THREE ESSAYS ON INNOVATION AND RESEARCH AND DEVELOPMENT

by

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Abstract

This thesis contains three research papers related to innovation. Chapter 1 examines the effect of research and development (R&D) on bankruptcy. I propose that R&D investment creates uncertainty, leading to a higher volatility of firm value and greater information asymmetry between insiders (especially senior executives) and outsiders (such as investors). Both higher firm-value volatility and higher information asymmetry can increase the risk of bankruptcy for firms. Using a large panel of United States (US) companies from 1979-2009, I find that consistent with my prediction, firms engaging in high levels of R&D are more likely to go bankrupt. Further, I explore the mechanism by which R&D influences corporate bankruptcy. Empirical evidence supports both of the firm-value volatility and asymmetric information channels. Chapter 2 studies the influence of the business cycle on the interactions between R&D and bankruptcy. I find that the effect of R&D on bankruptcy increased during economic downturns. With stringent financial constraints during downturns, R&D intensive firms are more likely to be affected than during economic expansions. I further find that firms are reluctant to decrease their R&D spending during recessionary periods and that firms taking a more aggressive posture in increasing R&D during downturns enjoy stronger sustained operating performance. Overall, results show that R&D is more risky in recessions than in booms. Chapter 3 examines mergers and acquisition (M&A) transactions between firms with patent citation links and shows such transactions generate better merger performance than acquisitions of firms without citation links. Specifically, I find that acquirers' announcement returns are positively related to citation links between the acquirer and target firms. I suggest that citation links might mitigate two possible concerns that investors could have: (1) the acquirer might overbid for the target firm due to the "winner's curse" problem, or (2) there would be failure at the post-merger integration process. My results are consistent with the hypothesis that citations links are related to high quality transactions, but I do not find evidence supporting the hypothesis that citations help acquirers avoid overpaying for target firms.

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Introduction

Innovation means exploiting new ideas to create new products or processes, or to improve quality or make changes that add value in other ways. The modern world requires significant innovation just to cope with increasing population, environmental damage (including global warming), and increasing natural resource scarcity. At the firm-specific level, many organizations are feeling the impact of globalization, technological progress, and other changes in the business environment. Innovation appears to be of increasing importance in business strategy and has become a major factor in sustaining business growth.

Research and development (R&D) is a process intended to create innovation that can provide a competitive advantage at the business, industry or national level. While the rewards to successful R&D can be very high, the process of technological innovation is complex and risky. The majority of R&D projects fail to provide positive financial results, so the relatively small number of successful projects must also pay for the projects that are unsuccessful or terminated early by management. In some industries, such as information technology and biotechnology, firms that are not able to generate successful R&D projects for a significant period are likely to go out of business. For these reasons, a company's R&D efforts are of high priority and must be carefully managed.

The three chapters of this thesis all relate to innovation and R&D. The first two chapters are closely related to each other and focus on how innovative activities affect the likelihood of bankruptcy. There is a large literature showing R&D investments create value for firms (e.g., Jaffe, 1986; Cockburn and Griliches, 1988; Hall, 1993, e.g., Woolridge and Snow, 1990; Szewczyck et al., 1996). However, increased spending on R&D does not necessarily correlate with successful corporate performance. For example, Apple, the developer of the iPad and iPhone, spends less on R&D than most of its competitors as its R&D/sales ratio is only 3%, compared to an industry median of 10%. Apple has well-honed capabilities in project selection and commercialization, backed by keen understanding of its customers. Thus innovation does not depend only on the amount of R&D undertaken, but on the ability to connect R&D activities to marketplace acceptance. Firms that spend a lot on R&D without achieving marketplace acceptance incur a significant risk of bankruptcy. Chapter 1 studies whether R&D expenditures increase the risk of bankruptcy for firms. Previous research on R&D focuses on its benefits and leaves this "dark side" of R&D un-explored. To the best of my knowledge, my paper is the first research to systematically investigate the effect of R&D on bankruptcy. I propose two channels through which R&D might influence bankruptcy. The first channel is related to the high intrinsic risk of R&D. It is associated with both larger positive outcomes and larger negative outcomes. It increases expected firm value, as emphasized by earlier research, but it also increases the variance of firm value. The likelihood of an outcome that is bad enough to induce bankruptcy could therefore be increased by R&D.

