JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS Vol. 48, No. 5, Oct. 2013, pp. 1607–1634

doi:10.1017/S0022109013000574

R&D Spillover Effects and Firm Performance Following R&D Increases

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Abstract

We examine how research and development (R&D) incoming spillovers affect long-run firm performance following firms' R&D increases. We use a stochastic frontier production method to capture R&D incoming spillover effects. Firms reaping more benefits from R&D investment made by other firms experience more improvement in profitability and more favorable long-run stock performance in the post-R&D-increase period. Firms with higher levels of R&D incoming spillovers recruit more key employees from other firms, suggesting that obtaining know-how through hiring is an important source of incoming spillovers. The evidence also shows that firms experiencing more R&D outgoing spillover effects tend to underinvest in R&D.

I. Introduction

A firm's research and development (R&D) investment is usually associated with superior performance. Chan, Martin, and Kensinger (1990) and Szewczyk, Tsetsekos, and Zantout (1996) find a positive short-term stock market reaction to announcements of increased R&D investment. Eberhart, Maxwell, and Siddique (2004), (2008) show that firms with significant R&D increases experience positive long-run abnormal stock returns and improved operating performance. These results suggest that investors underreact to R&D increases, and that R&D increases are, on average, even better investments than the market expects when the information is released.

The nature of R&D suggests that the performance of a firm is affected not only by its own R&D investment but also by the R&D investment of other firms.

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R&D usually has strong positive externalities (termed R&D spillover effects). By R&D spillover we mean that a privately owned firm does not or cannot appropriate all the positive outcomes of its own R&D investment. Griliches (1979) and Bernstein and Nadiri (1988) document that although a firm's R&D investment reduces its own production costs, costs of other firms also decline as a result of R&D spillover. Jaffe (1986) shows that when the potential R&D spillover pool increases by 1%, profits of other firms increase by 0.3%. These studies indicate that R&D investment produces benefits that accrue to parties other than the firm generating it. The reason may be that R&D investments (e.g., new technologies and innovations) are usually intangible and not always difficult for others to reverse engineer or steal.[1] Once a firm takes advantage of know-how created by other firms, a given R&D investment affects both the R&D investing firm and other firms.

Given the positive externalities of R&D investment, we argue that there is a positive relation between R&D incoming spillovers and firm performance. That is, when a firm reaps more spillover benefits from other firms' R&D investment, we expect it to experience more improvement in performance. Cassiman and Veugelers (2002) suggest that R&D spillovers can be seen from two perspectives: i) incoming spillovers, which assess a firm's ability to take advantage of innovations created by other firms; and ii) appropriability of a firm's own R&D, which evaluates a firm's ability to profit exclusively from its new technologies. The extent of incoming spillovers is influenced by the firm's absorptive capacity of R&D. R&D-increase firms that are associated with better learning and absorptive capabilities are more likely to benefit from R&D spillover effects (Cohen and Levinthal (1989)). They hence may experience greater improvements in profitability and higher market valuation.

R&D incoming spillovers might not have an immediate impact on firm valuation when there is an unexpected increase in R&D, because investors may have difficulty measuring the extent of the firm-specific incoming spillover effect (Griliches (1992), Henderson and Cockburn (1996), and Cassiman and Veugelers (2002)). Firms have different incoming spillovers, depending on technology flows from specialized conferences or meetings, foreign direct investment flow from international channels, an R&D investment itself, and the location of R&D generator and receiver (Jaffe (1986), Cohen and Levinthal (1989), Jaffe, Trajtenberg, and Henderson (1993), Cassiman and Veugelers (2002), and Alcácer and Chung (2007)). In other words, the complicated nature and variety of R&D incoming spillovers suggest that in general investors cannot concretely measure spillover effects on a firm's profitability. Thus, investors are likely slow to recognize the

[1]While patents and copyrights can be used to prevent this type of activity, they are not always effective. Levin, Klevorick, Nelson, Winter, Gilbert, and Griliches (1987) argue that patents are particularly effective in chemical industries because clear standards can be applied to assess a chemical patent's validity and to defend against infringement. In the case of advanced technologies, it is more difficult to prove infringement. One notable case is the graphical user interface (GUI) for Macintosh and Microsoft Windows. In 1988, Apple sued Microsoft for copyright infringement of the Apple Macintosh GUI. Despite its copyrights, almost all of Apple's claims were denied by the court on a contractual technicality.

full benefit of positive R&D externalities.[2] If investors underreact to the positive information of externalities conveyed in an R&D increase, we would expect the R&D incoming spillover effect to relate to long-run firm performance following the R&D increase. That is, a positive relation between R&D incoming spillovers and the long-run abnormal stock returns of R&D-increase firms would indicate that the market does not immediately incorporate positive R&D externalities into stock valuations, contrary to the efficient market hypothesis.

This study attempts to measure the R&D incoming spillover effect and its association with the long-run performance of R&D-increase firms. As there are various R&D spillover channels, we adopt a stochastic frontier production function to capture the R&D spillover effect. We model this effect, which is a nonnegative stochastic random variable, as part of the production function, because the positive effects of R&D spillovers appear primarily in manufacturing technology. From estimates of the production function, we can measure the effect of R&D spillovers for each firm observation and then investigate the relation between the incoming spillover effect and the long-run performance of R&D-investing firms.

To investigate the incoming spillover effect, we collect 7,554 U.S. firm-year observations of unexpected and significant increases in firm R&D between 1977 and 2005. Following Eberhart et al. (2004), we require firms in the sample to have an R&D intensity of more than 5% and an R&D increase of over 5%. We focus on these firms because they are the most likely to experience R&D incoming spillovers (Cohen and Levinthal (1989), Henderson and Cockburn (1996)). A firm with little R&D spending is less able to learn from the outside knowledge pool generated by other firms' R&D efforts.

To see whether our stochastic frontier production method captures the R&D incoming spillover effect, we examine recruiting news about our sample firms, because the hiring of key employees from other firms is a major source of R&D incoming spillovers (e.g., Levin et al. (1987), McEvily and Chakravarthy (2002), and Agarwal, Ganco, and Ziedonis (2009)). Sample firms with a higher level of incoming spillovers tend to recruit more key employees from other firms. This evidence implies that firms that hire more key personnel and hence take advantage of more know-how from other firms tend to enjoy more R&D incoming spillover effects.

We calculate the 5-year long-run abnormal return of our sample firms sorted by R&D incoming spillover. We use the standard Fama and French (1993) 3-factor model and the Carhart (1997) 4-factor model to estimate abnormal stock returns. The average monthly abnormal return following R&D increases is 0.67% to 1.08% for firms with the highest level of incoming spillover, compared to only 0% to 0.58% for firms with the lowest level of incoming spillover, depending on model and weighting scheme. The results overall support a positive relation between the R&D incoming spillover effect and the long-run performance of R&D-increase firms. Our results are robust to alternative measures of abnormal stock returns and various stochastic R&D spillover specifications. Evidence confirms as well that R&D investments are beneficial to other firms, but that the market

[2]Research on cognitive behavior also predicts that investors may underreact to complex information (e.g., Barberis, Shleifer, and Vishny (1998), Hong and Stein (1999), and Hirshleifer (2001)).

is slow to recognize the full extent of this benefit, contrary to what the efficient market hypothesis would predict.

To see if the abnormal returns we observe reflect risk factors that are not accounted for by our benchmarks, we follow Denis and Sarin (2001), Chan, Ikenberry, and Lee (2004), and Titman, Wei, and Xie (2004), and examine abnormal stock returns surrounding earnings announcements over the 5 years after R&D increases. We find significantly positive earnings-announcement abnormal returns for firms with high incoming spillovers but not for firms with low incoming spillovers. This result suggests that the long-run outperformance of R&D-increase firms with high incoming spillovers is not likely to be generated by the benchmark measurement errors suggested by Lyon, Barber, and Tsai (1999).

Evaluation of the operating performance of firms following significant R&D increases provides further evidence on the potential benefit of R&D incoming spillovers. We show that R&D-increase firms with high incoming spillovers tend to experience greater improvement in operating performance than firms with low incoming spillovers. This evidence again supports the importance of R&D incoming spillovers in explaining long-run firm performance following R&D increases.

Examination of R&D outgoing spillover effects indicates that sample firms with a higher level of R&D outgoing spillovers are more likely to display significantly negative abnormal R&D investment. This finding indicates that R&D outgoing spillovers cause an underinvestment in R&D because of the imperfect appropriability of benefits from such investment (Arrow (1962), Jones and Williams (1998)). We also find that R&D outgoing spillover effects are significantly negatively related to firm size and advertisement expenditure, and significantly positively related to industry R&D dispersion. Our results suggest that smaller firms, firms with less spending on brand name, and firms in industries with greater R&D dispersion are likely to experience R&D outgoing spillovers that make it harder for them to appropriate returns from R&D (Cassiman and Veugelers (2002), Feinberg and Gupta (2004), and Franco and Gussoni (2010)).

Our research makes two valuable contributions to the literature. First, we find that the market appears to underreact to R&D incoming spillover effects. Investors have difficulty in measuring the extent of these effects, given their complicated nature. Using a stochastic frontier production function to estimate R&D incoming spillovers, we show that the long-run performance of R&D-increase firms is positively related to the incoming spillover effect. This evidence suggests that the market is slow to incorporate positive R&D externalities into firm valuations. Second, we find that firms that are less able to appropriate their R&D benefits are also less likely to undertake R&D investment in the future. Using the production function to estimate R&D outgoing spillover effects, we show that firms with higher levels of R&D outgoing spillovers tend to experience negative abnormal R&D investment. We also discover several factors that significantly affect R&D outgoing spillovers.

The paper is organized as follows: In Section II, we review the literature and discuss the procedures we use to estimate the R&D incoming spillover effect. Section III describes the data and methodology. We examine how R&D incoming spillovers relate to post-R&D-increase stock performance in Section IV and to post-R&D-increase earnings-announcement stock returns and operating performance in Section V. Section VI provides additional evidence. The final section concludes.

II. R&D Spillovers

A. Literature Review on R&D Spillovers

An R&D spillover occurs when privately owned firms are unable to fully appropriate returns from their R&D investment. Arrow (1962) and Jones and Williams (1998) argue that R&D spillovers cause R&D investment to deviate from its optimal level. In this view, R&D spillovers promote underinvestment in R&D. Imperfect appropriability allows firms to take advantage of other firms' R&D to reduce production costs or enhance profitability.

