

An Examination of Long-Term Abnormal Stock Returns and Operating Performance Following R&D Increases

Author(s): Allan C. Eberhart, William F. Maxwell and Akhtar R. Siddique

Source: The Journal of Finance, Apr., 2004, Vol. 59, No. 2 (Apr., 2004), pp. 623-650

Published by: Wiley for the American Finance Association

Stable URL: https://www.jstor.org/stable/3694909

JSTOR is a not-for-profit service that helps scholars, researchers, and students discover, use, and build upon a wide range of content in a trusted digital archive. We use information technology and tools to increase productivity and facilitate new forms of scholarship. For more information about JSTOR, please contact support@jstor.org.

Your use of the JSTOR archive indicates your acceptance of the Terms & Conditions of Use, available at https://about.jstor.org/terms



and Wiley are collaborating with JSTOR to digitize, preserve and extend access to $The\ Journal\ of\ Finance$

An Examination of Long-Term Abnormal Stock Returns and Operating Performance Following R&D Increases

ALLAN C. EBERHART, WILLIAM F. MAXWELL, and AKHTAR R. SIDDIQUE*

ABSTRACT

We examine a sample of 8,313 cases, between 1951 and 2001, where firms unexpectedly increase their research and development (R&D) expenditures by a significant amount. We find consistent evidence of a misreaction, as manifested in the significantly positive abnormal stock returns that our sample firms' shareholders experience following these increases. We also find consistent evidence that our sample firms experience significantly positive long-term abnormal operating performance following their R&D increases. Our findings suggest that R&D increases are beneficial investments, and that the market is slow to recognize the extent of this benefit (consistent with investor underreaction).

There is a large and growing body of work showing that the market is slow to incorporate publicly available information, in contrast to the efficient market hypothesis (EMH) prediction. Some of these studies report that firm attributes (or characteristics) reveal mispricing that the market takes years to correct. Lakonishok, Shleifer, and Vishny (1994), for example, find that value (glamour) stock portfolios experience significantly positive (negative) long-term abnormal returns following the portfolio formations, consistent with the hypothesis that these stocks are undervalued (overvalued) at the time of the portfolio formations.

Other studies report long-term abnormal stock returns following corporate events such as seasoned equity offerings and stock repurchases (e.g., Eberhart and Siddique (2002), Ikenberry, Lakonishok, and Vermaelen (1995, 2000), and

*Eberhart is from the Georgetown University, McDonough School of Business; Maxwell is from the University of Arizona, Eller College of Business; and Siddique is from the Office of the Comptroller of the Currency. We thank Rick Green and two anonymous referees for their comments. We also thank Ken Cavalluzzo, Jay Coughenour, Lisa Fairchild, Roberto Gutierrez, David Ikenberry, Prem Jain, Mike Cooper, Lee Pinkowitz, Guojun Wu, and seminar participants at the 2002 Financial Management Association Meetings, Georgetown, George Washington, the 2002 University of Maryland Finance Symposium (joint with the Financial Economics and Accounting Conference), and the Fall 2002 Washington Area Finance Association for their comments. We also thank Douglas Brunt and Marcelo Teixeira for their research assistance. Eberhart received support from a McDonough School of Business Summer Research Grant and from a Steers Faculty Research Fellowship. Eberhart and Maxwell received support from the Georgetown University Capital Markets Research Center. The views expressed are those of the authors and do not necessarily represent the views of the Office of the Comptroller of the Currency.

Loughran and Ritter (1995)). Ikenberry and Ramnath (2002) refer to these as self-selected events because managers choose to undertake them at a particular point in time. Many of these studies find evidence that managers "time" a security offering (or repurchase) to take advantage of a "window of opportunity" when the firm's stock is mispriced.

We contribute to this literature by examining the long-term performance of firms following (unexpected) research and development (R&D) increases. Our focus on R&D increases offers several notable contrasts with previous studies. First, R&D increases differ from firm attributes because they represent a managerial decision. Second, these increases differ from events such as stock repurchases because managers seldom announce them formally. Third, these increases represent investment decisions, not financing decisions, and so there is no clear timing motive for managers (as suggested in the above studies).

Finally, there is something unique about R&D investments that differentiates them from other long-term investments. For example, the cost of an R&D increase is more clearly tangible because it is expensed, in contrast to the capitalization that occurs when plant, property, and equipment (PP&E) is increased. On the other hand, the potential benefit of an R&D increase reflects intangible information about future cash flows. Though other long-term investments also contain this intangible information component, they do not offer such a stark contrast between tangible and intangible information.

This contrast between tangible and intangible information is examined by Daniel and Titman (2001). They argue that investors misreact to intangible information, but not to tangible information. In this sense, R&D increases provide a natural experiment to test the ability of the market to incorporate correctly the intangible benefit of a long-term investment. If investors misreact to the intangible information contained in a firm's R&D increase, we should observe significant long-term abnormal stock returns following such increases. Therefore, even though Daniel and Titman's focus is on cross-sectional differences in abnormal stock returns (as it is, for example, in Daniel, Hirshleifer, and Subrahmanyam (2001)), their contrast between tangible and intangible information is uniquely applicable to our sample, and it provides a plausible explanation for why our results may not be expected to support our null hypothesis (the EMH).

We construct a sample of 8,313 cases where firms unexpectedly increase their R&D expenditures by an economically significant amount (we discuss these measures in more detail below). Our sample period spans a half-century (1951 to 2001), and we find consistent evidence that our sample firms' shareholders experience significantly positive long-term abnormal stock returns following these increases. We interpret these results as evidence of investor underreaction

¹ Though there are many other papers that investigate why investors may mis-react to information (e.g., Barberis, Shleifer, and Vishny (1998), Hong and Stein (1999) and Kadiyala and Rau (forthcoming)), they do not investigate the distinction between tangible and intangible information. The extent to which a mis-reaction is classified as an underreaction or an overreaction depends on whether the reference is to a particular event (as we focus on), or to a series of events (e.g., negative long-term abnormal stock returns following seasoned equity offerings may be classified as an overreaction to the run-up in stock prices before the offering).

to the benefit of R&D increases.² This interpretation, however, raises the question of what the benefit is of an R&D increase. That is, what is the benefit to which the market is underreacting?

To answer this question, we examine the operating performance of our sample firms following their R&D increases, and we find that they experience significantly positive abnormal operating performance. In short, our findings suggest that R&D increases are beneficial investments, and that the market is slow to recognize the full extent of this benefit.

We also investigate whether our findings differ across certain groups of firms. For example, Chan, Martin, and Kensinger (1990) posit that R&D investments are likely to be more beneficial for high-tech firms than for low-tech firms. More recently, Szewczyk, Tsetsekos, and Zantout (1996) argue that firms with better investment opportunities (i.e., high-growth firms, where their market-to-book (MB) ratio is greater than unity) are more likely to make better R&D investments.³

We partition our sample into high-tech firms, low-tech firms, high-growth firms, and low-growth firms. We find evidence that all four categories of firms benefit from R&D increases, as manifested in their significantly positive abnormal operating performance following these increases. We also report significantly positive long-term abnormal stock returns following R&D increases for all four categories. When we directly compare the groups, we find some evidence that high-tech firms have better abnormal operating performance than low-tech firms. These findings suggest that there is more for the market to underreact to with high-tech firms, and we do report some evidence that high-tech firms have significantly higher long-term abnormal stock returns than low-tech firms. In short, our findings suggest that the market is slow to recognize the full benefit of R&D increases for all of these subsamples, but the market appears to be particularly slow in recognizing the relatively greater benefit to high-tech firms.

In Section I, we discuss the sample selection procedures, and present some descriptive statistics. Section II contains our methods and Section III our empirical results. We summarize the paper in Section IV.

² Our results are also generally consistent with the Daniel, Hirshleifer, and Subrahmanyam (1998) dynamic model of misreaction to information, which predicts positive abnormal returns following favorable corporate discretionary events. Other studies that report evidence of underreaction include Ikenberry and Ramnath (2002) (they report that investors underreact to the benefit of stock split announcements). Moreover, Fama (1998) notes that the negative long-term abnormal returns to acquiring firms following mergers (e.g., Asquith (1983) and Agrawal, Jaffe, and Mandelker (1992)) can be classified as an underreaction to a bad investment decision (though he ultimately argues against the existence of underreactions and overreactions). Cusatis, Miles, and Woolridge (1993) also find that investors underreact to the benefits of spinoffs (also see Hertzel and Jain (1991) and Brav and Gompers (1997) for additional evidence on long-term performance).

³ Chauvin and Hirschey (1993) examine stock values, not market reactions to R&D increases, and find a positive relation between a firm's R&D spending and the market value of equity, after controlling for other factors affecting value. Sougiannis (1994) finds that stock market value is related to R&D expenditures in the short run, but the long-run market value is tied to the ability of the R&D investment to produce earnings.

I. Data

A. Sample Construction

We begin with a sample of 35,406 firm-year observations where firms increase their R&D in any year (i.e., from the beginning of the year to the end of the year) between 1951 and 2001, and have sufficient data available in COMPUSTAT and the Center for Research in Security Prices (CRSP) to compute our abnormal stock return and abnormal operating performance measures. On this initial sample, we impose two major requirements. First, because the market probably expects firms to increase their R&D as the firm grows, we define an unexpected R&D increase to be when a firm's ratio of R&D to assets increases. Second, because we are examining consolidated financial statements, we focus on firms that have an economically significant R&D increase. Consequently, we focus on firms that have (as of the beginning of their R&D increase year) an R&D intensity (i.e., the ratios of R&D to assets and R&D to sales) of at least 5 percent. The firm must also increase its dollar R&D by at least 5 percent, and increase its ratio of R&D to assets by at least 5 percent (e.g., from 10 percent to 10.5 percent). Our final sample consists of 8.313 firm-year observations (3.148 firms).