The second channel is related to the information asymmetry arising from R&D. R&D creates few tangible assets; it creates assets that are more difficult for outsiders to value than for insiders. Thus R&D would enhance the information asymmetry associated with outside financing. Without easy access to external capital, R&D intensive firms are less likely to survive a negative shock, holding other factors constant. Based on these two channels, R&D should increase the risk of bankruptcy. The empirical results confirm my hypothesis. Specifically, based on a large dataset of US public firms, I find that, holding other things equal, more R&D is always associated with a greater likelihood of bankruptcy. Furthermore, I empirically examine how R&D is positively related to bankruptcy. My results show that both firm-value volatility and information asymmetry play an important role in explaining the effect of R&D on bankruptcy.

In Chapter 2, I extend the basic analysis of Chapter 1 to consider the effect of economic downturns on the relationship between R&D and bankruptcy. If R&D could induce bankruptcy, R&D intensive firms should have the greatest operational difficulty during economic recession. I hypothesize that R&D effects on bankruptcy would be magnified during downturns. On the other hand, Schumpeter's creative destruction argument implies that a recession might have positive effects as the market destroys the losing, less innovative companies and reallocates resources to the winning companies that undertake successful innovation. In this paper, I examine whether firms' R&D decisions during recessions have a significant effect on performance. My analysis suggests that companies taking a more aggressive posture in increasing R&D during recessionary periods enjoy stronger sustained operating performance.

There are potential endogeneity issues associated with the finding that R&D leaders during recessions have significantly better post-recession performance. High performing firms might be more likely to invest in R&D during recession. Thus good performance might, in effect, cause more R&D rather than the reverse. To minimize this problem of reverse causality, I measure ex ante financial performance one year before the recession started and control for the lagged variables in the model to examine whether R&D strategies during recession could make a difference. The results are robust to controlling for firms' pre-recession performance. The increase in R&D during the recessionary period still has a significantly positive impact on the future corporate performance, though the magnitude of the effect becomes smaller. These results suggest that reverse causality is not a major issue.

Chapter 1 shows that R&D could increase firm risk and focuses on the low end results associated with R&D. Chapter 2 turns the attention to the high end of the outcome distribution of R&D and show that during downturns innovators have a greater chance of achieving better performance. The fact that R&D leaders have a greater chance of going bankrupt but they also have a greater chance of achieving better performance simply shows that R&D is very risky.

In Chapter 3, I move focus to mergers and acquisitions (M&A). M&A transactions are often a substitute for firms' internal R&D. In many cases, technology required for industrial purposes is available in the marketplace at some price. Before embarking on the lengthy and risky process of performing its own R&D, a company should perform a "make or buy" analysis. As inferred from Chapter 1, technology development is very risky because the technical success of R&D cannot be guaranteed. On the other hand, acquiring technology entails less risk, since the product or process can be seen and tested before the M&A contract is signed. Chapter 3 examines the role of patent citations in M&A transactions. I find that if two firms often cite each other's patents, the two firms are more likely to end up in an M&A transaction.

I further find that the existence of citation links between acquirer and target firms prior to M&A deal is positively related to acquirers' announcement returns and post-merger performance. The empirical results support the hypothesis that citation links give acquiring firms an information advantage about the quality of a match between two firms. Thus the presence of citation links between acquirer and target firms would indicate high quality deals, and there is a greater chance for a smooth post-deal integration. I also present evidence that the existence of a citation link between two firms has a positive impact on the probability of a subsequent M&A transaction between them.