According to the literature, there are several ways R&D know-how can spill over. R&D results may be copied or mimicked because know-how and innovation are usually intangible assets. To some extent, the knowledge spillover that Hanel and St-Pierre (2002) suggest is similar to this notion. That is, R&D results may be found in publicly available information. Protection by intellectual property rights could deter such potential knowledge transfer, but it is unlikely that all possible knowledge transfers can be limited this way (Arrow (1962)).

Moreover, the know-how generated by R&D activities may pass from a firm to a partner such as its subsidiary. If a manager moves from a firm to an embryonic organization, this migration may create knowledge spillovers, including the transfer of rules, routines, and procedures from the parent firm. Agarwal, Echambadi, Franco, and Sarkar (2004) call this the parent-progeny knowledge transfer relation. They find that new firms receiving technology from parent firms tend to perform better than other entrants.

Positive externalities from R&D are widely investigated in the literature, although there are different channels to spread the knowledge of R&D. Griliches (1979) and Bernstein and Nadiri (1988) argue that one firm's R&D investment could reduce the costs for other firms. Jaffe (1986) suggests that firms' net income will increase when the potential spillover pool increases. Megna and Mueller (1991), Geroski, Machin, and Reenan (1993), and Zantout and Tsetsekos (1994) find similar results. Henderson and Cockburn (1996) find a stronger R&D incoming spillover effect for firms with higher levels of R&D intensity. This finding confirms the conclusion of Cohen and Levinthal (1989) that a firm's R&D investment makes it better able to learn new technologies. Overall, the research documents the existence of an R&D spillover effect: The R&D of one firm can benefit the performance of other firms.

B. Stochastic R&D Spillover Effects

We use a production function to estimate the R&D incoming spillover effect for a specific firm because a firm's ability to absorb outside R&D knowledge should be reflected in its productivity. In a given year, we assume that firm i uses inputs including capital (K), labor (L), and research and development (RD) to produce output (Y), according to a Cobb-Douglas production function technique as follows:

$$\text{(1)} \qquad \log Y_i = a_0 + a_1 \log K_i + a_2 \log L_i + a_3 \log \text{RD}_i + a_4\text{TIME\_TREND} + u_i + v_i.$$

This setting suggests that the output level Y_i depends on a set of production factors (K_i, L_i, and RD_i); a time trend variable to capture general growth over time (Battese and Coelli (1992)); and two unobservable disturbance terms, u_i and v_i. We follow the stochastic frontier production analysis of Aigner, Lovell, and Schmidt (1977) in including the two error terms.[3] Here, v_i represents the symmetric disturbance and is assumed to be independent and identically distributed (i.i.d.) as N(0, σ_v^2); v_i is independent of the error term u_i, which is assumed to be i.i.d. half-normal distribution $|\text{U}|$, given $\text{U} \sim \text{N}(0, \sigma_u^2)$.

The economic implications of the production function in equation (1) are described as follows: The random variable u_i captures the incoming spillover effect of firm i from other firms, and the white noise v_i captures the impact of other random factors on the shocks of output. Here, u_i is nonnegative because the spillover effect represents a positive R&D externality. To provide a better understanding of u_i, we further interpret $u_i = \sum_{j=1,\, j\neq i}^{N} s_j\text{RD}_j + w_i$, indicating that the incoming spillover effect of firm i can be decomposed into two terms. The first term relates the incoming spillover effect of firm i to RD_j and s_j, where RD_j is the R&D level of firm j, and s_j is the extent to which firm i absorbs the R&D spillover effect from firm j (Cassiman and Veugelers (2002)). We require s_j to be nonnegative because spillover effects are positive by nature. The second term w_i represents the unobservable random source.

We follow Aigner et al. (1977) and estimate equation (1) using the maximum likelihood (ML) method. Given the distribution assumptions for u_i and v_i and the independence assumption between u_i and v_i, we can express the density function of $\varepsilon_i = u_i + v_i$ as

$$\text{(2)} \qquad f(\varepsilon_i) = \frac{2}{\sigma}\varphi\left(\frac{\varepsilon_i}{\sigma}\right)\Phi\left(\frac{\varepsilon_i\lambda}{\sigma}\right),$$

where $\sigma = \sqrt{\sigma_u^2 + \sigma_v^2}$ and $\lambda = \sigma_u/\sigma_v$; ϕ and Φ denote the standardized normal density and distribution functions. The log-likelihood function is

$$\text{(3)} \qquad \ln L(y_i\,|a_0, a_1, a_2, a_3, a_4, \lambda, \sigma) = \frac{N}{2}\ln\left(\frac{2}{\pi}\right) - N\ \ln\sigma + \sum_{i=1}^{N}\left\{\ln[\Phi(\varepsilon_i\lambda\sigma^{-1})] - \frac{1}{2\sigma^2}\varepsilon_i^2\right\}.$$

Accordingly, we are able to use the ML method to estimate parameters following the algorithm of quasi-Newton optimization.

In our estimation, output Y_i is measured by gross profit (i.e., sales minus cost of goods sold); capital K_i is measured by property, plant, and equipment (PPE);

[3]Stochastic frontier analysis is typically designed to estimate the technical efficiency of a firm. Researchers in finance have applied this stochastic frontier method to investigate various issues, including initial public offering (IPO) underpricing, agency costs, and trading costs (e.g., Hunt-McCool, Koh, and Francis (1996), Habib and Ljungqvist (2005), and Green, Hollifield, and Schürhoff (2007)).

labor L_i is number of employees; and RD_i is R&D expenditure.[4] To estimate the R&D incoming spillover effect of firm i, we use the conditional mean of u_i given ε_i:

$$\text{(4)} \qquad \mathrm{E}(u_i|\varepsilon_i) \quad = \quad \mu_{*i} + \sigma_* \left(\frac{\phi(-\mu_{*i}/\sigma_*)}{\Phi(\mu_{*i}/\sigma_*)} \right),$$

where $\mu_{*i} = \varepsilon_i(\sigma_u^2/\sigma^2)$ and $\sigma_* = \sigma_u \sigma_v/\sigma$. We obtain the estimated u_i by replacing ε_i, σ_i, and σ_v with their estimated values in equation (4). We sort sample firms into quintiles according to the estimated value of u_i. Firms with the lowest u_i values are placed in quintile 1, and firms with the highest u_i values in quintile 5.

III. Data and Methodology

A. Data

We begin by collecting data for U.S. firms listed on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), or the National Association of Securities Dealers Automated Quotation (NASDAQ). We exclude American depositary receipts and noncommon stocks. We obtain stock return information from the Center for Research in Security Prices (CRSP) and company financial information from Compustat. We require sample firms to have positive market capitalization and total assets. The sample period runs from Jan. 1977 through Dec. 2005.[5]

We examine the relation between the R&D incoming spillover effect and post-R&D-increase firm performance using a sample of firms that unexpectedly increase their R&D expenditures by an economically significant amount. Eberhart et al. (2004) define an unexpected R&D increase as an increase in a firm's R&D intensity (i.e., the ratios of R&D to assets and R&D to sales). They also argue that firms with an R&D intensity of more than 5% and an R&D increase of over 5% are likely firms that experience an economically significant R&D increase. Thus, we follow them and identify sample firms that meet five selection criteria: i) Their ratios of R&D expenditures to sales are over 5%; ii) their ratios of R&D expenditures to average total assets (beginning plus end-of-year assets divided by 2) are over 5%; iii) changes in their ratios of R&D expenditures to sales are over 5%; iv) changes in their ratios of R&D expenditures to average total assets are over 5%; and v) their percentage changes in R&D expenditures are over 5%. The final sample includes 7,554 firm-year observations.

Panel A of Table 1 presents summary statistics. Firm size is measured by the market value of common equity converted to 1980 dollars using the Consumer

[4]We follow the traditional stochastic frontier literature (e.g., Aigner et al. (1977), Battese and Coelli (1988), (1992)) and do not scale the input and output variables by a variable such as sales or book assets. Our conclusions are unchanged if we use a sales- or assets-scaled stochastic production function.

[5]Our sample period starts in 1977 because i) accounting treatment of R&D expense reporting was standardized in 1974 (Financial Accounting Standards Board Statement No. 2), and ii) there are too few observations with available information for the production function estimation during the period 1974–1976.

Price Index. The average firm size is $407 million, indicating that sample firms tend to be small. BM is the book value of common equity divided by the market value of common equity. The average BM is 0.52, suggesting that sample firms tend to be high-growth firms. When we divide the sample into five groups on the basis of R&D incoming spillover, we find that their R&D intensities are similar. Return on assets (ROA), defined as EBITDA (earnings before interest, taxes, depreciation, and amortization) divided by average total assets, tends to be higher

TABLE 1

Summary Statistics and Sample Distribution

Table 1 presents summary statistics and distribution for a sample of firms that unexpectedly increase their R&D expenditures by a significant amount between 1977 and 2005. The sample is identified according to the procedure described in Section III.A. Panel A reports mean and median firm characteristics (medians are reported in parentheses). The R&D incoming spillover is obtained from the residual (u_i) in the following Cobb-Douglas production function:

$$\log Y_i \quad = \quad a_0 + a_1 \log K_i + a_2 \log L_i + a_3 \log \mathrm{RD}_i + a_4 \mathrm{TIME\_TREND} + u_i + v_i,$$

where Y_i is gross profit; K_i is property, plant, and equipment; L_i is number of employees; RD_i is R&D expenditure; and TIME_TREND is the tth year since 1977. Residual u_i obeys half-normal $|U|$ given $U \sim N(0, \sigma_u^2)$, and residual v_i obeys Normal $N(0, \sigma_v^2)$. We sort our sample firms into quintiles according to the estimated value of u_i. Firms with the lowest u_i values are placed in quintile 1, and firms with the highest u_i values in quintile 5. Firm size is the market value of common equity converted to 1980 dollars using the Consumer Price Index. BM is the book value of common equity divided by the market value of common equity. Gross profit is sales minus cost of goods sold. R&D intensity is R&D expenditures divided by average total assets or sales. R&D growth rate is the percentage change in R&D expenditures. Return on assets (ROA) is EBITDA (earnings before interest, taxes, depreciation, and amortization) divided by average total assets. Panel B reports sample distribution by industry based on the primary 1-digit SIC code in Compustat (percentages are reported in parentheses). Panel C reports the number and proportion of R&D-increase firms that recruited top executives or key employees from other firms (proportions are reported in parentheses). We hand-collect recruiting news from the LexisNexis database for the 3,001 R&D-increase firms with the highest and lowest R&D incoming spillovers. Large firms are defined as firms with a market capitalization of over $100 million. We use Fisher's exact test to test the significance of differences in proportions; p-values are reported in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Summary Statistics