We also estimate the results over the 1974 to 2001 sample period separately, because 1974 is when accounting treatment of R&D expense reporting is standardized (Financial Accounting Standards Board Statement No. 2).⁶ Before 1974, firms have more discretion over their R&D reporting. Perhaps because of this standardization, and because of the significant overall growth in the number of firms covered in COMPUSTAT, the large majority of our firm-year observations are included in the 1974 to 2001 period.⁷ For this period, the sample consists of 8,090 firm-year observations (3,099 firms).

Because we compute all of our results in calendar time (where the standard errors are based on the time-series volatility), we circumvent the problems inherent in event-time measures—for example, a possible downward bias in the (cross-sectional) standard errors due to factors such as overlapping data.

⁴ COMPUSTAT data begin in 1950, and consequently the first year we can have an unexpected R&D increase is 1951.

⁵ We mention two major requirements for our sample for expositional purposes (clearly firms that meet the second criterion also meet the first criterion). The results are robust to other measures of an unexpected and economically significant R&D increase. For example, if we define an unexpected R&D increase as when the firm's ratio of R&D to sales increases, then the sample size is 8,932 firm-year observations (3,278 firms, using the above-described definition of an economically significant R&D increase). With this sample, we continue to report significantly positive abnormal operating performance and abnormal stock returns following the R&D increase.

⁶ Examining our sample over this more recent subperiod also addresses a concern, raised by Daniel and Titman (2001), that tests of the EMH (i.e., the traditional EMH that we are testing) that use data prior to 1974 make the unreasonable presumption that investors have the data and technology to exploit misevaluations. After 1974, they argue that the technology and data are clearly available.

⁷We do not argue that this standardization causes a dramatic change in R&D reporting (see Nix and Nix (1992) for a discussion of this standardization). Instead, our point is that there is an official standardization that occurs this year, and it provides a natural breakpoint for our long sample period.

As a further check on any possible problem associated with overlapping data, we also present the results for our sample of 4,910 firm-year observations (for the 1951 to 2001 period) and 4,775 firm-year observations (for the 1974 to 2001 period) where a firm can only be included in the sample once every 5 years. We refer to this as our 5-year sample. When we do not impose this 5-year requirement, we refer to the sample as our full sample (for the 1951 to 2001 sample period, and the 1974 to 2001 sample period).

Because our R&D increase "event" is based on accounting data, and not on any formal R&D increase announcement, we do not examine "announcement period" abnormal returns. More important, announcement period abnormal returns do not reveal whether the market is slow to incorporate the full extent of information contained in the R&D increase. We need to examine long-term abnormal stock returns to test the EMH, and we begin measuring these returns at the beginning of the fourth month following the fiscal year-end in which the firm increases its R&D. We use the three-month lag to allow the market to be informed of the accounting data.

Our measure of an unexpected and economically significant increase in R&D is just one important difference between our study and a recent study by Chan, Lakonishok, and Sougiannis (2001). They test whether the market fully incorporates the information in a firm's R&D intensity (e.g., R&D divided by sales), Consistent with the EMH, Chan, Lakonishok, and Sougiannis do not find any significant relation between R&D intensity and subsequent abnormal stock returns. 8 So their findings suggest that the market correctly incorporates R&D intensity into stock valuations, but they do not imply that the market correctly values R&D increases because high R&D intensity firms may not have increased their R&D recently (i.e., unexpectedly and by an economically significant amount). In other words, if a firm is relatively stable in its R&D (i.e., it has no significant and unexpected R&D increase in recent years), then there is no new information for the market to underreact to (i.e., regarding R&D increases), and these stocks should not be undervalued. Therefore, besides the fact that our sample size and sample period differ significantly from Chan, Lakonishok, and Sougiannis, our findings are not necessarily inconsistent with their results.

B. Descriptive Statistics

We show the descriptive statistics in Table I, and report all dollar figures in 2001 dollars. On average, as of the beginning of their R&D increase year, our sample firms have \$913.86 million in annual sales (COMPUSTAT Item 12) with a median of \$38.86 million. Their respective levels of book value of assets (COMPUSTAT Item 6; average = \$899.94 million, median = \$44.46 million) and common stock market values (average = \$1,308.65 million, median = \$87.21 million) are consistent with the fact that our average and median MB ratio is above unity (3.51 and 2.47, based on the sum of the book value of debt

⁸ Only when Chan, Lakonishok, and Sougiannis examine stocks with high R&D intensity *and* poor historical stock returns do they observe significantly positive abnormal stock returns.

Table I Descriptive Statistics

This table provides summary statistics for the sample of 8,313 (unexpected and economically significant) research and development increases by 3,148 firms. The sample period begins in 1951 and ends in 2001. The variables sales, book value of total assets, and market capitalization (i.e., equity market value) are measured as of the beginning of the sample firm's R&D increase year, and are adjusted by the CPI to reflect 2001 dollars. The market-to-book ratios and R&D intensity ratios are also measured as of the beginning of the R&D increase year. The percentage increase in dollar R&D is measured over the R&D increase year. The variable profit margin is the EBIT divided by sales; PM1 is the sum of EBIT and after-tax R&D (using the statutory Federal tax rate) divided by sales; PM2 is the sum of EBIT and after-tax R&D (using each firm's ratio of reported taxes to taxable income) divided by sales. The PMs and stock returns (net of the risk-free rate, r_f) are measured in calendar time for all sample firms within the 5-year period following their R&D increases. The weight for the value-weighted PM is the book value of total assets, and the weight for the value-weighted stock return is the market value of equity.

	Mean	Median	Std. Deviation
Sales (\$MM)	913.86	38.86	5,795.73
Total assets (\$MM)	899.94	44.46	5,512.14
Market capitalization (\$MM)	1,308.65	87.21	8,040.87
MB	3.51	2.47	3.25
R&D intensity measures (%)			
R&D/sales	12.974	10.361	8.076
R&D/assets	13.685	11.437	7.813
Increase in dollar R&D (%)	37.884	32.296	23.625
Equal-weighted annual PMs (%)			
PM	9.033	9.537	20.841
PM1	15.473	14.011	18.326
PM2	15.121	14.546	18.405
Value-weighted annual PMs (%)			
PM	12.705	13.467	12.462
PM1	17.835	17.893	13.551
PM2	18.009	17.700	13.482
Average monthly return (minus r_f)	(%)		
Equal-weighted	1.477	1.313	8.484
Value-weighted	0.953	0.882	4.924
High-tech firms average monthly r	eturn (minus r_f) (%)		
Equal-weighted	$1.5\overset{'}{1}1$	1.261	9.383
Value-weighted	0.927	0.688	5.959
Low-tech firms average monthly re	eturn (minus r_f) (%)		
Equal-weighted	1.198	1.273	7.474
Value-weighted	0.941	0.910	3.823
High-growth firms average monthl	y return (minus r_f) (%	5)	
Equal-weighted	1.525	1.383	10.003
Value-weighted	0.951	0.935	6.032
Low-growth firms average monthly	r return (minus r_f) (%))	
Equal-weighted	1.344	0.917	7.231
Value-weighted	0.934	0.893	3.743

(COMPUSTAT Item 12 + Item 34) and market value of common stock divided by the book value of assets). Our requirement that each sample firm must have an economically significant R&D (COMPUSTAT Item 46) increase ensures that our measures of R&D intensity and (dollar) R&D increases are large. The respective averages (medians) of R&D to sales and R&D to assets are 12.97 percent (10.36 percent) and 13.69 percent (11.44 percent), and the average (median) increase in dollar R&D is 37.88 percent (32.3 percent).

We use three different measures of raw operating performance: the primary measure is the profit margin (PM), defined as the earnings before interest and taxes (EBIT; COMPUSTAT Item 178) divided by sales. The other two PM measures adjust for the fact that R&D expenses reduce PMs, and we do not want to bias downward the estimated performance of firms that continue their R&D expenditures. The variable PM1 is the sum of EBIT and after-tax R&D (using the statutory federal tax rate) divided by sales; PM2 is the sum of EBIT and after-tax R&D (using each firm's ratio of reported taxes (COMPUSTAT Item 16) to taxable income (COMPUSTAT Item 170) as the tax rate) divided by sales.

The equal-weighted average and median PMs for our sample firms (measured in calendar time for all firms within 5 years of their R&D increase year, as we discuss in more detail below) are 9.03 percent and 9.54 percent. When we add back in the after-tax R&D expense, the PMs are higher by definition; the average (median) PM1 and PM2 is 15.47 percent (14.01 percent) and 15.12 percent (14.55 percent) respectively. The average and median value-weighted PMs (where the book value of assets is used as the weight) are actually higher for all three PM measures. The difference between the value- and equal-weighted PMs is probably attributable to the fact that a higher PM implies a higher book value of assets, ceteris paribus. On the other hand, the average and median equal-weighted raw returns (net of the risk-free rate, and measured in calendar time for all firms within 5 years of their R&D increase year) for our sample firms are higher than for the value-weighted returns (where the weight is the market value of stock), consistent with the generally higher returns that small firms earn, as noted in many previous studies.