Overall, my research integrates two important literatures that should be much more integrated: the economics literature on innovation and the large corporate finance literature. The first two chapters examine the relationship between R&D and bankruptcy, linking the literature on innovation and the corporate finance literature on bankruptcy. Chapter 3 marries the standard corporate finance literature with other parts of economics to provide a deep understanding of the M&A process in high-tech sector. Each chapter is organized as follows: Section 1 provides an introduction; Section 2 reviews the literature that motivates the current study; Section 3 describes the data and sample statistics; Section 4 presents empirical results; and Section 5 conludes.

Chapter 1: R&D and Bankruptcy: Is there a Dark Side to R&D?

1.1 Introduction

The literature on R&D mainly focuses on its benefits with little attention being paid to its potential negative effects. The purpose of this paper is to understand the dark side of R&D, in particular, the influence of R&D on corporate bankruptcy.

R&D can increase the risk of bankruptcy through two channels. First, R&D is intrinsically risky. It is associated with both larger positive outcomes and larger negative outcomes—increasing the variance of firm value. Thus the likelihood of a sufficiently bad outcome to induce bankruptcy could be increased by R&D even if R&D increases the expected value of the firm. Second, R&D creates projects that are harder for outsiders to value than for insiders. Thus, R&D generates a potentially significant information asymmetry associated with financing. Without easy access to outside sources of financing, R&D intensive firms could not survive a liquidity crisis in which their cash reserves suddenly dry up. The central empirical prediction is that the R&D variable should have predictive power beyond other commonly used predictors of bankruptcy. Consistent with this prediction, I find a positive and significant relationship between R&D and the likelihood of going bankrupt, based on a large dataset of US public firms covering the 1979-2009 period.

The positive association between R&D and bankruptcy could be subject to two kinds of endogeneity problems. First, managers of distressed firms may be more inclined to undertake risky R&D projects in an effort to "turn the company around." Such an effect would make R&D an endogenous variable and would induce a positive correlation between R&D and bankruptcy even if R&D did not itself increase the risk of bankruptcy. Second, it is also possible that well-established "blue chip" companies are more likely to invest in R&D since they have deep enough pockets to absorb any negative effects from such risky investments. In this case, such bias would induce a negative correlation between R&D and bankruptcy, leading to an underestimate of the effect of R&D on bankruptcy. To correct for the possible endogeneity, I use industry and geographic median R&D as instrumental variables (IVs) for firm-level R&D. After the correction, the R&D variable is still significant and has a larger effect, suggesting a correction of downward endogeneity bias.

Furthermore, I empirically examine the mechanism by which R&D influences corporate bankruptcy. I find that both firm-value volatility and information asymmetry explain a large part of bankruptcy risk; after controlling for them, the magnitude of the R&D effect is greatly reduced.

To better understand the influence of R&D on firm risk, I investigate how R&D expenditures influence firms' operations in the long run. I first extend the horizon of detecting bankruptcy from one year to three years and find that the magnitude of the effect of R&D on bankruptcy becomes even greater, indicating that the effect could persist for a long time. Second, I investigate the future volatility of firms' operating performance and find that R&D intensive firms are associated with more volatile operating performance. Moreover, using market beta to measure firms' systematic risk, I find a positive relation between past R&D expenditures and firm beta in the next period. Finally, I find that firms with higher R&D expenditures are associated with abnormally large subsequent stock returns, which is consistent with the view that R&D increases firm risk and shareholders require an associated risk premium.

As a robustness check, I do an extensive quartile analysis based on various firm characteristics. I first sort firms into quartiles based on their financial soundness and conduct the sub-sample analysis. I find that R&D has a significant effect on each quartile. This shows that the positive association between R&D and bankruptcy is robust to firms' financial conditions. Further, when firms are sorted based on their stock return volatility and information asymmetry, I find that the positive and significant relationship between R&D and bankruptcy only exists in the quartiles of firms with acute information asymmetry and volatile stock returns. These results provide support for the hypothesis that R&D affects the likelihood of bankruptcy through both the volatility channel and information asymmetry channel.