Incoming Spillover Group	*N*	Firm Size ($millions)	BM	Gross Profit ($millions)	R&D/Assets	R&D/Sales	R&D Growth Rate	ROA	Incoming Spillovers
All	7,554	407	0.52	85.47	0.16	0.21	0.71	0.02	1.26
		(51)	(0.40)	(14.27)	(0.13)	(0.13)	(0.41)	(0.08)	(1.23)
Quintile 1	1,489	320	0.55	67.25	0.15	0.31	0.81	−0.10	0.50
		(42)	(0.42)	(4.67)	(0.11)	(0.14)	(0.47)	(−0.04)	(0.49)
Quintile 2	1,502	465	0.60	110.94	0.14	0.20	0.67	0.01	0.90
		(54)	(0.47)	(15.46)	(0.11)	(0.11)	(0.36)	(0.09)	(0.89)
Quintile 3	1,518	654	0.52	137.30	0.15	0.17	0.63	0.05	1.24
		(72)	(0.40)	(22.74)	(0.12)	(0.12)	(0.36)	(0.11)	(1.24)
Quintile 4	1,533	358	0.51	70.14	0.17	0.19	0.70	0.05	1.59
		(52)	(0.39)	(17.77)	(0.15)	(0.14)	(0.43)	(0.10)	(1.59)
Quintile 5	1,512	235	0.43	41.64	0.19	0.19	0.75	0.09	2.05
		(46)	(0.33)	(14.58)	(0.16)	(0.14)	(0.47)	(0.13)	(2.04)

Panel B. Sample Distribution by Industry and Decade

	1-Digit SIC Code										
Decade	All	0	1	2	3	4	5	6	7	8	9
All	7,554	94	11	823	4,588	61	126	31	1,651	167	2
	(100.0%)	(1.2%)	(0.2%)	(10.9%)	(60.7%)	(0.8%)	(1.7%)	(0.4%)	(21.9%)	(2.2%)	(0.0%)
1970s	305	52	0	33	196	0	1	1	21	1	0
	(4.0%)	(0.7%)	(0.0%)	(0.4%)	(2.6%)	(0.0%)	(0.0%)	(0.0%)	(0.3%)	(0.0%)	(0.0%)
1980s	2,268	41	7	248	1,590	12	27	9	305	29	0
	(30.0%)	(0.5%)	(0.1%)	(3.3%)	(21.1%)	(0.2%)	(0.4%)	(0.1%)	(4.0%)	(0.4%)	(0.0%)
1990s	3,601	1	4	337	2,083	30	71	11	981	81	2
	(47.7%)	(0.0%)	(0.1%)	(4.5%)	(27.6%)	(0.4%)	(0.9%)	(0.2%)	(13.0%)	(1.1%)	(0.0%)
2000s	1,380	0	0	205	719	19	27	10	344	56	0
	(18.3%)	(0.0%)	(0.0%)	(2.7%)	(9.5%)	(0.3%)	(0.4%)	(0.1%)	(4.6%)	(0.7%)	(0.0%)

(continued on next page)

TABLE 1 (continued)

Summary Statistics and Sample Distribution

Panel C. Number and Proportion of Firms with Recruiting News

Incoming Spillover Group	Recruiting from Other Firms	Subsample by Firm Size: Large Firms	Subsample by Firm Size: Small Firms	Recruiting from Other R&D-Intensive Firms	Recruiting from Other Firms in the Same 3-Digit SIC Industry
Quintile 1	67 (4.50%)	42 (7.22%)	25 (2.76%)	35 (2.35%)	13 (0.87%)
Quintile 5	92 (6.08%)	55 (8.47%)	37 (4.29%)	54 (3.57%)	25 (1.65%)
Difference	−25 (−1.58%) [0.010]***	−13 (−1.26%) [0.061]*	−12 (−1.53%) [0.023]**	−19 (−1.22%) [0.011]**	−12 (−0.78%) [0.021]**

for sample firms with higher R&D incoming spillovers, probably because stochastic spillovers are estimated from the production function. Panel B of Table 1 presents sample distribution by industry and decade. As in Eberhart et al. (2004), most of our sample firms come from the manufacturing industry (Compustat 1-digit Standard Industrial Classification (SIC) code 3).

Other studies using survey data suggest that the hiring of key employees from other firms is an important source of R&D incoming spillovers (e.g., Levin et al. (1987)). If our estimated u_i captures the R&D spillover effect, we should expect firms with the highest level of incoming spillovers to be associated with more recruiting news than firms with the lowest level of incoming spillovers. Panel C of Table 1 gives the number and proportion of R&D-increase firms that over the sample period recruited top executives or key employees from other firms.[6] We retrieve articles from the LexisNexis database to hand-collect recruiting news for the 3,001 R&D-increase firms with the highest and lowest levels of R&D incoming spillovers in our sample. The numbers (proportions) of firms that recruit key persons from other firms are 67 (4.50%) and 92 (6.08%) for the lowest and highest spillover groups, respectively.[7] The difference of −1.58% between the two proportions is statistically significant at the 1% level, using Fisher's exact test. This finding holds for both large and small firms, where large firms are defined as firms with a market capitalization of over $100 million. Panel C also shows that our results remain unchanged when the recruiting of key persons is limited to other R&D-intensive firms (firms with ratios of R&D to assets of over 5%) or other firms in the same 3-digit SIC industry.[8] The overall evidence in Panel C supports a conclusion that one important source of R&D spillovers is recruitment

[6]Examples of key employees are vice president of R&D, chief technology officer, president and chief operating officer, pharmaceutical director, managing director, senior director for global medical affairs, and executive vice president of sales and operations.

[7]Among the 3,001 R&D-increase firms with the highest and lowest incoming spillovers, we can find only 159 firms that have recruiting news. This low proportion is probably due to the limited media coverage of R&D-increase firms. For example, Chan et al. (1990) find only 167 announcements of R&D increases in the *Dow Jones News Retrieval Service* database from June 1979 through June 1985, and Szewczyk et al. (1996) find only 252 such announcements in the same database between June 1979 and Dec. 1992.

[8]Results are similar if R&D-intensive firms are firms with ratios of R&D to sales of over 5%.

of key employees from other firms and that our estimation procedure based on stochastic frontier analysis is able to capture the R&D spillover effect.

B. Long-Run Performance Measures

We follow Eberhart et al. (2004) and use the Fama and French (1993) 3-factor model and the Carhart (1997) 4-factor model to measure abnormal return performance over the 5-year period after an R&D increase. We measure long-run abnormal stock returns at the beginning of the 5th month following the fiscal year-end in which the firm increases its R&D because our R&D increases are based on accounting data, and a 4-month lag allows the market to be informed of the accounting data. As Berk, Green, and Naik (2004) document that an investment in R&D may lead to a change in a firm's systematic risk, we also follow Eberhart et al. (2004) and estimate the 3-factor and 4-factor models using rolling regression estimates of each factor loading.[9] To avoid a bad model problem or potential bias in the estimation of long-run return performance, we further examine abnormal returns for the short period in which quarterly earnings announcements occur, an approach widely used in the literature (e.g., Chopra, Lakonishok, and Ritter (1992), La Porta, Lakonishok, Shleifer, and Vishny (1997), Denis and Sarin (2001), Chan et al. (2004), and Titman et al. (2004)). We compute abnormal stock returns over a 5-day (−2, +2) window centered around quarterly earnings announcement dates for 20 quarters following the end of the fiscal year in which the firm increases its R&D, where the abnormal return is the difference between the sample firm's announcement-period return and its size/book-to-market matching firm's return. If there are positive long-run abnormal returns following R&D increases, we are likely to see positive subsequent earnings announcement abnormal returns, as the stock valuation adjusts to new information.

Following Barber and Lyon (1996) and Lie (2001), we measure operating performance by ROAs with two adjustments. We add after-tax R&D to EBITDA (as in Eberhart et al. (2004)) because R&D expenses reduce profit. We also subtract cash from assets because cash is not productive. The abnormal ROA is the ROA of the sample firm minus the ROA of its matching firm, where the matching firm is selected by ROA and industry.[10] We use the 5-year change in abnormal ROA following an R&D increase as the operating performance measure.

IV. R&D Incoming Spillovers and Long-Run Stock Performance Following R&D Increases

Table 2 presents the long-term abnormal stock return test results. For both standard 3-factor and 4-factor models and equal- and value-weighted measures,

[9]To save space, we describe the details of measuring long-run abnormal stock returns in the legend of Table 2. We thank Kenneth French for making risk factors publicly available at his Web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/).

[10]For each sample firm we select all non-R&D-increase firms in the same 2-digit SIC industry that have ROA within ±20% or within ±0.01. If no firms meet this criterion, we relax the industry criterion to a 1-digit SIC. If still no firms meet the criterion, we disregard the SIC code. From these firms, we select the firm with the lowest $|\text{ROA}_{\text{SAMPLE\_FIRM}} - \text{ROA}_{\text{MATCHING\_FIRM}}|$.

the average abnormal returns for the whole sample over the 5 years after R&D increases range from 0.32% to 0.91% per month, all statistically significant at the 1% level. The rolling regression results indicate our results are robust to accounting for changes in risk over time. This evidence suggests that our sample firm shareholders experience significantly positive long-term abnormal stock returns following economically significant R&D increases, consistent with findings in Eberhart et al. (2004).[11]