The difference between equal- and value-weighted raw returns (again, net of the risk-free rate) also holds across the four subsamples that we examine (i.e., high-tech, low-tech, high-growth, low-growth). Moreover, the equal-weighted raw returns are higher for the high-tech and high-growth firms relative to the low-tech and low-growth firms. The value-weighted returns, however, are similar across the four subsamples. As expected, the standard deviation of returns is higher for the high-tech (growth) firms compared to the low-tech (growth) firms.

Though we do not report the numbers in Table I, we compute the pre-event stock returns and operating performance for our sample firms. Following Chan, Lakonishok, and Sougiannis (2001), we compute the (raw) buy-and-hold stock returns for the preceding 36 months. The median and average (raw monthly) pre-event stock return is a significant 0.32 percent and 0.25 percent. When we subtract the stock returns of their matched firms (we explain our matching

procedure in more detail below), however, the difference is an insignificant median of -0.05 percent and an insignificant average of 0.00 percent. With the operating performance measured over the preceding 5 years (i.e., year -5 through year -1), the typical (annual) PM is 4 percent; with the PM of their matched firms subtracted, the typical difference is 2 percent. So our sample firms do appear to be abnormally profitable before their R&D increases, but they do not experience any greater pre-event returns than their matched firms before their R&D increases.

Table II shows the distribution of our sample across the 12 Fama and French industry codes. Not surprisingly, most of our sample firms are in the business equipment industry (i.e., computers, software, and electronic equipment, category 6) but we have firms in nearly every industry, with the second largest representation in the healthcare, medical equipment, and drugs industry (category 10). When we use the Chan, Martin, and Kensinger (1990) high-tech and low-tech industry categories, we find that most of our firms fit in the high-tech category, but we still have over 2,000 observations in the low-tech category. Similarly, most of our firms are high-growth firms (again, with MB ratio above unity), but we have nearly 2,000 observations for low-growth firms.

We also show the distribution of our sample firms over time in Table II. As noted above, the bulk of our sample is concentrated in the post-1974 period. This uneven distribution over time underscores the importance of our use of calendar-time performance measures (as we discuss in more detail below). Overall, the industry distributions are stable over time, especially for the last three decades.

II. Methods

There is much debate surrounding the existence of long-term abnormal stock returns (e.g., following corporate events). Fama (1998), for example, argues that long-term abnormal return measures are particularly vulnerable to incorrectly estimating expected returns due to the mismeasurement of risk(s) (i.e., the bad-model problem). Similarly, Mitchell and Stafford (2000) argue that abnormal return estimates may be biased if factor model estimates of expected returns are incomplete in measuring risks. One common method of addressing uncertainty over the measure of expected returns is to examine the robustness of the results to alternative measures.

Another method for addressing risk measurement concerns is the use of zero-investment portfolio returns (e.g., Ikenberry and Ramnath (2002)). These portfolios appeal to the matched firm method of controlling for risk that previous studies use (e.g., Loughran and Ritter (1995)), while also incorporating the advantages of the calendar-time factor models. These portfolios consist of long

⁹ As we explain in more detail below, PM is one of our matching criteria. Therefore, even though there is a significant difference in the PM of our sample firms and our matched firm in the 5-year period preceding the R&D increase, there is no significance difference as of the matching year (i.e., beginning of year zero).

Table II

Distribution of the Sample over Time, by Type, and by Industry

This table reports the percentage of sample observations by decade, type, and industry. To form our sample, we search for firms with both COMPUSTAT and CRSP data that increase their R&D in any year between 1951 and 2001. On this initial sample, we impose two requirements. First, we define an unexpected R&D increase as when a firm's ratio of R&D to assets increases. Second, we focus on firms that have an economically significant (unexpected) R&D increase. Consequently, we require that firms have a percentage increase in dollar R&D of at least 5 percent, an initial ratio of R&D to sales of at least 5 percent, an initial ratio of R&D to assets of at least 5 percent, and an increase in the ratio of R&D to assets of at least 5 percent. Firms are designated by SIC codes into high- and low-tech using the Chan, Martin, and Kensinger (1990) designations. We designate firms as high- and low-growth based on their MB ratios (MB > 1 is defined as high growth). We also show the percentage of observations by decade in the 12 industry classifications identified by Fama and French (i.e., http://mba.tuck.dartmouth.edu/pages/faculty/ken.french): 1. Consumer nondurables: food, tobacco, textiles, apparel, leather, toys. 2. Consumer durables: cars, TVs, furniture, household appliances. 3. Manufacturing: machinery, trucks, planes, off furn, paper, com printing. 4. Energy oil, gas, and coal extraction and products. 5. Chemicals and allied products. 6. Business equipment; computers, software, and electronic equipment, 7. Telephone and television transmission, 8 Utilities, 9, Shops; wholesale, retail, and some services (laundries, repair shops). 10. Healthcare, medical equipment, and drugs. 11. Money and finance. 12. Other: everything else.

Decade	No	of Obs	ervation	ıs I	High-Tec	h L	ow-Tecl	h I	Iigh-Gr	owth	Low-	Growth
1950s			16		87.5%		12.5%		0.0	%	10	0.0%
1960s		1	07		75.7%		24.3%		27.1°	%	7	2.9%
1970s		6	61		69.3%		30.7%		65.2	%	3	4.8%
1980s		2,2	96		74.0%		26.0%		80.8	%	1	9.2%
1990s		4,3	06		74.3%		25.7%		78.6	%	2	1.4%
2000s		9	27		72.3%		27.7%		72.0	%	2	8.0%
Total		8,3	13		73.6%		26.4%		76.6	%	2	3.4%
				ma and	French		,					
Decade	1	2	3	4	5	6	7	8	9	10	11	12
1950s	0.0%	0.0%	18.8%	0.0%	6.3%	18.7%	0.0%	0.0%	0.0%	56.2%	0.0%	0.0%
1960s	0.0%	0.0%	11.2%	0.0%	10.3%	51.4%	0.0%	0.0%	0.9%	24.3%	0.0%	1.9%
1970s	0.5%	1.2%	13.2%	0.5%	3.5%	52.5%	0.2%	0.0%	1.5%	13.2%	0.3%	13.4%
1980s	0.9%	1.4%	10.1%	0.3%	1.8%	55.5%	0.3%	0.0%	0.9%	18.9%	0.6%	9.3%
1990s	0.4%	1.5%	7.2%	0.1%	1.2%	52.7%	0.4%	0.0%	1.5%	23.1%	0.5%	11.4%
2000s	0.2%	1.3%	3.6%	0.0%	0.8%	55.6%	1.3%	0.0%	1.9%	17.8%	0.2%	17.4%
Total	0.5%	1.4%	8.2%	0.2%	1.6%	53.7%	0.5%	0.0%	1.4%	20.6%	0.5%	11.5%

positions in the sample firm stocks and short positions in their matched firm stocks (e.g., matched based on characteristics such as book-to-market and size). The zero-investment portfolio returns are then adjusted for risk again using a factor model (e.g., the Fama and French (1993) three-factor model, or the Carhart (1997) four-factor model). Any remaining residual return is deemed to be "abnormal."

Independent of the method of estimating expected returns, Fama (1998), and Mitchell and Stafford (2000) argue that event-time returns are an inappropriate metric for computing long-term abnormal returns. For example, as

suggested above, event-time returns have a cross-sectional dependence problem that biases the standard error downwards, and consequently biases tests using this return metric toward an incorrect rejection of the EMH. Barber and Lyon (1997), however, show that the arithmetic summation of returns (as is done with calendar-time returns) does not precisely measure investor experience, and Lyon, Barber, and Tsai (1999) demonstrate that the calendar-time method is generally misspecified in nonrandom samples. Moreover, Loughran and Ritter (2000) argue that the calendar-time return metric has low power.

There is also a debate regarding the use of value-weighted calendar-time returns versus equal-weighted calendar-time returns. Loughran and Ritter (2000), for instance, argue that equal weighting is better because it does not obscure the mispricing that is more likely to occur with smaller firms (as the value weighting does). On the other hand, Fama (1998) argues that value weighting is more appropriate because it more accurately gives the total wealth effects experienced by investors.

We use calendar-time returns (value- and equal-weighted) and the zero-investment approach, despite concerns that these methods are biased in favor of the EMH. ¹⁰ Because the bulk of our results still reject the EMH, any possible bias of these methods in favor of the EMH only strengthens our results.

Our use of calendar-time returns (we also use calendar-time measures of operating performance) and our long sample period also address any possible concern that our results are driven by brief calendar periods where firms that just happen to increase their R&D do abnormally well. Titman (2002), for example, argues that it may not be irrational for the market to systematically underreact or overreact over any relatively short interval.

A. Long-Term Abnormal Security Returns Following R&D Increases

The Fama and French three-factor model test for long-term abnormal stock returns is shown in equation (1):

$$R_{pt} - R_{ft} = \alpha + b(R_{mt} - R_{ft}) + sSMB_t + hHML_t + \varepsilon_{pt}, \tag{1}$$

where R_{pt} is the average raw return for stocks in calendar month t (where a sample stock is included if month t is within the 60-month period following its R&D increase), R_{ft} is the 1-month T-bill return, R_{mt} is the CRSP value-weighted market index return, SMB_t is the return on a portfolio of small stocks minus the return on a portfolio of large stocks, and HML_t is the return on a portfolio of stocks with high book-to-market ratios minus the return on a portfolio of stocks with low book-to-market ratios.