It is important to understand the effect of R&D on bankruptcy risk for two reasons. First, as is well-established in the literature, bankruptcy has costs. It is not simply a costless transfer of control over assets from equity holders to creditors. Direct costs include lawyers' and accountants' fees, other professional fees, and the value of the managerial time spent in administering the bankruptcy. Warner (1976) finds the direct cost of bankruptcy for large, publicly-held corporations averages 5.3 percent of the market value of the firm. There are also indirect costs of bankruptcy. Altman (1984) emphasizes that bankruptcy disrupts firm-customer and firm-supplier relationships, causing firms to lose sales and profits. Moreover, high risk firms may be less likely to obtain credit or to issue securities to fund new growth opportunities that would otherwise be worthwhile. If these costs are large enough and if the effect of R&D on bankruptcy is large enough, these effects would perhaps temper the enthusiasm of policy makers for policies that are intended to promote R&D, such as subsidies or very protective intellectual property regimes. In addition, it might be possible to gain insight regarding how to efficiently mitigate the effects of R&D on bankruptcy, either at the corporate level or at the public policy level.

To the best of my knowledge, this is the first paper to systematically investigate the effect of R&D on bankruptcy. Prior studies have focused on the positive association between R&D and firm performance while leaving the "dark side" of R&D under-explored. Franzen et al. (2007) show that R&D intensive firms are more likely to be falsely classified as financially distressed due to the conservative accounting treatment of R&D. My paper examines whether R&D is actually related to bankruptcy directly and shows that, when all else is equal, more R&D is associated with a greater likelihood of bankruptcy.

1.2 Literature Review

There is a large literature showing R&D investments create value for firms. The market value of traded firms is positively affected by R&D investments (e.g., Jaffe, 1986; Cockburn and Griliches, 1988; Hall, 1993). Stock prices react positively to announcements of new R&D investments (e.g., Woolridge and Snow, 1990; Szewczyck et al., 1996). This paper, in contrast, analyzes a potential negative effect of R&D investment.

The Booz-Allen-Hamilton Global Innovation 1000 study (2006) demonstrates that increased spending on R&D does not necessarily correlate with successful commercialization. The study reports that of the 1,000 companies reviewed, 94 (including Google and Apple—perhaps the two best-known firms in the information technology sector) consistently outperformed their peers in key performance measures while spending less than median firms in their respective industries on R&D as a percentage of sales. In addition to the knowledge stock generated by R&D, various other assets are necessary to the success of the company. Most firms that undertake R&D also carry out production of the resulting products. Bringing products to market requires other assets' support, such as marketing, sales, operational and administrative work. Thus, the return to R&D could be limited by other assets. Given such limits, we might not get a better result with just more and more R&D alone. There should exist an optimal level of R&D intensity at which point a firm is able to maximize its performance. Similar to the optimal capital structure, which balances the tax advantages and bankruptcy costs of debt financing, to find the optimal R&D intensity we need to examine its costs, as well as the benefits widely studied in prior literature.

I believe this is the first paper to relate R&D to bankruptcy and show that more R&D is associated with a higher likelihood of bankruptcy. Prior studies have examined the relationships between R&D and bankruptcy predictors, such as return volatility and information asymmetry, but they have not provided empirical studies on whether R&D is directly related to bankruptcy. There are two reasons R&D could be associated with bankruptcy. First, R&D increases the riskiness of the firm. The empirical findings of Chan et al. (2001) suggest that R&D intensity is positively correlated with stock return volatility. Fung (2006) provides an analytical framework for such a relationship and argues that R&D leads to high degree of uncertainty surrounding firms' future prospects. The prospects of R&D intensive companies, particularly those that have few tangible assets, are tied to the success of new, untested technologies and thus are highly unpredictable. Fixed expenditures on R&D are usually initially required to develop a new technology or a new product, but the outcome is far from assured. The return to R&D, if any, is likely to take a long time to materialize, and the profitable part of the lifecycle of the resulting process or product might be short in the face of fast-changing technology. Fixed expenditure commitments offset by uncertain revenues therefore increases the risk of the cash flow. As a result, the increase in operating leverage resulting from R&D activities might increase the firm-value volatility.

