating that R&D spending was an effective explanatory factor for stock returns. We found that spending on R&D also had a consistent significant impact stock prices over the longer horizons. We found that R&D spending was an important channel in improving firm value through a firm's attempt to communicate with the stock market.

This study faced a few limitations as well. First, this study could not address the specific uses of R&D expenditures. As the financial statements provide only the total amount spent on R&D, an analysis of the specific uses of this amount is still needed. For example, if we were to know how much was invested into the core industry or into long- or short-term projects, this examination would be more fruitful.

Second, this study did not take industrial considerations into account. As importance of R&D expenditures is heterogenous across industries, this aspect should have been controlled in the analysis. Third, this study could be more effective with the consideration of external factors. For example, as management investment decisions of a firm are often influenced by its ownership and control structures, a study that takes this fact into account would be more effective.

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