We also estimate the abnormal stock returns with a momentum factor (i.e., *UMD*, return on high momentum stocks minus the return on low momentum

¹⁰ We also do not purge the sample firms in the calculation of the risk factors, and that further biases our results in favor of the EMH (Loughran and Ritter (2000)). We also use alternative measures of expected stock returns (i.e., the Fama and French three-factor model, and the Carhart four-factor model).

stocks) included as an additional risk factor.¹¹ Because Carhart (1997) shows the importance of momentum in expected return measures, we refer to the following model as the Carhart four-factor model:

$$R_{nt} - R_{ft} = \alpha + b(R_{mt} - R_{ft}) + sSMB_t + hHML_t + mUMD_t + \varepsilon_{nt}.$$
 (2)

The intercept (α) in equations (1) and (2) is the abnormal return measure. We correct the standard errors in equations (1) and (2) for heteroskedasticity and autocorrelation using the quadratic spectral kernel as recommended by Andrews (1991).

Berk, Green, and Naik (2000) demonstrate that a firm's systematic risk may change because of an investment in R&D. In recognition of this point, we also estimate equations (1) and (2) with rolling regression estimates of each factor loading (e.g., b, s, and h in equation (1)). ¹² Specifically, we use the first 60 months of portfolio returns (i.e., from 1952 to 1958) to estimate the factor loadings for equations (1) and (2). ¹³ We then estimate the abnormal returns in month 61 (i.e., April 1958) as the difference between the actual portfolio return and the expected portfolio return (defined as the factor loadings estimated over the previous 60 months times their respective month 61 factor returns). For the next month (month 62), we estimate the factor loadings for month 2 to month 61, and the abnormal return is defined the same way as for month 61 (except that the updated factor loadings and month 62 factor returns are used). We repeat this step for every month, and then average the time series of these abnormal return and factor loading estimates. We use the time-series volatility of these estimates to compute the standard errors of their respective averages.

To control for risk in two steps with the zero-investment portfolio method, we first compute the difference between the monthly return on a sample firm that is within 60 months of its R&D increase and the monthly return on its matched firm (the same matched firm we use for the operating performance tests as described below). Then we compute the cross-sectional average of these zero-investment returns each calendar month. The portfolio returns are now analogous to the R_{pt} that we show in equations (1) and (2). The alphas estimated from the time-series regressions of these returns on the risk factors in equations (1) and (2) are the abnormal return estimates of the zero-investment return method.

Finally, to account for any possible survivorship bias in our sample, we use the Shumway (1997, for NYSE/AMEX firms) and Shumway and Warther (1999,

¹¹ We thank Kenneth French for providing data for the *HML*, *SMB*, and *UMD* factors on his web site (i.e., http://mba.tuck.dartmouth.edu/pages/faculty/ken.french). We also thank him for providing data on the 12 Fama and French industry classifications.

 $^{^{12}}$ Because we are using portfolio returns, we focus on any possible change in risk over time for the portfolio.

¹³ Because 1950 is the first year that data are available on COMPUSTAT, these data are presumed to be known to the public by the beginning of April 1951 (our sample firms in this period have December fiscal year-ends). Therefore, April 1952 is the first month in which we measure the stock returns following an unexpected R&D increase (i.e., the first R&D increase that occurs between 1950 and 1951 is known as of the beginning of April 1952).

for Nasdaq firms) correction for delisting bias for the firms in our sample that are delisted for performance reasons (e.g., bankruptcy or failure to meet capital requirements). That is, we use -30 percent as the last return for NYSE/AMEX firms and -55 percent as the last return for Nasdaq firms that delist for performance reasons. We refer to this sample as our delisted-adjusted sample.

B. Operating Performance Measures

We measure our sample firms' operating performance for 5 years following the year in which they unexpectedly increase R&D by an economically significant amount. We measure abnormal operating performance as a sample firm's (raw) operating performance minus its matched firm's (raw) operating performance. Loughran and Ritter (1997), among others, choose matched firms that do not have the same corporate event as the sample firm during the event year. Therefore, we begin with a group of matched firms, in the same two-digit SIC code as the sample firm, that do not unexpectedly increase its R&D by an economically significant amount during the sample firm's R&D increase year. ¹⁴ From these initial screens, the matched firm is defined as the firm with a PM that is closest to the sample firm's PM as of the beginning of its R&D increase year. If a matched firm is no longer available in subsequent years, we use the next closest firm as of the beginning of the sample firm's R&D increase year. We refer to the respective abnormal operating performance measures as APM, APM1, and APM2.

As an additional check, we choose another group of matched firms based on the book-to-market ratio (i.e., equity capitalization divided by the book value of equity), size (i.e., equity capitalization), and momentum (defined in this case as 36-month return/12-month return). That is, as of the beginning of a sample firm's R&D increase year, we choose a matched firm that has jointly the lowest absolute value of the difference (with the sample firm) in these characteristics (Ikenberry and Ramnath (2002) also use these variables as matching criteria). As with our full sample results, these matched firms may increase their R&D, they just cannot have an unexpected and economically significant R&D increase at the time of the matching. We refer to this as our alternative matched sample, and the results with this sample bolster our other results.

To our knowledge, all previously published studies that examine operating performance do so in event time. Yet the same statistical concerns about clustering and cross-sectional correlations that apply to event-time returns also apply to operating performance measures. Therefore, as noted earlier, we compute the operating performance measures in calendar time.

¹⁴ So the matched firm may have an R&D increase; it just does not increase its ratio of R&D to assets or have an economically significant increase in its R&D (as discussed above).

¹⁵ There are a variety of momentum definitions in the literature, and by following previous momentum definitions used in various tests throughout our paper, we use two different definitions (i.e., 36-month return/12-month return, and the *UMD* factor in the Carhart four-factor model). To avoid confusion, we define (or redefine) momentum whenever we are using a variable definition that differs from a previous definition.

For each calendar year, we compute the abnormal operating performance for every sample firm that increases its R&D (again, unexpectedly and by an economically significant amount) within the previous 5 years. Because of the skewness in operating performance measures across firms, previous work (e.g., Barber and Lyon (1996) and Loughran and Ritter (1997)) recommends median measures. We follow this convention, and compute the median abnormal operating performance for each calendar year. We then compute the time-series average of this annual abnormal performance measure, and use the time-series volatility of this annual measure to estimate the standard error. We refer to this as our equal-weighted abnormal operating performance measure.

As noted above, we also compute a value-weighted abnormal operating performance measure. That is, for each calendar year, we compute the value-weighted average abnormal operating performance across the sample of firms that increase their R&D within the previous 5 years. Again, we use the book value of assets to measure the value weights, so the weight applied to a firm is the ratio of its book value of assets to the total book value of assets for the sample firms that increase their R&D within the previous 5 years. We then compute the time-series average of these annual abnormal performance measures, and use the time-series volatility of these annual measures to estimate the standard error.

If a firm has only 1 year of operating performance in the 5-year period following its R&D increase, we still include the firm in the sample, and this should reduce any survivorship bias concerns. We cannot use a Shumway correction for delisting with COMPUSTAT data as we do for the CRSP data, but as an additional survivorship bias check, we compute the results where we do not replace a matched firm in the event that its operating performance ceases to be reported in COMPUSTAT. In other words, a sample firm can drop out of the sample due to its own "delisting" from COMPUSTAT, or due to the "delisting" of its matched firm. To the extent that the sample firm's "delisting" creates any survivorship bias, this concern is offset by the loss of sample firms that are dropped because their matched firm is "delisted." We refer to this as our nonreplacement matched sample.

Finally, an R&D increase may provide other benefits besides the increase in a firm's PMs. This increase may also increase the scale of the firm as manifested in its percentage change in earnings (i.e., EBIT). To test this possibility, we also compute the abnormal earnings change (AEC) for our sample firms, defined as the sample firm's earnings change minus its matched firm's earnings change. If a firm's earnings are negative as of year -1 (i.e., the base year), then we use its "normalized" earnings (i.e., its average earnings over the preceding 5-year period) in place of its negative earnings.

III. Empirical Results

A. Long-Term Abnormal Stock Returns

Table III shows the long-term abnormal security return test results for the 1951 to 2001 sample period. In panel A, we show the results for our full sample

Table III Long-Term Abnormal Stock Returns: 1951 to 2001

This table provides long-term abnormal stock returns for the sample of 8,313 R&D increases by 3,148 firms from 1951 to 2001. To examine whether there are any long-term abnormal stock returns following R&D increases, we use the Fama and French (1993) three-factor model:

$$R_{pt} - R_{ft} = \alpha + b(R_{mt} - R_{ft}) + sSMB_t + hHML_t + \varepsilon_{pt},$$

where R_{ot} is the average raw return for stocks in calendar month t (where a sample stock is included if month t is within the 60-month period following its R&D increase), R_{ti} is the 1-month T-bill return, R_{mt} is the CRSP value-weighted market index return, SMB_{i} is the return on a portfolio of small stocks minus the return on a portfolio of large stocks, and HML_t is the return on a portfolio of stocks with high book-to-market ratios minus the return on a portfolio of stocks with low book-to-market ratios. We also estimate the abnormal stock returns with a momentum factor (i.e., UMD, return on high momentum stocks minus the return on low momentum stocks) included as an additional risk factor. Because Carhart (1997) shows the importance of momentum in expected return measures, we refer to the following model as the Carhart four-factor model:

$$R_{pt} - R_{ft} = \alpha + b(R_{mt} - R_{ft}) + sSMB_t + hHML_t + mUMD_t + \varepsilon_{pt}.$$

from 1952 to 1958) to estimate the factor loadings. We then estimate the abnormal returns in month 61 (i.e., April 1958) as the difference between the actual portfolio return and the expected portfolio return (defined as the factor loading estimated over the previous 60 months times their respective the time-series volatility of these abnormal return estimates and factor loading to estimate the standard errors of their respective averages. The actor returns). We repeat this step for every month, and then average the time series of these abnormal returns and the factor loadings. We use delisted-adjusted sample (panel D) uses the Shumway correction for firms that delist for performance reasons (e.g., bankruptcy). The p-values are overlapping data, we also present the results for our sample of 4,910 firm-year observations by 3,128 firms where a firm can only be included in the sample once every 5 years. We refer to this as our 5-year sample (panel B). To control for changes in risk over time, we also estimate the Fama-French The intercept (α) in the above equations is the abnormal return measure. We correct the standard errors in the above equations for heteroskedasticity and autocorrelation using the quadratic spectral kernel as recommended by Andrews (1991). To directly address any possible problem associated with and Carhart models with rolling regression estimates of each factor loading (panel C). Specifically, we use the first 60 months of portfolio returns (i.e., reported in parentheses below each coefficient estimate.