TABLE 2

R&D Incoming Spillovers and Long-Run Stock Performance Following R&D Increases

Table 2 presents long-run abnormal stock returns (in percentage) for the sample of R&D increases. Standard Fama and French (1993) 3-factor and Carhart (1997) 4-factor models are specified as follows:

$$r_{pt} - r_{ft} = \alpha_p + \beta_p(r_{mt} - r_{ft}) + s_p\mathrm{SMB}_t + h_p\mathrm{HML}_t + e_{pt},$$
$$r_{pt} - r_{ft} = \alpha_p + \beta_p(r_{mt} - r_{ft}) + s_p\mathrm{SMB}_t + h_p\mathrm{HML}_t + w_p\mathrm{WML}_t + e_{pt},$$

where r_{pt} is the value- or equal-weighted return on portfolio p in month t; r_{ft} is the return on 1-month T-bills in month t; r_{mt} is the return on a market index in month t; SMB_t is the difference in the returns of a portfolio of small and big stocks in month t; HML_t is the difference in the returns of a portfolio of high book-to-market stocks and low book-to-market stocks in month t; WML_t is the difference in the returns of a portfolio of prior-year high return stocks and prior-year low return stocks in month t; and $e_{p,t}$ is the error term for portfolio p in month t. We include a sample stock in portfolio p if month t is within the 60-month period following its R&D increase. We measure long-run abnormal stock returns at the beginning of the 5th month following the fiscal year-end in which the firm increases its R&D. The estimated intercept from the regression captures the average monthly abnormal return over the 5-year period following R&D increases. We also estimate the equations with rolling regression estimates of each factor loading. We use the first 60 months of portfolio returns to estimate the factor loadings and then obtain the expected portfolio return in month 61 by multiplying the factor loadings estimated over the previous 60 months by their respective month 61 factor returns. The abnormal return in month 61 is the difference between the actual portfolio return and the expected portfolio return. We repeat this step for every month. We then average the time series of monthly abnormal return estimates and perform a significance test based on the time-series volatility of these estimates. The measure of R&D incoming spillover is described in Table 1. Firms with the lowest level of incoming spillovers are placed in quintile 1, and firms with the highest level of incoming spillovers in quintile 5. The t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Value-Weighted				Equal-Weighted			
	3-Factor Model		4-Factor Model		3-Factor Model		4-Factor Model	
Incoming Spillover Group	Standard	Rolling	Standard	Rolling	Standard	Rolling	Standard	Rolling
All	0.3247 (2.86)***	0.2072 (1.83)*	0.3336 (2.86)***	0.1956 (1.67)*	0.6494 (3.63)***	0.5243 (2.83)***	0.9120 (5.28)***	0.6552 (3.68)***
Quintile 1	0.0230 (0.13)	−0.1411 (−0.70)	−0.0002 (−0.00)	−0.2185 (−1.03)	0.3525 (1.77)*	0.2977 (1.45)	0.5835 (2.97)***	0.3851 (1.89)*
Quintile 2	0.3671 (2.05)**	0.0354 (0.21)	0.3972 (2.17)**	0.0135 (0.08)	0.6401 (3.14)***	0.3743 (1.73)*	0.8374 (4.10)***	0.4755 (2.25)**
Quintile 3	0.2444 (1.51)	0.1981 (1.22)	0.2456 (1.48)	0.2350 (1.37)	0.5949 (3.27)***	0.6042 (3.05)***	0.8192 (4.58)***	0.7574 (3.84)***
Quintile 4	0.6335 (3.25)***	0.4110 (2.05)**	0.6979 (3.50)***	0.4109 (2.00)**	0.8257 (4.11)***	0.7058 (3.40)***	1.1441 (5.98)***	0.8717 (4.40)***
Quintile 5	0.9293 (3.48)***	0.8818 (3.10)***	1.0787 (3.97)***	0.9518 (3.26)***	0.6672 (3.00)***	0.6563 (2.63)***	1.0009 (4.68)***	0.8233 (3.61)***

Table 2 also shows a positive relation between R&D incoming spillovers and post-R&D-increase abnormal returns. For example, with the value-weighted measure, the average monthly abnormal return for firms with the highest level of incoming spillovers is 0.93% with the standard 3-factor model and 1.08% with the standard 4-factor model (both statistically significant at the 1% level), compared

[11]We also perform two robustness checks on the small-firm effect: i) We exclude firms smaller than the sample median, or ii) we remove stocks in size decile 1. Our conclusion remains unchanged.

to only 0.02% and 0% for firms with the lowest level of incoming spillovers (both insignificantly different from 0). The results are similar for the equal-weighted measure and the rolling regression method.[12] The overall evidence in Table 2 indicates that firms with greater R&D incoming spillovers appear to reap more technology benefits, producing higher abnormal stock returns.

In Table 3, we examine the long-run performance of R&D-increase firms in the post-1990 period, particularly because of the expansion of technology in electronics-related industries (Jorgenson and Stiroh (1999) and Stiroh (2002)). Rapid growth in the technology of an economy suggests that not only R&D investment per se but also R&D spillovers may improve the technology levels of individual firms. Table 3 shows that R&D incoming spillovers are still positively related to the long-run abnormal return of R&D-increase firms, consistent with the findings in Table 2.

TABLE 3

R&D Spillovers and Long-Run Abnormal Returns Following R&D Increases in the Post-1990 Period

Table 3 presents long-run abnormal stock returns (in percentage) for the sample of R&D increases in the post-1990 period. The measure of R&D incoming spillovers is described in Table 1, and the measure of abnormal returns is described in Table 2. Firms with the lowest level of incoming spillovers are placed in quintile 1, and firms with the highest level of incoming spillovers in quintile 5. The *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Value-Weighted				Equal-Weighted			
	3-Factor Model		4-Factor Model		3-Factor Model		4-Factor Model	
Incoming Spillover Group	Standard	Rolling	Standard	Rolling	Standard	Rolling	Standard	Rolling
All	0.4228 (3.47)***	0.3982 (2.85)***	0.4232 (3.37)***	0.3946 (2.79)***	0.9225 (3.71)***	0.9321 (3.46)***	1.3040 (5.69)***	1.1815 (4.66)***
Quintile 1	0.1846 (0.86)	0.2522 (0.99)	0.1979 (0.90)	0.4117 (1.55)	0.7520 (2.70)***	0.5030 (1.18)	1.0824 (4.02)***	0.6034 (1.39)
Quintile 2	0.2951 (1.73)*	0.2706 (1.51)	0.3887 (2.23)**	0.2620 (1.45)	0.9112 (3.67)***	0.9253 (3.44)***	1.2442 (5.28)***	1.1728 (4.57)***
Quintile 3	0.4157 (2.15)**	0.3304 (1.56)	0.3876 (1.95)*	0.3341 (1.55)	0.9595 (3.88)***	1.0143 (2.71)***	1.2773 (5.40)***	1.2466 (3.38)***
Quintile 4	0.7711 (2.96)***	0.6169 (2.15)**	0.8119 (3.03)***	0.6323 (2.11)**	1.0918 (3.95)***	1.1400 (3.50)***	1.5390 (6.12)***	1.4874 (4.86)***
Quintile 5	1.0107 (2.96)***	1.3039 (2.93)***	1.2208 (3.53)***	1.3198 (2.95)***	0.9194 (2.98)***	1.0955 (2.97)***	1.4058 (4.98)***	1.4139 (4.03)***

Table 4 presents long-run abnormal returns for high-tech and low-tech subsamples, according to the classification schemes of Chan et al. (1990) and Eberhart et al. (2004).[13] For high-tech firms, we find a positive relation between R&D incoming spillovers and the long-run stock performance of R&D-increase firms.

[12]Following Shumway (1997) and Shumway and Warther (1999), we also correct for a delisting bias for firms in our sample that are delisted for performance reasons. Our conclusions remain unchanged for the delisted-adjusted sample.

[13]High-tech firms include firms in such industries as pharmaceutical preparations; services-computer programming; data processing; services-computer processing; data preparation; industrial instruments for measurement, display and control of process variables; instruments for measuring and testing of electricity and signals; laboratory analytical instruments; optical instruments and lenses; surgical and medical instruments and apparatus; musical instruments; semiconductors and related

The results hold for equal- and value-weighted measures and for standard factor models and the rolling regression method. We do not find an R&D incoming spillover effect for low-tech firms. In general, low-tech firms do not earn significant long-run abnormal returns across incoming spillover groups.

TABLE 4

R&D Spillovers and Post-R&D-Increase Abnormal Returns for High- and Low-Tech Firms

Table 4 presents long-run abnormal returns (in percentage) for subsamples of high-tech firms (Panel A) and low-tech firms (Panel B) according to the classification schemes of Chan et al. (1990) and Eberhart et al. (2004). The measure of R&D incoming spillovers is described in Table 1, and the measure of abnormal returns is described in Table 2. Firms with the lowest level of incoming spillovers are placed in quintile 1, and firms with the highest level of incoming spillovers in quintile 5. The *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Incoming Spillover Group	Value-Weighted				Equal-Weighted			
	3-Factor Model		4-Factor Model		3-Factor Model		4-Factor Model	
	Standard	Rolling	Standard	Rolling	Standard	Rolling	Standard	Rolling
Panel A. High-Tech Firms								
Quintile 1	0.1193	−0.0650	0.0481	−0.1588	0.3704	0.3356	0.6074	0.4287
	(0.57)	(−0.29)	(0.22)	(−0.69)	(1.80)*	(1.58)	(2.98)***	(2.02)**
Quintile 2	0.3399	0.0082	0.3772	0.0011	0.6556	0.3786	0.8453	0.4757
	(1.86)*	(0.05)	(2.02)**	(0.01)	(3.17)***	(1.71)*	(4.07)***	(2.19)**
Quintile 3	0.2465	0.2024	0.2497	0.2403	0.5995	0.6219	0.8261	0.7773
	(1.50)	(1.24)	(1.48)	(1.38)	(3.24)***	(3.10)***	(4.54)***	(3.88)***
Quintile 4	0.6423	0.4148	0.7100	0.4294	0.8163	0.6804	1.1387	0.8514
	(3.24)***	(2.04)**	(3.50)***	(2.06)**	(4.05)***	(3.25)***	(5.94)***	(4.22)***
Quintile 5	0.9416	0.8749	1.0886	0.9426	0.6652	0.6433	1.0007	0.8071
	(3.48)***	(3.04)***	(3.95)***	(3.18)***	(2.96)***	(2.55)**	(4.63)***	(3.49)***
Panel B. Low-Tech Firms								
Quintile 1	−0.4231	−0.4228	−0.4450	−0.3329	−0.3747	−0.4034	−0.1340	−0.1896
	(−1.14)	(−1.12)	(−1.17)	(−0.86)	(−0.88)	(−0.93)	(−0.31)	(−0.43)
Quintile 2	−0.0816	−0.4704	0.2274	−0.1486	−0.0449	−0.0779	0.2715	0.2324
	(−0.18)	(−0.99)	(0.50)	(−0.31)	(−0.12)	(−0.19)	(0.72)	(0.56)
Quintile 3	0.4194	−2.2919	0.6082	−1.8648	0.6274	−2.1073	0.9188	−1.6691
	(0.78)	(−1.30)	(1.10)	(−1.03)	(1.37)	(−1.21)	(1.98)**	(−0.94)
Quintile 4	0.1072	0.1603	0.4000	0.2428	0.3938	0.3566	0.8842	0.6475
	(0.22)	(0.26)	(0.82)	(0.37)	(0.76)	(0.54)	(1.71)*	(0.94)
Quintile 5	−0.1598	−0.1954	0.0477	0.3228	0.4763	0.4096	0.6632	0.9317
	(−0.24)	(−0.27)	(0.07)	(0.44)	(0.80)	(0.63)	(1.09)	(1.41)

We also examine long-run stock performance for subsamples of value firms and other firms, where firms in the top book-to-market quintile are classified as value firms. The results (untabulated) show that the abnormal returns of value firms are not statistically significant, while the other firms earn positive abnormal returns. We also find that the R&D incoming spillover effect exists only for the other-firm category.