Second, R&D will enhance the information asymmetry of the firm. Uncertainty often results in information asymmetry. Aboody and Lev (2000) show that R&D activities contribute substantially to the information asymmetry between managers and investors. Corporate executives frequently have better information about the likelihood of success and the nature of the contemplated innovation project than outside investors do; therefore, the financing of R&D-intensive firms faces a similar set of incentive misalignments as those outlined in the "lemons" (adverse selection) problem modeled by Akerlof (1970). The lemons' premium for R&D-intensive firms will be higher than that for ordinary firms, because investors have more difficulty distinguishing good firms from bad when the associated projects are long-term R&D investments rather than short-term or low-risk projects (Leland and Pyle, 1977). Reducing information asymmetry via full disclosure has limited efficacy due to firms' reluctance to reveal their innovative activity to the market. There could be a substantial cost in doing so as it risks revealing the same information to their competitors (Bhattacharya and Ritter, 1983). Thus the implication of asymmetric information coupled with the costliness of mitigating the problem is that R&D-intensive firms will face a higher cost of external capital versus internal capital.

In addition to a relatively high cost of capital, information asymmetry arising from R&D would limit firms' access to credit. Debt is not a good financing source for R&D. On average, R&D-intensive firms tend to have lower leverage than other firms. The knowledge assets created by R&D investments are intangible, partly embedded in human capital, and usually specialized to the particular firm in which it resides; however, banks and other debt holders prefer to use physical assets to secure loans. Thus, lenders are reluctant to lend when the project involves investment in substantial R&D rather than in tangible assets, such as plant and equipment. In addition, debt financing usually requires a stable source of cash flow, which makes it more difficult for R&D-intensive firms that often see little or no cash flow for long periods of time until R&D materializes into revenue-generating assets. For both of these reasons, R&D firms are either unable or reluctant to use debt financing.

R&D investment adds more uncertainty to firms, leading to higher firm-value volatility and higher information asymmetry between insiders (managers) and outsiders (investors). Both high firm-value volatility and high information asymmetry expose firms to higher bankruptcy risk. I hypothesize that R&D would increase the likelihood of bankruptcy.

The work of Eisdorfer and Hsu (2009) could be most related to my study. They used patent data to show that technology competition could drive firms to bankruptcy and argue that firms taking part in unproductive R&D are more likely to go bankrupt. My paper, however, takes a further step to ask whether the ex-ante R&D decision is associated with bankruptcy.

Trajtenberg (1990) shows that patent-based metrics are better at measuring the innovative activity of the firm. In contrast, this paper focuses on R&D expenditures for the following reasons: first, not all firms patent their innovations, either because some inventions do not meet the patentability criteria or because the inventor is relying on secrecy or other means to protect its innovation; and second, patents only measure successful innovations. It is not possible to use patent data to study the innovation risk and uncertainty without incurring a very substantial selection bias.

1.3 Data and Model Specification

1.3.1 Sources

I define a firm as bankrupt if it is delisted from the exchange on which it trades due to poor performance. I do not look at bankruptcy filings under either Chapter 7 or Chapter 11 of the bankruptcy code, because it is hard to get a complete database of bankruptcy filings. It is normal to use delistings as an ex-post financial distress measure, as in Campbell et al. (2008) and Shumway (1997). This operational definition of "bankruptcy" captures firms that perform so poorly that their stocks are delisted from the exchange, an event that often precedes bankruptcy. I obtain the delisting data from CRSP and keep only those delistings that are due to bad performance (delisting codes 400-599). Arguably, such delistings might be a better measure of the general failure that I am trying to capture than formal bankruptcy filings would be. At a minimum, these delistings are closely correlated with any reasonable concept of firm failure.

My sample period is from 1979 to 2009. I choose 1979 as the earliest year for identifying bankruptcy because the Bankruptcy Reform Act of 1978 allowed for greater strategic use of bankruptcy, significantly broadened what constitutes a valid claim, combined Chapters X, XI and XII into a single Chapter 11, and thus became more debtor-friendly. Such a substantial law change likely caused the associations between R&D decisions and bankruptcy to shift. Furthermore, U.S. GAAP was changed in 1974 to require firms to immediately expense their R&D expenditures.[1] For the above two reasons, I restrict my tests to the period from 1979 to 2009.