	Fame	Fama and French Three-Factor Model	Three-Factor A	J odel		Carha	Carhart Four-Factor Model	Model	
	Intercept	9	s	ų	Intercept	9	s	h	ш
				Panel A: Full Sample	Sample				
Equal weight	0.693	1.114	1.344	-0.231	0.736	1.109	1.337	-0.252	-0.037
1	(0.002)	(0.000)	(0.000)	(0.063)	(0.000)	(0.000)	(0.000)	(0.031)	(0.652)
Value weight	0.427	0.962	0.072	-0.155	0.532	0.952	0.055	-0.205	-0.089
	(0.004)	(0.000)	(0.195)	(0.058)	(0.001)	(0.000)	(0.320)	(0.012)	(0.129)

			P?	Panel B: Five-Year Sample	ar Sample				
Equal weight	0.664	1.112	1.369	-0.218	0.728	1.106	1.358	-0.249	-0.055
Value weight	(0.003)	(0.000)	(0.000)	(0.084)	(0.000)	(0.000)	(0.000)	(0.037)	(0.534)
value weight	(0.014)	(0.000)	(0.138)	(0.024)	(0.003)	(0.000)	(0.246)	(0.003)	(0.103)
			Panel	Panel C: Rolling Regression Metho	ression Method				
Equal weight	0.571	1.098	1.203	-0.254	0.540	1.098	1.209	-0.242	0.029
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.019)
Value weight	0.390	0.952	0.115	-0.314	0.362	0.964	0.148	-0.312	0.013
	(0.002)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.268)
			Panel	Panel D: Delisted-Adjusted Sampl	ljusted Sample				
Equal weight	0.563	1.114	1.324	-0.231	0.608	1.109	1.316	-0.252	-0.039
	(0.011)	(0.000)	(0.000)	(0.060)	(0.002)	(0.000)	(0.000)	(0.030)	(0.641)
Value weight	0.413	0.962	0.070	-0.154	0.519	0.952	0.053	-0.204	-0.090
	(0.005)	(0.000)	(0.206)	(0.059)	(0.001)	(0.000)	(0.337)	(0.012)	(0.124)

using the Fama and French three-factor model and the Carhart four-factor model. With the equal- and value-weighted measures, the alphas are significantly positive with the Fama and French three-factor model (0.69 percent and 0.43 percent), and with the Carhart four-factor model (0.74 percent and 0.53 percent). Moreover, the coefficient estimates for the risk factors are generally consistent with the estimates reported in previous studies.

In panel B, we report the results for our 5-year sample. These results are very similar to the full sample results we report in panel A; that is, we find significantly positive abnormal stock return estimates in each case.

We report the rolling regression results in panel C. With the Fama and French three-factor model and the Carhart four-factor model, the equal- and value-weighted alphas are significantly positive. These findings show that our results are robust to accounting for changes in risk over time. Finally, our delisted-adjusted sample results reported in panel D continue to show evidence of significantly positive abnormal returns. Though the abnormal returns are slightly lower than the abnormal returns we present in panel A (without the Shumway correction), the difference is only about one basis point with the value-weighted returns. Therefore, there does not appear to be any evidence that our positive abnormal stock returns are driven by potential survivorship bias.

Table IV displays the abnormal return estimates for the 1974 to 2001 sample period for the full sample (panel A), the 5-year sample (panel B), the rolling regression approach (panel C), and the delisted-adjusted sample (panel D). As with Table III, the abnormal return estimates are significantly positive in each panel for the equal- and value-weighted measures (except in one case in panel D). One difference is that the negative coefficient estimate for the momentum factor in the Carhart model is more consistently significant in this table. We report above that our sample firms do not have negative raw (or abnormal) buy-and-hold stock returns in the 36-month period preceding the beginning of the R&D increase year. In the context of the multifactor Carhart model (using arithmetic calendar-time returns), however, there does appear to be a significant negative momentum factor in stock returns, ceteris paribus. We think this highlights the importance of using the Carhart model in our abnormal return tests, and the use of momentum as a matching characteristic in the alternative matched sample that we use in our zero-investment portfolio return tests. Moreover, though the equal-weighted abnormal returns are higher than the value-weighted abnormal returns in both tables (and in the other tables reporting abnormal stock returns), the value-weighted abnormal returns are still economically significant, with a minimum monthly abnormal return of 25.2 basis points in panel C of Table IV.

Though the rolling regression method controls for changes in the risk of the portfolio over time, we perform an additional check on changes in risk at the individual firm level. Specifically, we estimate each firm's factor loadings over the 60-month period following its R&D increase (to account for the possibility of higher risk for the firm in its post-R&D increase period, as suggested by Berk et al. (2000)). Then we multiply the firm's factor loading estimates times the realizations of the risk factors to estimate its expected return. The difference

Table IV Long-Term Abnormal Stock Returns: 1974 to 2001

This table provides long-term abnormal stock returns for the sample of 8,090 R&D increases by 3,099 firms from 1974 to 2001. See Table III for a detailed discussion of the tests. The intercept (α) is the abnormal return measure. The p-values are reported in parentheses below each coefficient estimate.

	Fame	and French	ama and French Three-Factor Model	odel		Carha	Carhart Four-Factor Model	Model	
	Intercept	9	S	h	Intercept	q	8	h	ш
				Panel A: Full Sample	Sample		:	-	
Equal weight	0.617	1.104	1.515	-0.243	0.810	1.080	1.498	-0.344	-0.161
)	(0.023)	(0.000)	(0.000)	(0.062)	(0.002)	(0.000)	(0.000)	(0.004)	(0.065)
Value weight	0.267	0.969	0.013	-0.136	0.536	0.936	-0.010	-0.278	-0.225
	(0.080)	(0.000)	(0.808)	(0.050)	(0.001)	(0.000)	(0.824)	(0.000)	(0.000)
			4	Panel B: Five-Year Sample	ear Sample				
Equal weight	0.562	1.104	1.565	-0.225	0.784	1.077	1.546	-0.341	-0.185
	(0.040)	(0.000)	(0.000)	(0.094)	(0.004)	(0.000)	(0.000)	(0.006)	(0.054)
Value weight	0.306	0.980	0.055	-0.178	0.628	0.941	0.028	-0.346	-0.268
	(0.042)	(0.000)	(0.394)	(0.016)	(0.000)	(0.000)	(0.588)	(0.000)	(0.000)
			Panel	C: Rolling Reg	Panel C: Rolling Regression Method				
Equal weight	0.604	1.053	1.332	-0.259	0.770	1.033	1.288	-0.325	-0.138
	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Value weight	0.252	0.892	-0.043	-0.334	0.471	0.894	-0.070	-0.412	-0.197
	(0.073)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
			Panel	D: Delisted-A	Panel D: Delisted-Adjusted Sample				
Equal weight	0.410	1.104	1.488	-0.244	0.604	1.080	1.472	-0.345	-0.161
	(0.130)	(0.000)	(0.000)	(0.059)	(0.019)	(0.000)	(0.000)	(0.003)	(0.073)
Value weight	0.259	0.969	0.012	-0.136	0.528	0.936	-0.010	-0.278	-0.225
	(0.089)	(0.000)	(0.819)	(0.050)	(0.001)	(0.000)	(0.810)	(0.000)	(0.000)

between the firm's actual return and its expected return is its abnormal return. Using equal weights and value weights, we then average these abnormal returns for each month for all firms within 60 months of their R&D increase, and then we compute the time-series average of these monthly abnormal returns (using the time-series volatility to estimate the statistical significance of the average). We do not show the results in the table, but the average abnormal return is significant at the 5 percent level or better every time, and ranges from a low of 30 basis points per month (i.e., using value-weighted returns with the Fama and French three-factor model for the 1974 to 2001 sample period), to a high of 56 basis points per month (i.e., using equal-weighted returns with the Fama and French three-factor model for the 1974 to 2001 sample period).

In Table V, we present the zero-investment portfolio regression results for the 1974 to 2001 sample period. With the full sample results in panel A, using the firms matched based on industry, size, and profitability as discussed above, the value-weighted alphas are insignificant but the equal-weighted abnormal returns are significantly positive. With our alternative matched sample in panel B (i.e., matched based on size, book-to-market, and momentum), the equal-weighted and value-weighted abnormal returns are significantly positive (with the Fama and French three-factor model and the Carhart four-factor model). These results show that, even after accounting for risk in two stages, we still find significantly positive abnormal stock returns in most cases. More generally, nearly all the results presented in Tables III–V show that the stock market is slow to recognize the full benefit of R&D increases.