In Table 5, we follow Eberhart et al. (2004) and examine long-run abnormal returns using the zero-investment portfolio regression. Daniel and Titman (1997) argue that a firm's characteristics (e.g., size and book-to-market ratio) are

devices; telephone and telegraph apparatus; radiotelephone communications; telephone communications; telegraph and other message communications; cable and other pay television services; and services-telephone interconnect systems.

TABLE 5

R&D Spillovers and Long-Run Abnormal Returns Following R&D Increases: Zero-Investment Portfolios

Table 5 presents long-run abnormal returns (in percentage) using the zero-investment portfolio regression, where the return of a hedging portfolio (a long position in R&D-increase firms and a short position in their size/book-to-market matching firms) is used as the dependent variable. We obtain the abnormal return (Jensen's α) based on the regression models

$$r_{pt} - r_{qt} = \alpha + (\beta_p - \beta_q)(r_{mt} - r_{ft}) + (s_p - s_q)\mathrm{SMB}_t + (h_p - h_q)\mathrm{HML}_t + e_t,$$

$$r_{pt} - r_{qt} = \alpha + (\beta_p - \beta_q)(r_{mt} - r_{ft}) + (s_p - s_q)\mathrm{SMB}_t + (h_p - h_q)\mathrm{HML}_t + (w_p - w_q)\mathrm{WML}_t + e_t,$$

where p and q denote portfolios of R&D-increase firms and matching firms, and $(\beta_p - \beta_q)$, $(s_p - s_q)$, $(h_p - h_q)$, and $(w_p - w_q)$ are differences in factor loadings on market risk, size, book-to-market, and momentum premiums. See Table 2 for a detailed discussion of these regression tests. The measure of R&D incoming spillovers is described in Table 1. Firms with the lowest level of incoming spillovers are placed in quintile 1, and firms with the highest level of incoming spillovers in quintile 5. The t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Incoming Spillover Group	Value-Weighted				Equal-Weighted			
	3-Factor Model		4-Factor Model		3-Factor Model		4-Factor Model	
	Standard	Rolling	Standard	Rolling	Standard	Rolling	Standard	Rolling
All	0.2572	0.1108	0.2987	0.1159	0.6295	0.3929	0.7426	0.4217
	(1.75)*	(0.75)	(1.98)**	(0.78)	(4.18)***	(2.67)***	(4.88)***	(2.84)***
Quintile 1	−0.0308	−0.1488	−0.0467	−0.2576	0.4131	0.2296	0.4776	0.1876
	(−0.14)	(−0.63)	(−0.21)	(−1.04)	(2.36)**	(1.29)	(2.66)***	(1.04)
Quintile 2	0.4054	0.0308	0.4462	0.0032	0.6215	0.2696	0.6386	0.2361
	(2.01)**	(0.16)	(2.16)**	(0.02)	(3.17)***	(1.31)	(3.17)***	(1.14)
Quintile 3	0.0974	0.0464	0.1505	0.1420	0.5927	0.4973	0.6313	0.4969
	(0.51)	(0.24)	(0.77)	(0.70)	(3.45)***	(2.73)***	(3.58)***	(2.62)***
Quintile 4	0.7785	0.4833	0.8746	0.4383	0.8392	0.5768	0.9277	0.5773
	(2.99)***	(1.82)*	(3.28)***	(1.63)	(4.55)***	(3.12)***	(4.93)***	(3.09)***
Quintile 5	0.7017	0.5303	0.9521	0.6436	0.6092	0.4383	0.7330	0.4398
	(2.09)**	(1.51)	(2.81)***	(1.80)*	(2.96)***	(1.94)*	(3.50)***	(2.05)**

associated with its stock return even after controlling for the general Fama and French (1993) common risk factors. To capture any potential effect of firm characteristics, we perform a zero-investment portfolio regression using the return of a hedging portfolio (i.e., a long position in R&D-increase firms and a short position in their size/book-to-market matching firms) as the dependent variable. We again find positive long-run abnormal returns for R&D-increase firms, although the results are weaker. Eberhart et al. (2004) also show weaker results when they use a zero-investment portfolio regression. We further find that R&D incoming spillovers still affect the market valuation of R&D-increase firms. There is a positive relation between incoming spillovers and long-run abnormal returns.

V. R&D Incoming Spillovers and Post-R&D-Increase Earnings Announcement Returns and Operating Performance

A. Abnormal Returns Surrounding Earnings Announcements

Table 6 presents average 5-day announcement-period abnormal returns centered around quarterly earnings announcement dates over the entire 5 years and in each year following R&D increases. For the whole sample, the average earnings

TABLE 6

Earnings Announcement Abnormal Returns Following R&D Increases

Table 6 presents average 5-day (−2, +2) announcement-period abnormal returns (in percentage) centered around quarterly earnings announcement dates over the entire 5 years and in each of the 5 years following R&D increases. We measure the abnormal return by the difference between the sample firm's 5-day announcement-period return and its size/book-to-market matching firm's return. To mitigate the effects of outliers, we winsorize the top and bottom 0.5% extreme values. R&D incoming spillovers are described in Table 1. Firms with the lowest level of incoming spillovers are placed in quintile 1, and firms with the highest level of incoming spillovers in quintile 5. The *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Incoming Spillover Groups	Entire 5 Years	Year 1	Year 2	Year 3	Year 4	Year 5
All	0.28	0.33	0.37	0.16	0.27	0.25
	(6.48)***	(3.72)***	(3.98)***	(1.65)*	(2.60)***	(2.26)**
Quintile 1	−0.32	−0.45	−0.08	−0.39	−0.48	−0.19
	(−3.28)***	(−2.27)**	(−0.39)	(−1.83)*	(−2.02)**	(−0.74)
Quintile 2	0.22	0.56	0.19	−0.05	−0.13	0.45
	(2.42)**	(3.09)***	(0.98)	(−0.26)	(−0.62)	(2.03)**
Quintile 3	0.43	0.54	0.75	0.02	0.28	0.52
	(4.71)***	(2.86)***	(3.81)***	(0.12)	(1.27)	(2.24)**
Quintile 4	0.53	0.66	0.52	0.52	0.73	0.06
	(5.30)***	(3.30)***	(2.43)**	(2.34)**	(3.12)***	(0.22)
Quintile 5	0.52	0.28	0.43	0.68	0.93	0.38
	(4.99)***	(1.35)	(1.97)**	(2.93)***	(3.70)***	(1.39)

announcement abnormal return over the entire 5 years in the post-R&D-increase period is 0.28%, statistically significant at the 1% level. Average abnormal returns for the whole sample are 0.33%, 0.37%, 0.16%, 0.27%, and 0.25% in the 1st–5th years after R&D increases, respectively, all statistically significant at the 10% level or better.

Table 6 also shows that R&D incoming spillovers are positively related to earnings announcement abnormal returns. Over the entire 5 years after R&D increases, firms with the highest level of incoming spillovers experience an average earnings announcement abnormal return of 0.52% (statistically significant at the 1% level), compared to −0.32% for firms with the lowest level of incoming spillovers (statistically significant at the 1% level). In each of the 5 years following R&D increases, firms in the top spillover quintile earn significantly positive abnormal returns in the 2nd, 3rd, and 4th years, while firms in the bottom spillover quintile experience significantly negative abnormal returns in the 1st, 3rd, and 4th years. The evidence in Table 6 suggests that the positive relation between R&D incoming spillovers and the long-run stock performance of R&D-increase firms is not likely to be generated by benchmark measurement errors.

B. Abnormal Operating Performance

Table 7 presents cross-sectional regression analyses of the changes in abnormal operating performance over the 5-year post-R&D-increase period. In Model 1, our measure of RD_INCOMING_SPILLOVERS is the explanatory variable. As the mean reversion process of profitability is highly nonlinear, we include nonlinearity controls by incorporating expected earnings, past earnings changes, and their nonlinear ingredients (as in Fama and French (2000)). We include year dummy variables to control for the potential effects of year-specific differences. Model 1 shows that the coefficient on the RD_INCOMING_SPILLOVERS

TABLE 7

Cross-Sectional Regression Analyses of Changes in Abnormal Operating Performance Following R&D Increases

Table 7 presents cross-sectional regression analyses of the changes in abnormal operating performance over the 5 years following R&D increases. Operating performance is measured by the sum of EBITDA and after-tax R&D divided by assets minus cash. Abnormal operating performance is operating performance of the sample firm minus its matching firm's, where the matching firm is selected based on operating performance and the industry. The measure of RD_INCOMING_SPILLOVERS is described in Table 1. SIZE is the market value of common equity. BM is the book-to-market ratio. PRIOR_RETURN is the buy-and-hold return over the year prior to the R&D increase. RD_INTENSITY is the ratio of R&D to assets. ACCRUALS are earnings minus cash flows from operating activities. HHI is the Herfindahl-Hirschman Index, which is defined as the sum of the squared fraction of industry sales by all firms in the 3-digit SIC industry. Since the mean reversion process of profitability is highly nonlinear, we include nonlinearity controls by incorporating expected earnings, past earnings changes, and their nonlinear ingredients (as in Fama and French (2000)). The *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Independent Variable	Model 1	Model 2	Model 3
Intercept	−12.5656	−7.0480	−1.2900
	(−1.32)	(−0.62)	(−0.11)
RD_INCOMING_SPILLOVERS	4.4153	3.5154	3.4191
	(2.96)***	(2.34)**	(2.17)**
SIZE		0.1448	0.0230
		(0.33)	(0.05)
BM		−4.6101	−4.8941
		(−2.65)***	(−2.74)***
PRIOR_RETURN		−0.8682	−0.9546
		(−0.89)	(−0.95)
RD_INTENSITY			−24.0563
			(−1.49)
ACCRUALS			−8.0928
			(−1.11)
HHI			−10.4154
			(−1.58)
Nonlinearity controls	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Adj. R^2	0.1292	0.1339	0.1322

variable is positive and statistically significant at the 1% level. This result indicates a more favorable improvement in post-R&D-increase abnormal operating performance for firms with high R&D incoming spillovers.