For my analysis, I augment the sample of bankrupt (de-listed) firms by including all the firms in Compustat which had not gone bankrupt. The full sample includes all U.S. public firms that had common shares traded on the NYSE, AMEX, or NASDAQ exchanges during my sample period. Firms that incorporated outside the United States are excluded. Financial firms (SIC codes 6000-6999) and utility firms (SIC codes 4900-4999) are also excluded from the sample due to differences in regulatory oversight for these industries.

1.3.2 R&D Sectors

This paper studies the effect of R&D on bankruptcy, so firms in industries that do not engage in R&D activity at all are excluded. I use four-digit SIC industries as the base for this screen and define R&D industries as industries that have at least one public firm reporting R&D expenditures. Firms in other industries are excluded. This screening process eliminates about 1% of firms. The final sample is 17,556 firms, with 189,669 firm-years.

Among the key variables of interest in my analysis are the proxies for firms' R&D intensity. The first measure I use is the ratio of R&D expenditures to the book value of total assets. Following the literature (e.g., Lerner, 2006), I assume that any firm that reported total assets

[1] Statement of Financial Accounting Standards, SFAS, No. 2, 1974

but did not report R&D expenses had no R&D expenses in that year. The second variable used to proxy for R&D intensity is the ratio of R&D expenditures to sales. Although I focus primarily on results using the R&D/assets variable, my qualitative findings throughout remain the same when I use the R&D/sales variable instead.

The average R&D/assets ratio in my sample is 0.06 and median is 0. Only 41.4% of firm-years have R&D expenditures, even after restricting the sample to R&D industries. To test whether R&D intensity plays a different role for bankruptcy in industries that are R&D-intensive, I consider a subset of firms in what I define as the "high-tech sector."

Despite general agreement on the characteristics of high-tech firms, there is no consensus on precisely which industries should be classified as high-tech. Here, I follow Brown et al. (2009) and use the official definition of high-tech industries offered by the United States Department of Commerce.[2] More specifically, the high-tech sector consists of firms from the following seven industries defined by three-digit SIC codes: drugs (SIC 283), office and computing equipment (SIC 357), communications equipment (SIC 366), electronic components (SIC 367), scientific instruments (SIC 382), medical instruments (SIC 384), and software (SIC 737). The mean (median) R&D/assets ratio for the high-tech sample is 0.15 (0.08) and 77.7% of high-tech firms are shown to have R&D expenses in an average year.

1.3.3 Control Variables

All the financial variables come from CRSP/Compustat Merged Database[3]. I require that firms in my sample have positive assets for each year they are in the data set.

First, I control for fundamental firm characteristics that would affect a firm's risk by using firm size and book-to-market ratio. Fama and French (1992) show that size and book-to-market effects can explain the differences in stock returns beyond a stock's market beta. I use

[2] "An Assessment of United States Competitiveness in High-Technology Industries," United States Department of Commerce, February 1983, International Trade Administration.
[3] The CRSP/COMPUSTAT Merged Database allows for concurrent database access to CRSP's stock data and Standard & Poor's Compustat fundamental data.

the natural logarithm of book value of assets as a measure of firm size. I do not use the measure `of market capitalization because there would be large declines in the market value of equity prior to bankruptcy.

Second, I control for leverage. I compute leverage as the ratio of total debt to the book value of total assets. Book measures of leverage are more appropriate than market values here, as large declines in the market value of equity prior to bankruptcy would drive up the market leverage even when the underlying level of liabilities did not change. Leverage for R&D intensive firms is generally lower than for firms that do less R&D. Such low leverage capital structure could lead to a decrease in bankruptcy likelihood. Failure to control for leverage would therefore cause omitted variable bias in the direction of underestimating the effect of R&D intensity on bankruptcy.