Our remaining abnormal return tests use our subsamples of high-tech, low-tech, high-growth, and low-growth firms in Table VI. With the equal-weighted returns, we find significantly positive abnormal return estimates across all the categories (except with the Fama and French three-factor model for the low-growth firms). With value weighting, the abnormal returns are significantly positive for the high-tech and high-growth firms. With the low-tech and low-growth firms, however, the value-weighted abnormal returns are insignificantly different from zero using the Fama and French three-factor model or the Carhart four-factor model. When we compare the high-tech alphas to the low-tech alphas using the Wald test, we find that the high-tech alphas are significantly higher for the value-weighted and equal-weighted returns.

We do not find any significant difference between the long-term abnormal stock return performance of high-growth versus low-growth firms. This finding may be considered counter to Daniel and Titman's (2001) suggestion that low-growth firms should have significantly higher long-term abnormal stock returns than high-growth firms. In this sense, Daniel and Titman's arguments do not fully explain all of our results, and consequently more theoretical work may be needed.

¹⁶ Because, as we show in Tables III and IV, the results are qualitatively similar for the 1951 to 2001 sample period, we present the remaining abnormal stock return results with the 1974 to 2001 sample period.

Table V ero-Investment Portfolios: 1974 to 200

This table presents the results for the 1974 to 2001 sample period for the zero-investment portfolio tests. To control for risk in two steps with the increase and the monthly return on its matched firm (matched based on two-digit SIC code industries, size, and profitability). Then we compute the cross-sectional average of these zero-investment returns each month. The alphas (i.e., intercepts) estimated from the time-series regressions of these returns on the risk factors in Fama–French and Carhart models are the abnormal return estimates of the zero-investment return method. In panel B, we use the same procedure with our alternative matched sample (i.e., matched based on size, book-to-market, and momentum). See Table III for a zero-investment portfolio method, we first compute the difference between the monthly return on a sample firm that is within 60 months of its R&D detailed discussion of these regression tests. The p-values are reported in parentheses below each coefficient estimate. Zero-Investment Portfolios: 1974 to 2001

	-							The second secon	
	Fam	na and French	Fama and French Three-Factor Model	fodel		Carha	Carhart Four-Factor Model	Model	
	Intercept	9	s	h	Intercept	q	s	h	ш
				Panel A: Full Sample	Sample				
Equal weight	0.294	0.049	0.123	-0.180	0.334	-0.033	0.044	0.120	-0.201
	(0.000)	(0.154)	(0.003)	(0.000)	(0.000)	(0.238)	(0.169)	(0.004)	(0.000)
Value weight	-0.030	-0.038	-0.951	-0.147	0.082	-0.093	-0.052	-0.960	-0.205
	(0.829)	(0.395)	(0.000)	(0.018)	(0.617)	(0.116)	(0.259)	(0.000)	(0.013)
			Panel	Panel B: Alternative	Matched Sample	e			Tr. Co.
Equal weight	0.125	-0.016	0.126	-0.268	0.129	-0.020	0.124	-0.331	-0.090
	(0.003)	(0.898)	(0.000)	(0.181)	(0.002)	(0.842)	(0.000)	(0.119)	(0.519)
Value weight	0.095	0.100	0.967	-0.083	0.075	0.094	960.0	-0.125	-0.061
	(0.073)	(0.142)	(0.000)	(0.510)	(0.039)	(0.164)	(0.000)	(0.446)	(0.586)

Table VI Tests by Subsamples: 1974 to 2001

This table provides long-term abnormal stock returns for subsamples of the 8,090 R&D increases by 3,099 firms from 1974 to 2001. Firms are designated into high- and low-tech designations using the Chan, Martin, and Kensinger (1990) designations. We designate firms as high- to lowgrowth based on MB ratios (MB > 1 is defined as high growth). The intercept (α) is the abnormal return measure. See Table III for a detailed discussion of the tests. The p-values are reported in parentheses below each coefficient estimate.

	Fama	Fama and French Three-Factor Mode	[hree-Factor]	Model		Carha	Carhart Four-Factor Model	Model	
	Intercept	p	S	h	Intercept	p p	S	h	ш
				Panel A: High-tech Sample	ech Sample				
Equal weight	0.653	1.123	1.544	-0.265	0.866	1.097	1.526	-0.377	-0.177
Value weight	0.303 0.303 (0.079)	0.972 (0.000)	0.015	-0.171 (0.032)	0.627 (0.001)	0.933	-0.013 (0.775)	-0.341 (0.000)	-0.270 (0.000)
				Panel B: Low-tech Sample	ech Sample				
Equal weight	0.427	1.035	1.407	-0.135	0.544	1.020	1.397	-0.196	760.0-
Value weight	$(0.072 \\ 0.064$	(0.000) 1.031	$(0.000) \\ 0.195$	$(0.213) \\ 0.123$	$(0.020) \\ 0.118$	(0.000) 1.024	$(0.000) \\ 0.191$	$(0.044) \\ 0.095$	(0.185) -0.045
1	(0.689)	(0.000)	(0.126)	(0.276)	(0.510)	(0.000)	(0.118)	(0.379)	(0.714)
			Ъ	Panel C: High-growth Sample	owth Sample				
Equal weight	0.627	1.101	1.487	-0.225	0.807	1.080	1.472	-0.320	-0.150
V7.1	(0.017)	(0.000)	(0.000)	(0.085)	(0.001)	(0.000)	(0.000)	(0.007)	(0.071)
value weignt	(0.077)	(0.000)	(0.853)	-0.150 (0.052)	(0.001)	(0.000)	-0.012 (0.775)	(0.000)	(0.000)
			Н	Panel D: Low-growth Sample	owth Sample				
Equal weight	0.389	1.119	1.666	-0.493	0.728	1.078	1.639	0.670	-0.280
Value weight	0.212 (0.733)	0.972	0.987	-0.492 (0.103)	0.850 (0.252)	0.894	0.936	-0.825 (0.022)	-0.528 (0.008)

Though we do not tabulate the results in the paper, we also examine whether pre-event performance measures explain differences in the alphas. ¹⁷ For example, we split our sample on pre-event stock returns (i.e., the raw 36-month stock return before the R&D increase year). We compare the long-term abnormal stock returns of those firms in the upper 30 percent of pre-event stock returns (i.e., high-return stocks) to those in the lower 30 percent of pre-event stock returns (i.e., low-return stocks). We also compare the abnormal stock returns of high-return and low-return stocks for the subsamples of high-tech firms, low-tech firms, high-growth firms, and low-growth firms. For the entire sample, and for each of the subsamples, we find no significant difference between the abnormal stock returns using value or equal-weighted returns with the Fama and French three-factor model or the Carhart four-factor model. Hence, pre-event stock return performance does not explain the differences in the (subsequent) long-term abnormal returns across stocks.

We also split our sample firms based on their past operating performance. For each sample firm, we measure its average operating performance over the 5-year period preceding its R&D increase year. We find no significant difference in abnormal stock returns when we split our entire sample, and each of the four subsamples, into high past operating performance firms (i.e., those in the top 30 percent of the 5-year average PM) and low past operating performance firms (i.e., those in the lower 30 percent of the 5-year average PM).

These findings are another point of difference between our paper and Chan, Lakonishok, and Sougiannis (2001). As we suggest above, their focus is on the characteristic of R&D divided by equity capitalization or sales, and they find that differences in pre-event stock returns reveal differences in the subsequent long-term abnormal stock returns of firms with a particular R&D characteristic (e.g., firms with a high ratio of R&D to equity capitalization). With our focus on the "event" of an unexpected and economically significant R&D increase, we find that pre-event stock return differences do not portend any significant difference in subsequent long-term abnormal stock returns.

Finally, we split our sample (and each of our four subsamples) according to their equity capitalizations, where large (small) firms are defined as those in the upper (lower) 30 percent of the sample. We do not find any consistent evidence that small firms outperform large firms or vice versa (these results are also available from the authors). In combination with the size variable in the factor models of expected stock returns that we use, and with our use of size as a matching criteria in the zero-investment portfolio approach, and with our use of value-weighted returns, we have extensively examined the possibility that the abnormal stock returns we document are limited to small stocks, and our results do not support this proposition.

¹⁷ Tabulated results are available from the authors.

¹⁸ We also find no significant difference in abnormal stock returns when we split the sample based on relative momentum (i.e., our sample firms preceding [raw] stock returns minus the stock returns of their matched firms) or relative prior operating performance (i.e., APM measured over the preceding 5 years).

B. Operating Performance for the Samples

We report the abnormal operating performance of our sample firms in Table VII in panel A. For the 1951 to 2001 sample period, each of the equal-weighted and value-weighted abnormal PMs are significantly positive, ranging from a low of 0.75 percent to a high of 3.64 percent. Similarly, all of the abnormal PMs are positive and highly significant for the 1974 to 2001 sample period, ranging up to 5.22 percent.

The equal- (value-) weighted AEC is insignificantly negative (negative) for the 1951 to 2001 period, and insignificantly negative (positive) for the 1974 to 2001 period. In short, our results provide strong evidence that R&D increases lead to abnormally high profitability, but we do not find any evidence that such increases expand the firm's scale. 19

For the 5-year sample in panel B, we find that the equal- and value-weighted abnormal operating performance is positive for each measure for the 1951 to 2001 sample period. The only insignificant case is the equal-weighted APM. For the 1974 to 2001 sample period, the results are similar despite the fact that the number of time-series observations for this sample period is less than 30 (recall that abnormal operating performance is measured annually). The equal- and value-weighted AEC is insignificant (for both sample periods), consistent with the results we report for other samples.