In Models 2 and 3, we add several control variables. SIZE is the market value of common equity. BM is the book-to-market ratio. PRIOR_RETURN is the buy-and-hold return over the year prior to the R&D increase. RD_INTENSITY is the ratio of R&D to assets. We control for these four variables because they are important asset pricing factors (Fama and French (1992), Jegadeesh and Titman (1993), Lakonishok, Shleifer, and Vishny (1994), and Chan, Lakonishok, and Sougiannis (2001)). ACCRUALS are earnings minus cash flows from operating activities, which we control for because future earnings are associated with current accounting accruals (Sloan (1996)). HHI is the Herfindahl-Hirschman Index, defined as the sum of the squared fraction of industry sales by all firms in the 3-digit SIC industry. HHI measures the potential effect of industry competition.[14]

[14]Massa, Rehman, and Vermaelen (2007) argue that firms in concentrated industries tend to respond aggressively to the share repurchase announcements of their industry counterparts. This mimicking effect may result in lower stock market reactions to share repurchase announcements. Similarly, firms in concentrated industries may increase R&D to undo the negative valuation effect of their competitors' R&D increases. This mimicking behavior may reduce the profitability of R&D-increase firms.

In Model 2, we control for the three variables used for matching in our estimation of abnormal stock returns (SIZE, BM, and PRIOR_RETURN). After including these control variables, we still find that R&D-increase firms with higher levels of incoming spillovers tend to experience greater improvement in subsequent abnormal operating performance. In Model 3, we add the controls for RD_INTENSITY, ACCRUALS, and HHI. Results in Model 3 are consistent with the results so far. As the economic benefits associated with R&D incoming spillovers are reflected in firms' operating performance in the post-R&D-increase period, the overall evidence in Table 7 supports a conclusion that R&D incoming spillovers are important in explaining long-run firm performance following R&D increases.[15]

VI. Additional Evidence

A. Fama and MacBeth Regressions

We investigate the impact of R&D incoming spillovers on the sample firms' long-run performance using the Fama and MacBeth (1973) regression methodology. This methodology allows us to control for other potential influences. We use the 60 post-R&D-increase monthly stock returns for each sample firm as the dependent variable.

We control for other asset pricing factors beyond the control variables in Table 7.[16] ASSETS_GROWTH is change in book assets divided by beginning-year assets. TURNOVER is trading volume divided by shares outstanding. CAPITAL_INVESTMENT is (the capital expenditures-to-sales ratio divided by its last 3-year average) minus 1 (as in Titman et al. (2004)). CAPITAL_INVESTMENT_MISSING_DUMMY equals 1 if CAPITAL_INVESTMENT is not available, and 0 otherwise. NET_SHARE_ISSUE is the 1-year change in stock split-adjusted shares outstanding (as in Pontiff and Woodgate (2008)). NET_SHARE_ISSUE_MISSING_DUMMY equals 1 if NET_SHARE_ISSUE is not available, and 0 otherwise. ROA_CHANGE is the 1-year change in return on assets. HIGH-TECH_DUMMY equals 1 for a high-tech firm, and 0 otherwise. We control for the potential effects of industry-specific differences by including 1-digit SIC dummy variables in the regression. All regression coefficient estimates are averaged over time and tested by the time-series volatility using Newey and West (1987) heteroskedasticity and autocorrelation adjustments.

Table 8 presents the results of Fama-MacBeth (1973) regressions. Model 1 shows that the coefficient on RD_INCOMING_SPILLOVERS is positive and statistically significant at the 1% level. In Model 2 with all the control variables, the coefficient on RD_INCOMING_SPILLOVERS remains statistically significantly positive. In Model 3, we add an interaction term, RD_INCOMING_SPILLOVERS $\times$ ROA_CHANGE. If R&D incoming spillovers positively affect

[15]We obtain similar results in Table 7 if we replace RD_INCOMING_SPILLOVERS by RD_INCOMING_SPILLOVER_RANK based on quintile.

[16]See Sloan (1996), Chan et al. (2001), Pastor and Stambaugh (2003), Titman et al. (2004), Cooper, Gulen, and Schill (2008), and Pontiff and Woodgate (2008).

the stock returns of R&D-increase firms because of improved profitability, this interaction term should be positive. This coefficient is positive and statistically significant at the 1% level, providing further support for the relation between R&D incoming spillovers and long-run stock returns following R&D increases.[17]

TABLE 8

Fama-MacBeth Regressions

Table 8 presents the results of Fama-MacBeth (1973) regressions. We use the 60 post-R&D-increase monthly stock returns to each sample firm as the dependent variable. The measure of RD_INCOMING_SPILLOVERS is described in Table 1. SIZE, BM, PRIOR_RETURN, RD_INTENSITY, ACCRUALS, and HHI are defined in Table 7. ASSETS_GROWTH is change in book assets divided by beginning-year assets. TURNOVER is trading volume divided by shares outstanding. CAPITAL_INVESTMENT is (the capital expenditures-to-sales ratio divided by its last 3-year average) minus 1. CAPITAL_INVESTMENT_MISSING_DUMMY equals 1 if CAPITAL_INVESTMENT is not available, and 0 otherwise. NET_SHARE_ISSUE is the 1-year change in stock-split-adjusted shares outstanding. NET_SHARE_ISSUE_MISSING_DUMMY equals 1 if NET_SHARE_ISSUE is not available, and 0 otherwise. ROA_CHANGE is the 1-year change in return on assets. HIGH-TECH_DUMMY equals 1 for a high-tech firm, and 0 otherwise. We control for the potential effects of industry-specific differences by including 1-digit SIC dummy variables in the regression. All regression coefficient estimates are averaged over time and tested by the time-series volatility using Newey and West (1987) heteroskedasticity and autocorrelation adjustments. The *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Independent Variable	Model 1	Model 2	Model 3
Intercept	0.0106	0.0234	0.0237
	(1.97)**	(3.11)***	(3.03)***
RD_INCOMING_SPILLOVERS	0.0017	0.0017	0.0015
	(2.80)***	(1.99)**	(1.77)*
SIZE		−0.0015	−0.0015
		(−4.35)***	(−4.33)***
BM		0.0087	0.0086
		(10.35)***	(9.90)***
PRIOR_RETURN		0.0005	0.0002
		(0.45)	(0.20)
RD_INTENSITY		−0.0041	−0.0046
		(−1.15)	(−1.18)
ACCRUALS		−0.0048	−0.0055
		(−1.45)	(−1.89)*
HHI		−0.0085	−0.0084
		(−4.65)***	(−4.71)***
ASSETS_GROWTH		−0.0057	−0.0058
		(−6.14)***	(−5.71)***
TURNOVER		0.0002	0.0001
		(0.20)	(0.13)
CAPITAL_INVESTMENT		0.0050	0.0040
		(0.82)	(0.74)
CAPITAL_INVESTMENT_MISSING_DUMMY		−0.0051	−0.0051
		(−2.08)**	(−2.06)**
NET_SHARE_ISSUE		−0.0064	−0.0065
		(−6.94)***	(−6.86)***
NET_SHARE_ISSUE_MISSING_DUMMY		−0.0009	0.0010
		(−0.37)	(0.64)
ROA_CHANGE		0.0101	0.0084
		(1.59)	(1.19)
HIGH-TECH_DUMMY		0.0010	0.0011
		(0.64)	(0.68)
RD_INCOMING_SPILLOVERS × ROA_CHANGE			0.0209
			(3.80)***
Industry dummies	Yes	Yes	Yes
Avg. R^2	0.0289	0.1050	0.1112

[17]The results in Table 8 are similar if we replace RD_INCOMING_SPILLOVERS by RD_INCOMING_SPILLOVER_RANK.

B. Robustness Checks for Various Stochastic R&D Spillover Specifications

We use various stochastic R&D spillover estimations to check the robustness of our results. We change the assumption for u_i by replacing the half-normal distribution with an exponential or a truncated normal distribution. We also use the translog production function in Christensen, Jorgenson, and Lau (1973) to estimate the incoming R&D spillover effect:

$$
\begin{aligned}
(5) \qquad \log Y_i \;=\; & a_0 + a_1 \log K_i + a_2 \log L_i + a_3 \log \mathrm{RD}_i + a_{11}(\log K_i)^2 \\
& + a_{22}(\log L_i)^2 + a_{33}(\log \mathrm{RD}_i)^2 \\
& + a_{12} \log K_i \log L_i + a_{23} \log L_i \log \mathrm{RD}_i \\
& + a_{13} \log K_i \log \mathrm{RD}_i + a_4 \mathrm{TIME\_TREND} + u_i + v_i,
\end{aligned}
$$

where the input variables and random variables are as defined in equation (1).

Table 9 presents the results of these robustness checks for post-R&D-increase long-run abnormal stock returns estimated by factor models. Panels A and B present the abnormal returns sorted by R&D incoming spillovers using the assumptions of exponential distribution and truncated normal distribution for u_i. Panel C gives the results using the translog production function to estimate the spillover effect. The overall results again document a positive relation between R&D incoming spillovers and the long-run stock performance of R&D-increase firms.

In untabulated results, we specify the u_i term using the exponential or truncated normal distribution in the translog production function. We also use different algorithm methods in ML optimization, including the conjugate gradient method, trust region method, double-dogleg method, Nelder-Mead simplex method, and Newton-Raphson method with ridging. Our conclusions remain unchanged.

As our purpose in this study is to examine the relation between R&D incoming spillovers and the long-run performance of R&D-increase firms, we require s_j and u_i in the production function (1) to be positive to capture the effect of incoming spillovers. R&D investments by one firm may enhance its competitive advantage and have negative effects on other firms in the same industry (Chan et al. (1990)). In our setting, this competitive effect, if any, is included in the random error term v_i. The stochastic frontier model developed by Aigner et al. (1977) and Battese and Coelli (1992) does not allow for a third random term to capture the competitive effect.