In panel C, we present the results using our alternative sample of matched firms. We focus on the 1974 to 2001 sample, and the results show significantly positive equal- and value-weighted abnormal PMs in five out of six cases. Consistent with other matching procedure results, our sample firms' equal- and value-weighted AEC is insignificant.

We present the results for our nonreplacement matched sample in panel D (again, where the sample firm is dropped from the sample if its operating performance is no longer available, or if its matched firm's operating performance is no longer available). The results continue to show significantly positive equal-and value-weighted measures of abnormal operating performance in all but one case. Therefore, the positive abnormal operating performance results that we report do not appear to be attributable to any potential survivorship bias. More generally, in looking across panels A–D of Table VII, the results provide strong support in nearly every case for the argument that R&D increases are beneficial investments.

In Table VIII, we report the abnormal operating performance measures for our subsamples. The equal- and value-weighted abnormal PMs for the high-tech firms are consistently positive and significant (the abnormal earnings growth is insignificant, similar to the full sample results). The low-tech firm abnormal PMs also tend to be significantly positive, but the results are more mixed, with a significantly negative equal-weighted APM, and an insignificant value-weighted APM1.

¹⁹ As a robustness check, we also examine our sample firms' abnormal change in sales (i.e., the percentage change in sales for our sample firms minus the percentage change in sales for their matched firms), and we find no consistent evidence of any significant change with this variable.

Table VII Operating Performance

We examine the operating performance of firms (as reported in COMPUSTAT) following their announcement of an increase in research and development (R&D) expenditures between 1951 and 2001. There are 8.313 firm-year observations for 3.148 firms from 1951 to 2001, and 8.090 firmyear observations by 3,099 firms from 1974 to 2001. We measure our sample firms' operating performance for 5 years following the year in which they (unexpectedly) increase R&D. We use three different measures of raw operating performance; the primary measure is the profit margin, defined as the EBIT divided by sales. The other two PM measures adjust for the fact that R&D expenses reduce PMs. The variable PM1 is the sum of EBIT and after-tax R&D (using the statutory Federal tax rate) divided by sales: PM2 is the sum of EBIT and after-tax R&D (using each firm's ratio of reported taxes to taxable income as the tax rate) divided by sales. We measure abnormal operating performance as a sample firm's (raw) operating performance minus its matched firm's (raw) operating performance. Given statistical concerns about clustering and cross-sectional correlations, we compute the operating performance measures in calendar time. For each calendar year, we compute the abnormal operating performance for every sample firm that increases its R&D within the previous 5 years and compute the median abnormal operating performance for each calendar year. We also compute a value-weighted average abnormal operating performance measure (using the book value of assets as the weight). We compute the time-series average of these annual abnormal performance measures, and use the time-series volatility of these annual measures to estimate the standard error. To choose matched firms, we begin with a group of firms in the same two-digit SIC code as the sample firm that do not increase their R&D (unexpectedly or by an economically significant amount) in the increase year. From these initial screens, the matched firm is defined as the firm with a PM that is closest to the sample firm's PM as of its R&D increase year. If a matched firm is no longer available in subsequent years, we use the next closest firm as of the R&D increase year. We refer to the respective abnormal operating performance measures as APM, APM1 and APM2. Because an R&D increase may provide other benefits besides the increase in a firm's PMs (e.g., this increase may also increase the scale of the firm as manifested in its percentage change in earnings (i.e., EBIT)), we also compute the AEC for our sample firms, defined as the sample firm's earnings change minus its matched firm's earnings change. If a firm's earnings are negative as of year -1 (i.e., the base year), then we use its "normalized" earnings (i.e., its average earnings over the preceding 5-year period) in place of its negative earnings. To directly address any possible problem associated with overlapping data, we also present the results for our sample where a firm can only be included in the sample once every 5 years. We refer to this as our 5-year sample (panel B). As an additional check, we choose another group of matched firms based on the book-to-market ratio, size, and momentum. That is, as of the beginning of a sample firm's R&D increase year, we choose a matched firm that has the lowest absolute value of the difference in these characteristics with the sample firm. We refer to this as our alternative matched sample (panel C). If a firm has only 1 year of operating performance in the 5-year post-announcement period, we still include the firm in the sample, and this should reduce any survivorship bias concerns. Nevertheless, we also compute the results where we do not replace a matched firm in the event that its operating performance ceases to be reported in COMPUSTAT. In other words, a sample firm can drop out of the sample due to its own "delisting" from COMPUSTAT, or the "delisting" of its matched firm. We refer to this as our nonreplacement matched sample (panel D). The p-values are reported in parentheses below each coefficient estimate.

Sample Period	Weighting	APM	APM1	APM2	AEC
		Panel A: Full S	ample		
1951–2001	Equal	0.745	3.192	3.167	6.577
		(0.005)	(0.000)	(0.000)	(0.382)
1951-2001	Value	3.327	2.786	3.639	0.154
		(0.010)	(0.000)	(0.000)	(0.996)
1974-2001	Equal	0.080	2.818	2.476	-1.798
	-	(0.014)	(0.000)	(0.000)	(0.188)
1974-2001	Value	5.220	3.898	5.205	4.777
		(0.016)	(0.001)	(0.000)	(0.940)

Table VII—Continued

Sample Period	Weighting	APM	APM1	APM2	AEC
	P	anel B: Five-Yea	r Sample		
1951–2001	Equal	0.030	2.501	2.185	-1.692
	•	(0.227)	(0.000)	(0.000)	(0.274)
1951-2001	Value	1.131	1.888	2.145	-3.665
		(0.000)	(0.000)	(0.000)	(0.235)
1974-2001	Equal	0.370	2.424	1.924	-1.798
	-	(0.295)	(0.000)	(0.000)	(0.188)
1974-2001	Value	2.757	3.524	3.844	4.777
		(0.000)	(0.001)	(0.000)	(0.940)
	Panel (C: Alternative M	atched Sample		
1974–2001	Equal	5.797	3.054	4.723	-0.552
		(0.000)	(0.072)	(0.001)	(0.155)
1974-2001	Value	2.738	-0.032	1.413	-0.023
		(0.029)	(0.169)	(0.025)	(0.966)
	Panel D: l	Nonreplacement	Matched Sampl	e	
1974–2001	Equal	-0.084	2.621	2.107	-0.241
	-	(0.010)	(0.000)	(0.000)	(0.171)
1974-2001	Value	0.888	1.732	1.832	0.772
		(0.000)	(0.000)	(0.000)	(0.465)

When we directly compare the abnormal PMs between the two subsamples. the high-tech firms have economically significant higher abnormal PMs. For example, the three value-weighted abnormal PMs for the high-tech firms are more than twice as high as the respective value-weighted abnormal PMs for the low-tech firms (these differences are statistically significant as measured by the Wald test, and the test statistics are available from the authors).²⁰ These results are consistent with the long-term abnormal stock return results we report above; that is, the significantly higher abnormal operating performance that our high-tech firms experience suggests that there is more for the market to underreact to, and we report above that the high-tech alphas are significantly higher than the low-tech alphas. The results are also broadly supportive of the event-study results reported by Chan, Martin, and Kensinger (1990), but our results do not support their specific suggestion that low-tech firms are harmed by such increases. Our results suggest that low-tech firms also benefit; it is just that the statistical significance and size of the benefit is not as strong as it is for high-tech firms.21

²⁰ As suggested above, one explanation for finding relatively higher abnormal operating performance with value-weighting (relative to equal-weighting) is the fact that more profitable firms should have higher book values of assets, ceteris paribus.

²¹ Chan, Martin, and Kensinger (1990) find that (high) low-tech firms have (positive) negative abnormal stock returns around announced increases in R&D, but they do not examine their subsequent operating performance. Therefore, besides the significant differences in our sample construction, size, and methods, our finding that low-tech firms have significantly positive abnormal operating performance is not inconsistent with their direct findings; our results are just inconsistent with the suggestion of the findings that R&D increases by low-tech firms are bad investments.

Table VIII Operating Performance for Subsamples

This table details the operating performance for subsamples of the 8,090 R&D increases by 3,099 firms from 1974 to 2001. Firms are designated into high- and low-tech designations using the Chan, Martin, and Kensinger (1990) designations. We designate firms as high- to low-growth based on MB ratios (MB > 1 is defined as high growth). Operating performance measures are calculated as described in the previous table header. The p-values are reported in parentheses below each coefficient estimate.

Weighting	APM	APM1	APM2	AEC
	Par	nel A: High-tech Firm	s	
Equal	0.149	3.090	2.786	0.331
	(0.002)	(0.000)	(0.000)	(0.884)
Value	8.030	4.615	6.538	6.316
	(0.046)	(0.023)	(0.007)	(0.443)
	Pa	nel B: Low-tech Firms	3	
Equal	-0.107	2.139	1.654	-0.762
•	(0.096)	(0.000)	(0.000)	(0.002)
Value	1.543	1.521	2.859	-4.613
	(0.000)	(0.331)	(0.000)	(0.215)
	Pane	el C: High-growth Firm	ns	
Equal	0.127	2.885	2.675	-1.695
-	(0.000)	(0.000)	(0.000)	(0.257)
Value	7.353	4.102	6.186	3.854
	(0.026)	(0.013)	(0.002)	(0.578)
	Pane	el D: Low-growth Firm	ns	
Equal	-0.462	2.485	1.512	-3.199
	(0.003)	(0.000)	(0.000)	(0.340)
Value	0.813	3.119	2.866	-1.255
	(0.070)	(0.000)	(0.000)	(0.242)

We show the results for the high-growth and low-growth firms in panels C and D. The abnormal PMs are consistently positive and significant for the high-growth firms. With the low-growth firms, the abnormal PMs are also significantly positive except for the equal-weighted APM. Though the size of the abnormal PMs is higher for the high-growth firms, it is not significantly higher at the 10 percent level. Overall, our results suggest that R&D increases are beneficial for all groups, consistent with the underreaction we observe across these groups in Table VI. High-tech firms, however, appear to receive the greatest boost in operating performance from R&D increases (again, consistent with the higher alphas we report for these firms in Table VI). ²²

²² At first glance, our findings on the beneficial effects of R&D increases on operating performance appear to differ from Jensen's (1993) suggestion that that R&D investments are detrimental. There are several differences between our study and Jensen's study, however, and so we should not expect to perfectly replicate his findings. For example, his measurement of expected operating performance is substantially different from the standard method that we use in our study. Most important, however, is that he does not examine firms that unexpectedly increase their R&D by an economically significant amount. Instead, he selects firms based on their *level* of R&D. So our findings are not directly comparable to Jensen's results.

In short, there is a wide range in the magnitude of the 60 abnormal PM measures that we report in Tables VII and VIII. We think this wide range is attributable partly to the fact that this is, to our knowledge, the first study to examine value-weighted operating performance measures, in addition to the standard equal-weighted measures that we report and that are reported in all previous studies. To our knowledge, again, our study is also the first to examine operating performance in calendar time. Notwithstanding the wide range in the magnitude of the abnormal PM measures, there is little variation in their significance with nearly 90 percent of the results showing significant positive abnormal operating performance.²³ Consequently, we think there is a clear and consistent pattern of superior operating performance.

IV. Conclusion

Do R&D increases lead to better than expected operating performance, and is the market slow to recognize this benefit? We answer these questions by examining a sample of 8,313 cases where firms unexpectedly increase their R&D by an economically significant amount over our 1951 to 2001 sample period. For the 5-year period following their R&D increases, we find consistently strong evidence that firms experience significantly positive abnormal operating performance. We also find consistent evidence that shareholders experience significantly positive abnormal stock returns for the 5-year period following their firm's R&D increase.

Our findings are consistent with evidence showing that firm attributes reveal mispricing that the market takes years to correct (e.g., Lakonishok et al. (1994)), and with studies reporting that the market is slow to incorporate the information contained in corporate events such as IPOs (e.g., Loughran and Ritter (1995)). Our examination of R&D increases, however, differs from studies examining firm attributes and subsequent abnormal returns, because R&D increases represent a managerial decision. Our study also differs from studies examining events such as stock repurchases, because R&D increases are investment decisions (not financing decisions) and they are seldom announced.

Instead, we argue that R&D increases provide an ideal test of the ability of the market to correctly incorporate the intangible information contained in a firm's long-term investment decision (Daniel and Titman (2001) posit that investors misreact to this type of information). Our results provide strong evidence that investors systematically underreact to the benefit of an R&D increase.

²³ As we suggest above, our sample firms do continue to invest in R&D in event years one through five, and that is why we compute the PM1 and PM2 numbers. For our typical sample firm, the typical ratio of R&D to sales in event years one through five is 11 percent. When we compare our sample firm's ratios of R&D to sales to that of their matched firms, the typical difference is three percent. So the fact that our sample firms have relatively higher ratios of R&D to sales (compared to their matched firms) emphasizes the importance of computing the APM1 and APM2 measures (i.e., these measures compare the "core" profit margins, before R&D investments are subtracted). Even without adjusting for future R&D differences, however, our APM measures are almost always significantly positive (i.e., 15 out of the 20 APM measures we present in Tables VII and VIII are significantly positive).

REFERENCES

- Agrawal, Anup, Jeffrey Jaffe, and Gershon Mandelker, 1992, The post-merger performance of acquiring firms: A re-examination of an anomaly, *Journal of Finance* 47, 1605–1621.
- Andrews, Donald, 1991, Heteroskedasticity and autocorrelation consistent covariance matrix estimator. Econometrica 50, 953-966.
- Asquith, Paul, 1983, Merger bids, uncertainty and stockholder returns, *Journal of Financial Economics* 11, 51–83.
- Barber, Brad, and John Lyon, 1996, Detecting abnormal operating performance: The empirical power and specification of test statistics, *Journal of Financial Economics* 41, 359-399.
- Barber, Brad, and John Lyon, 1997, Detecting long-run abnormal stock returns: The empirical power and specification of test statistics. *Journal of Financial Economics* 54, 341–372.
- Barberis, Nicholas, Andrei Shleifer, and Robert Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307–343.
- Berk, Jonathan, Richard Green, and Vasant Naik, 2000, Valuation and return dynamics of new ventures, Working paper, University of California, Berkeley.
- Brav, Alon, and Paul Gompers, 1997, Myth or reality? The long-run underperformance of initial public offerings: Evidence from venture and nonventure capital-backed companies, *Journal of Finance* 52, 1791–1821.
- Carhart, Mark, 1997, On persistence in mutual fund performance, Journal of Finance 52, 57-82.
- Chan, Louis K.C., Josef Lakonishok, and Theodore Sougiannis, 2001, The stock market valuation of research and development expenditures, *Journal of Finance* 56, 2431–2456.
- Chan, Su Han, John Martin, and John Kensinger, 1990, Corporate research and development expenditures and share value, *Journal of Financial Economics* 26, 255-276.
- Chauvin, Keith, and Mark Hirschey, 1993, Advertising, R&D expenditures and the market value of the firm, *Financial Management* 22, 128–140.
- Cusatis, Patrick, James Miles, and Randall Woolridge, 1993, Restructuring through spinoffs, *Journal of Financial Economics* 33, 293–311.
- Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor psychology and security market under- and over-reactions, *Journal of Finance* 40, 793–808.
- Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam, 2001, Overconfidence, arbitrage, and equilibrium asset pricing, *Journal of Finance* 56, 793–808.
- Daniel, Kent, and Sheridan Titman, 2000, Market efficiency in an irrational world, NBER Working paper No. 7489.
- Daniel, Kent, and Sheridan Titman, 2001, Market reactions to tangible and intangible information, Working paper, Northwestern University.
- Eberhart, Allan, and Akhtar Siddique, 2002, The long-term performance of corporate bonds (and stocks) following seasoned equity offerings, *Review of Financial Studies* 15, 1385–1406.
- Fama, Eugene F., 1998, Market efficiency, long-term returns, and behavioral finance, *Journal of Financial Economics* 49, 283-306.
- Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.
- Hertzel, Michael, and Prem Jain, 1991, Earnings and risk changes around stock repurchase tender offers, *Journal of Accounting and Economics* 14, 253–274.
- Hong, Harrison, and Jeremy Stein, 1999, A unified theory of underreaction, momentum trading and overreaction in asset markets, *Journal of Finance* 54, 2143–2184.
- Ikenberry, David, Josef Lakonishok, and Theo Vermaelen, 1995, Market underreaction to open market share repurchases, *Journal of Financial Economics* 39, 181–208.
- Ikenberry, David, Josef Lakonishok, and Theo Vermaelen, 2000, Stock repurchases in Canada: Performance and strategic trading, *Journal of Finance* 55, 2373–2397.
- Ikenberry, David, and Sundaresh Ramnath, 2002, Underreaction to self-selected news: The case of stock splits, *Review of Financial Studies* 15, 489–526.
- Jensen, Michael, 1993, The modern industrial revolution, exit, and the failure of internal control systems, *Journal of Finance* 48, 831–880.

- Kadiyala, Padma, and Raghavendra Rau, 2004, Investor reaction to corporate event announcements: under-reaction or over-reaction? *Journal of Business* (forthcoming).
- Lakonishok, Josef, Andrei Shleifer, and Robert Vishny, 1994, Contrarian investment, extrapolation, and risk, Journal of Finance 49, 1541–1578.
- Loughran, Tim, and Jay Ritter, 1995, The new issues puzzle, Journal of Finance 50, 23-51.
- Loughran, Tim, and Jay Ritter, 1997, The operating performance of firms conducting seasoned equity offering, *Journal of Finance* 52, 1959–1970.
- Loughran, Tim, and Jay Ritter, 2000, Uniformly least powerful tests of market efficiency, *Journal of Financial Economics* 55, 361–389.
- Lyon, John, Brad Barber, and Chih-Ling Tsai, 1999, Improved methods for tests of long-run stock abnormal returns. *Journal of Finance* 54, 165-201.
- Mitchell, Mark, and Erik Stafford, 2000, Managerial decisions and long-term stock price performance, *Journal of Business* 73, 287–320.
- Nix, David, and Paul Nix, 1992, An historical review of the financial accounting treatment of research and development costs, *The Accounting Historians' Journal* 19, 51-78.
- Shumway, Tyler, 1997, The delisting bias in CRSP data, Journal of Finance 52, 327-340.
- Shumway, Tyler, and Vincent Warther, 1999, The delisting bias in CRSP's Nasdaq data and its implications for the size effect, *Journal of Finance* 54, 2361–2379.
- Sougiannis, Theodore, 1994, The accounting based valuation of corporate R&D, *Accounting Review* 69, 44–68.
- Szewczyk, Samuel, George Tsetsekos, and Zaher Zantout, 1996, The valuation of corporate R&D expenditures: Evidence from investment opportunities and free cash flow, *Financial Management* 25, 105–110.
- Titman, Sheridan, 2002, Discussion of "Underreaction to self-selected news events," Review of Financial Studies 15, 527-532.