As a robustness check, we include an interaction variable in the production function (1) to control for the potential competitive effect of R&D. The competitive effect is likely to be stronger in industries with a lower degree of competition and a stronger propensity to spend on R&D. The less competitive an industry is, the greater the rents that can be extracted from rival firms, because of the change in the competitive position of the R&D investing firm (Lang and Stulz (1992) and Chen, Ho, and Shih (2007)). Also, R&D innovation plays a more crucial

TABLE 9

R&D Incoming Spillovers and Long-Run Stock Performance Following R&D Increases: Various Robustness Checks

Table 9 presents robustness checks of our results using various stochastic R&D spillover estimations. The measure of R&D incoming spillovers is described in Table 1, and the measures of abnormal returns (in percentage) based on factor models are described in Table 2. In Panels A and B, we use the assumptions of exponential distribution and truncated normal distribution for u_i. In Panel C, we use a translog production function as in Christensen et al. (1973) to estimate the incoming R&D spillover effect:

$$\begin{aligned}\log Y_i \quad = \quad & a_0 + a_1 \log K_i + a_2 \log L_i + a_3 \log \mathrm{RD}_i + a_{11}(\log K_i)^2 + a_{22}(\log L_i)^2 + a_{33}(\log \mathrm{RD}_i)^2 \\ & + a_{12} \log K_i \log L_i + a_{23} \log L_i \log \mathrm{RD}_i + a_{13} \log K_i \log \mathrm{RD}_i + a_4 \mathrm{TIME\_TREND} + u_i + v_i,\end{aligned}$$

where the input variables and random variables are as defined in equation (1). In Panel D, we use the following production function:

$$\begin{aligned}\log Y_i \quad = \quad & a_0 + a_1 \log K_i + a_2 \log L_i + a_3 \log \mathrm{RD}_i + a_4 \mathrm{TIME\_TREND} \\ & + b_1 \mathrm{HHI}_i \times \mathrm{INDUSTRY\_RD\_INTENSITY}_i + u_i + v_i,\end{aligned}$$

where HHI is the sales-based industry Herfindahl-Hirschman Index and INDUSTRY_RD_INTENSITY is the R&D intensity of the industry (measured by the average ratio of R&D expenditures to book assets for all firms in the 3-digit SIC industry). Firms with the lowest level incoming spillovers are placed in quintile 1, and firms with the highest level of incoming spillovers in quintile 5. The *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Value-Weighted				Equal-Weighted			
	3-Factor Model		4-Factor Model		3-Factor Model		4-Factor Model	
Incoming Spillover Group	Standard	Rolling	Standard	Rolling	Standard	Rolling	Standard	Rolling
Panel A. Assuming u_i Obeys Exponential Distribution								
Quintile 1	−0.0122 (−0.08)	−0.0645 (−0.41)	0.0781 (0.50)	0.0076 (0.05)	0.2682 (1.32)	0.2777 (1.31)	0.5576 (2.83)***	0.3849 (1.86)*
Quintile 2	0.3021 (1.71)*	0.0354 (0.22)	0.2898 (1.60)	0.0189 (0.11)	0.5544 (2.83)***	0.4110 (2.00)**	0.7672 (3.94)***	0.5403 (2.66)***
Quintile 3	0.5652 (2.72)***	0.3337 (1.58)	0.4733 (2.23)**	0.3164 (1.45)	0.7811 (4.00)***	0.6936 (3.30)***	1.0035 (5.18)***	0.8705 (4.22)***
Quintile 4	0.5251 (2.03)**	0.5140 (1.94)*	0.6848 (2.61)***	0.4470 (1.65)*	0.7899 (3.51)***	0.6242 (2.72)***	1.0781 (4.89)***	0.7435 (3.35)***
Quintile 5	1.1338 (4.82)***	0.9738 (3.95)***	1.2010 (4.98)***	1.0147 (4.06)***	0.7941 (3.81)***	0.6172 (2.72)***	1.0794 (5.33)***	0.8175 (3.67)***
Panel B. Assuming u_i Obeys Truncated Normal Distribution								
Quintile 1	−0.0042 (−0.02)	−0.0439 (−0.22)	0.0553 (0.28)	−0.0239 (−0.11)	0.2542 (1.13)	0.2921 (1.25)	0.5511 (2.52)**	0.3982 (1.72)*
Quintile 2	0.1012 (0.56)	−0.1114 (−0.64)	0.2251 (1.22)	−0.0356 (−0.20)	0.5186 (2.61)***	0.3811 (1.81)*	0.7386 (3.74)***	0.5371 (2.58)***
Quintile 3	0.4555 (2.00)**	0.1009 (0.46)	0.4147 (1.78)*	0.0138 (0.06)	0.8897 (3.98)***	0.7013 (3.14)***	1.1168 (5.01)***	0.7716 (3.54)***
Quintile 4	0.3141 (1.82)*	0.2351 (1.33)	0.2767 (1.56)	0.2251 (1.20)	0.7237 (3.72)***	0.6507 (3.22)***	0.9922 (5.25)***	0.8172 (4.17)***
Quintile 5	0.9962 (4.51)***	0.8687 (3.78)***	1.0751 (4.76)***	0.9246 (3.95)***	0.7563 (3.86)***	0.5836 (2.79)***	1.0453 (5.54)***	0.7962 (3.92)***
Panel C. Using Translog Production Function								
Quintile 1	−0.0480 (−0.22)	−0.2673 (−1.09)	0.0703 (0.32)	−0.2004 (−0.80)	0.3400 (1.46)	0.2178 (0.87)	0.6326 (2.77)***	0.3438 (1.34)
Quintile 2	0.1485 (0.72)	0.0072 (0.03)	0.1513 (0.72)	−0.0580 (−0.25)	0.6480 (3.38)***	0.6685 (3.29)***	0.8424 (4.41)***	0.7726 (3.89)***
Quintile 3	0.2537 (1.33)	0.2896 (1.54)	0.2353 (1.20)	0.3068 (1.53)	0.5865 (2.85)***	0.6093 (2.84)***	0.8189 (4.01)***	0.7344 (3.45)***
Quintile 4	0.4810 (2.44)**	0.2549 (1.40)	0.4797 (2.37)**	0.1803 (0.97)	0.7468 (3.66)***	0.5809 (2.65)***	1.0259 (5.16)***	0.7153 (3.34)***
Quintile 5	0.6871 (3.44)***	0.4684 (2.48)**	0.7445 (3.64)***	0.5292 (2.76)***	0.7633 (3.78)***	0.6060 (2.87)***	1.0720 (5.54)***	0.8481 (4.13)***

(continued on next page)

TABLE 9 (continued)

R&D Incoming Spillovers and Long-Run Stock Performance Following R&D Increases: Various Robustness Checks

	Value-Weighted				Equal-Weighted			
	3-Factor Model		4-Factor Model		3-Factor Model		4-Factor Model	
Incoming Spillover Group	Standard	Rolling	Standard	Rolling	Standard	Rolling	Standard	Rolling
Panel D. Using Production Function That Includes an Interaction Variable to Capture the Potential R&D Competitive Effect								
Quintile 1	−0.0077 (−0.04)	−0.2215 (−0.54)	0.0596 (0.28)	−0.1541 (−0.37)	0.3610 (1.45)	0.1923 (0.66)	0.6875 (2.87)***	0.4161 (1.45)
Quintile 2	0.0417 (0.27)	−0.1319 (−0.55)	0.1820 (1.19)	0.0037 (0.02)	0.5052 (2.47)**	0.2340 (0.76)	0.7745 (3.94)***	0.4281 (1.41)
Quintile 3	0.3591 (2.25)**	0.0516 (0.19)	0.3881 (2.37)**	0.0050 (0.02)	0.6286 (3.08)***	0.3468 (0.82)	0.9460 (4.98)***	0.5606 (1.34)
Quintile 4	0.3316 (1.85)*	0.1571 (0.76)	0.2992 (1.63)	0.1708 (0.81)	0.7045 (3.43)***	0.4510 (1.12)	1.0312 (5.40)***	0.6779 (1.71)*
Quintile 5	0.8612 (3.91)***	0.7822 (3.22)***	0.9234 (4.10)***	0.7874 (3.19)***	0.6805 (3.24)***	0.6345 (2.40)**	1.0183 (5.23)***	0.8955 (3.54)***

role in competition in a higher-R&D-intensive industry (Arrow (1962), Krugman (1991)). We modify the production function as follows:

$$\text{(6)} \qquad \log Y_i = a_0 + a_1 \log K_i + a_2 \log L_i + a_3 \log \mathrm{RD}_i + a_4 \mathrm{TIME\_TREND} + b_1 \mathrm{HHI}_i \times \mathrm{INDUSTRY\_RD\_INTENSITY}_i + u_i + v_i,$$

where HHI is the sales-based industry Herfindahl-Hirschman Index and INDUSTRY_RD_INTENSITY is the R&D intensity of the industry (measured by the average ratio of R&D expenditures to book assets for all firms in the 3-digit SIC industry).[18] Panel D of Table 9 shows that the same results hold. R&D-increase firms with higher levels of R&D incoming spillovers still experience more favorable long-run stock performance. The coefficient on the interaction term HHI × INDUSTRY_RD_INTENSITY is −0.72 (statistically significant at the 5% level), indicating that this interaction variable captures the potential R&D competitive effect.

C. R&D Outgoing Spillover Effects

We note at the outset that R&D spillovers may result in an underinvestment in R&D because of the free rider problem. This underinvestment feature has to do with the appropriability of R&D results rather than incoming spillovers (Cassiman and Veugelers (2002)). A firm that is less able to appropriate R&D benefits would be more likely to have R&D outgoing spillover effects. Thus, R&D outgoing spillover effects could lead to firm underinvestment.

We use the production function to estimate the outgoing spillover effect for each of our firm-year observations. We run a regression using the pre-R&D-increase time-series data:

[18]The results are similar if we use a sales-scaled industry R&D intensity or if we exclude sample firm i when computing INDUSTRY_RD_INTENSITY.

$$\sum_{j \neq i} u_{jt} \quad = \quad a_0 + a_1 \mathrm{RD}_t + a_2 \mathrm{logSALE}_t + \xi_t, \tag{7}$$

where RD_t is R&D expense in year t, $\mathrm{logSALE}_t$ is the logarithm of sales in year t, and ξ_t is white noise. Here, u_j is the incoming spillover effect for firm j that has a positive R&D expenditure. We then sum up the u_j for each 2-digit SIC industry. Thus, a_1 reflects how much a firm's R&D investment spills over to its industry peers; a higher value indicates more outgoing spillover effects. Similar to the process examining R&D incoming spillover effects, we rank sample firms according to the estimated value of a_1. Firms with the lowest a_1 values are placed in quintile 1, and firms with the highest a_1 values are in quintile 5.

We use abnormal R&D investment to measure to what extent R&D investment deviates from the optimal level. We calculate the abnormal level of R&D as the difference in R&D-to-assets ratios between sample firms and their matching firms. We identify matching firms using size, BM, and the R&D-to-assets ratio.

Table 10 presents the results for abnormal R&D investment sorted by R&D outgoing spillover quintiles over the entire 5-year period and in each of the 5 years following R&D increases. Firms in quintile 5 (firms with the highest level of R&D outgoing spillovers) experience an average abnormal R&D investment of −1.02% over the entire 5-year post-R&D-increase period (statistically significant at the 1% level), compared to −0.16% for firms in quintile 1 (statistically insignificantly different from 0). Table 10 also shows that firms in the top quintile exhibit significantly negative abnormal R&D investment in the 3rd–5th years following R&D increases. The abnormal investment for firms in the bottom quintile

TABLE 10

R&D Outgoing Spillover Effects and Abnormal R&D Investment

Table 10 presents the abnormal R&D investment of sample firms sorted by R&D outgoing spillover quintiles over the entire 5-year period and in each of the 5 years following R&D increases. We use the production function to estimate the outgoing spillover effect for each of our firm-year observations. We run a regression using the pre-R&D-increase time-series data:

$$\sum_{j \neq i} u_{jt} \quad = \quad a_0 + a_1 \mathrm{RD}_t + a_2 \mathrm{logSALE}_t + \xi_t,$$

where RD_t is R&D expense in year t, $\mathrm{logSALE}_t$ is the logarithm of sales in year t, and ξ_t is white noise. Here, u_j is the incoming spillover effect for firm j that has a positive R&D expenditure. We then sum up the u_j for each 2-digit SIC industry. A higher a_1 indicates more outgoing spillover effects. We rank sample firms according to the estimated value of a_1. Firms with the lowest a_1 values are placed in quintile 1, and firms with the highest a_1 values in quintile 5. We calculate the abnormal level of R&D as the difference in R&D-to-assets ratios between sample firms and their matching firms. We identify matching firms using size, BM, and the R&D-to-assets ratio. The t-statistics are reported in parentheses. There are fewer observations in this table because of data unavailability. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Outgoing Spillover Groups	*N*	Entire 5 Years	Year 1	Year 2	Year 3	Year 4	Year 5
Quintile 1	1,448	−0.16%	0.35%	−0.70%	−0.34%	−0.06%	−0.05%
		(−0.63)	(0.82)	(−1.00)	(−0.63)	(−0.09)	(−0.09)
Quintile 2	1,231	−0.54%	0.34%	−0.91%	−1.03%	−0.74%	−0.43%
		(−1.68)*	(0.69)	(−1.11)	(−1.17)	(−1.27)	(−0.62)
Quintile 3	1,634	−0.98%	0.42%	−1.33%	−1.90%	−1.37%	−0.87%
		(−3.55)***	(0.87)	(−2.29)**	(−2.57)***	(−2.03)**	(−1.44)
Quintile 4	1,423	−0.01%	0.64%	0.51%	−0.26%	−0.79%	−0.35%
		(−0.01)	(1.34)	(1.01)	(−0.44)	(−1.28)	(−0.56)
Quintile 5	1,441	−1.02%	−0.37%	−0.55%	−0.98%	−1.87%	−1.51%
		(−4.17)***	(−0.78)	(−1.09)	(−1.87)*	(−3.07)***	(−2.35)**

is insignificantly different from 0 for each of the 5 years after the R&D increase. The evidence in Table 10 suggests overall that firms experiencing more R&D outgoing spillover effects tend to underinvest in R&D.

We also examine the factors that make it hard for firms with high outgoing spillovers to appropriate R&D benefits. Levin et al. (1987) argue that patents tend to be more effective in preventing R&D outgoing spillovers in the chemical industry because clear standards can be applied to assess a chemical patent's validity and to defend against infringement. Cassiman and Veugelers (2002) indicate that firms may use brand names as strategic protection against R&D outgoing spillovers. Feinberg and Gupta (2004) argue that the greater the dispersion of R&D within an industry, the greater the potential outgoing spillover. Sanna-Randaccio and Veugelers (2007) suggest that industry competition could raise the cost of outgoing spillovers because rivals may have a greater absorptive capacity. Finally, Franco and Gussoni (2010) argue that firm size is a crucial factor in determining outgoing spillovers because large firms may have more resources to protect their innovations.

In Table 11, we show cross-sectional regression analysis of the R&D outgoing spillover effect. The dependent variable is the R&D outgoing spillover effect estimated from equation (7) or the rank of R&D outgoing spillover by quintile. CHEMICAL_DUMMY equals 1 if a firm is in the chemical industry (2-digit SIC code 28), and 0 otherwise. ADVERTISEMENT_EXPENSE is advertisement expense divided by total assets, reflecting potential spending on brand name. RD_HHI is the R&D-based Herfindahl-Hirschman Index, computed using R&D expense. RD_HHI reflects the extent of R&D dispersion within an industry. HHI and SIZE are as defined above. We control for the potential effects of year-specific differences by including year dummy variables in the regression.

TABLE 11

Cross-Sectional Regression Analyses of R&D Outgoing Spillover Effects

Table 11 presents cross-sectional regression analyses of R&D outgoing spillover effects. The dependent variable is the R&D outgoing spillover effect estimated from equation (7) or the rank of R&D outgoing spillovers based on the quintiles. CHEMICAL_DUMMY equals 1 if a firm is in the chemical industry (2-digit SIC code 28), and 0 otherwise. ADVERTISEMENT_EXPENSE is advertisement expense divided by total assets. RD_HHI is the R&D-based Herfindahl-Hirschman Index, computed using R&D expense. HHI and SIZE are defined in Table 7. The *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable	
Independent Variable	RD_OUTGOING_SPILLOVERS	RD_OUTGOING_SPILLOVER_RANK
Intercept	12.8893	3.0422
	(1.51)	(16.09)***
CHEMICAL_DUMMY	−1.0942	−0.1077
	(−0.67)	(−2.24)**
ADVERTISEMENT_EXPENSE	−35.5917	−0.6112
	(−2.99)***	(−2.05)**
RD_HHI	−10.7221	−0.3238
	(−1.76)*	(−2.26)**
HHI	2.2920	0.0109
	(0.29)	(0.06)
SIZE	−2.2002	−0.0499
	(−7.38)***	(−6.81)***
Year dummies	Yes	Yes
Adj. R^2	0.0443	0.0634

The coefficients on ADVERTISEMENT_EXPENSE, RD_HHI, and SIZE in Table 11 are all significantly negative, suggesting that firms spending less on brand name, firms in industries with greater R&D dispersion, and smaller firms are likely to suffer higher R&D outgoing spillovers. These results are consistent with the predictions of Cassiman and Veugelers (2002), Feinberg and Gupta (2004), and Franco and Gussoni (2010). The coefficient on CHEMICAL_DUMMY is significantly negative only when we use the rank of R&D outgoing spillovers as the dependent variable. Finally, we do not find that industry competition significantly affects R&D outgoing spillovers.

D. Evidence without the Sample Restriction of R&D Intensities and Increases

As our aim is to examine whether post-R&D long-term firm performance reported in Eberhart et al. (2004), (2008) is partially attributable to R&D incoming spillovers, we have looked at R&D-intensive firms that increase their R&D to be consistent with these prior studies. Now, we relax this restriction and examine the relation between R&D incoming spillovers and subsequent long-term abnormal returns for all R&D investing firms. Table 12 reports the results.

TABLE 12

R&D Incoming Spillovers and Long-Run Stock Performance Following R&D Investment: Relaxing the Sample Restriction

Table 12 presents long-run abnormal stock returns (in percentage) for all R&D investing firms by relaxing the restriction that the sample firms are R&D-intensive and have increased their own R&D. The measure of R&D incoming spillovers is described in Table 1, and the measures of abnormal returns based on factor models are described in Table 2. Firms with the lowest level of incoming spillovers are placed in quintile 1, and firms with the highest level of incoming spillovers in quintile 5. The *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Value-Weighted				Equal-Weighted			
	3-Factor Model		4-Factor Model		3-Factor Model		4-Factor Model	
Incoming Spillover Group	Standard	Rolling	Standard	Rolling	Standard	Rolling	Standard	Rolling
All	0.1014	0.1043	0.1224	0.1274	0.1874	0.1616	0.4001	0.3306
	(1.80)*	(1.98)**	(2.13)**	(2.40)**	(2.10)**	(1.81)*	(5.49)***	(4.69)***
Quintile 1	0.0997	0.0707	0.1136	0.0861	0.0082	0.0449	0.1293	0.1992
	(1.47)	(1.14)	(1.64)	(1.36)	(0.09)	(0.47)	(2.15)**	(2.32)**
Quintile 2	0.0717	0.1718	0.1436	0.2550	0.0814	0.0638	0.2812	0.2709
	(0.81)	(1.84)*	(1.62)	(2.83)***	(0.85)	(0.66)	(3.08)***	(3.27)***
Quintile 3	0.2588	0.2962	0.2707	0.3394	0.1592	0.1430	0.3778	0.3177
	(2.43)**	(2.79)***	(2.48)**	(3.13)***	(1.60)	(1.44)	(3.58)***	(3.80)***
Quintile 4	0.3500	0.3216	0.4093	0.3389	0.3047	0.2844	0.4678	0.4327
	(3.24)***	(2.36)**	(3.74)***	(2.49)**	(2.87)***	(2.67)***	(3.25)***	(4.87)***
Quintile 5	0.3811	0.3920	0.4397	0.3963	0.4380	0.3131	0.4330	0.4687
	(2.79)***	(2.48)**	(3.16)***	(2.48)**	(3.17)***	(2.36)**	(2.53)**	(4.07)***

We find a positive relation between R&D incoming spillovers and long-term abnormal returns for all R&D investing firms without imposing any requirements on R&D intensity or increase. The results hold for equal- and value-weighted measures and for standard factor models and the rolling regression method. This evidence indicates that R&D investing firms with greater R&D incoming spillovers experience higher abnormal stock returns. The evidence is also consistent with our findings on the relation between R&D outgoing spillovers and subsequent R&D investment. That is, if firms do not need to do much R&D in order to benefit from R&D spillovers, they are less likely to invest in R&D in the future when they are less able to prevent R&D outgoing spillovers.

VII. Conclusion

We examine how R&D incoming spillovers affect long-run firm performance following R&D increases. Using a stochastic frontier production function and a sample of firms with unexpected and significant increases in R&D between 1977 and 2005, we document a significantly positive relation between R&D incoming spillovers and long-run abnormal stock returns of R&D-increase firms. The results are robust to various approaches to measuring abnormal stock returns and various estimations of stochastic R&D spillovers. We also show that R&D-increase firms with higher levels of R&D incoming spillovers experience greater improvements in subsequent abnormal operating performance. Our evidence suggests that firms that benefit more from the R&D investment of other firms experience more improvement in profitability and more favorable long-run stock performance in the post-R&D-increase period.

We also look for evidence in manager recruiting for our sample firms. Firms with higher levels of R&D incoming spillovers tend to recruit more key employees from other firms. This result indicates that recruitment of managers as a way to benefit from the know-how of other firms is an important source of R&D incoming spillovers.

Finally, we show that sample firms with a high level of R&D outgoing spillovers tend to display significantly negative abnormal R&D investment. This result indicates that R&D outgoing spillovers may cause firms to underinvest in R&D. We also show that R&D outgoing spillover effects are significantly negatively related to advertisement expenditure and firm size, and significantly positively related to industry R&D dispersion. This evidence suggests that firms that spend less on brand name, firms that are smaller, and firms that have more industry R&D dispersion are likely to find it harder than others to appropriate R&D benefits.

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