Moreover, R&D intensive firms would increase their cash holdings when their cash flows become riskier. Bates et al. (2009) show that R&D intensive firms tend to hold more cash due to this precautionary motive. To examine the marginal effect of R&D on bankruptcy, I control for the availability of liquid assets as measured by cash plus marketable securities, scaled by the book value of total assets. I refer to this variable as the cash ratio. I expect a negative relation between the cash ratio and the likelihood of bankruptcy.

I include year fixed effects to control for macroeconomic factors. I also control for two-digit SIC industry fixed effects to account for the industry variations on the likelihood of a firm going bankrupt. Also, as my regressions use firm-level time series and cross-sectional data, the standard errors are clustered by firm to correct for heteroskedasticity and serial correlation.

1.3.4 Empirical Specification

The econometric model is illustrated as follows:

$$\Pr(Bankrupt_{i,t}) = \Phi(\beta RD_{i,(t-3,t)} + \gamma Z_{i,t-1} + \mu_j + \mu_t)$$

where $Bankrupt_{i,t}$ is a dummy equal to one if firm *i* went bankrupt at year *t*, and zero otherwise. Φ is the cumulative standard normal distribution function. $RD_{i,(t-3,t)}$ denotes firm *i*'s R&D variables over the previous three years. $Z_{i,t-1}$ denotes control variables at year *t-1*. Finally, μ_j and μ_t denote two-digit SIC industry dummies and year dummies to capture industry and time fixed effects respectively.

I use the mean of R&D intensity over the previous three years to predict bankruptcy. Compared to using the one-year lag of R&D to predict bankruptcy, including a three-year lag and a two-year lag partially alleviates the reverse causality concerns that firms with high bankruptcy risk would do more R&D to turn around their struggling businesses. For each firm-year, I require that firms have financial data available over the previous three years. In this way, I eliminate firms that existed in Compustat for less than three years. Such firms fall into two categories: those that went bankrupt less than three years after appearing in Compustat and those that were newly listed in 2007 or later. For the former, we don't have enough data to analyze what lead to their bankruptcy. For the latter, it is unlikely to have enough time to observe a meaningful outcome. I realize that such methodology could introduce survival bias in that the firms that survive might have different characteristics than those that survived for less than three years. In robustness checks, I keep all the firm-year observations. This does not affect the results significantly, suggesting that survival bias is not a major problem.

1.4 Empirical Results

1.4.1 Descriptive Statistics: Distribution of Bankruptcy Rates

Table 1.1 reports the distribution of bankruptcy rates from 1979-2009. As the table shows, the average annual bankruptcy rate is 1.7%, slightly higher than the 0.97% reported in Hillegeist et al. (2004). The latter identifies 756 bankruptcy filing over the 1980-2000 period; in contrast, this paper has 3,187 performance-related delistings. The data indicates that the annual failure rates generally reflect the overall health of the economy. The bankruptcy rate reached a peak at 3% in 1991, 2001 and 2009, the years of last three economic downturns.

Surprisingly, firms in the high-tech sample have a lower bankruptcy rate with an average of 1.54%. The possible explanation is that R&D intensive industries have higher entry barriers, which mitigate competition and protect existing firms from new entrants.

I further divide the sample into two groups: R&D firms and zero-R&D firms. Zero-R&D firms are defined as those which did not do any R&D in the previous three years. Firms that reported positive R&D during the previous three years are classified as R&D firms. Within the high-tech sample, I find that R&D firms have a higher bankruptcy likelihood than zero-R&D firms. The differences between the two groups of firms are significant at the 1% level. This univariate comparison is in line with my prediction that firms with higher levels of R&D should be more likely to go bankrupt.

However, for the full sample, zero-R&D firms have a slightly higher average bankruptcy likelihood than R&D firms, which could be due to the industry effects on bankruptcy risk. Because of the competition mitigation effect of R&D, firms in R&D intensive industries have a lower bankruptcy likelihood than firms in low-tech sectors. On the other hand, R&D has the risk effect. R&D expenditures are discretionary expenditures, producing no tangible asset and having high degree of uncertainty. To analyze the innovation risk itself, we have to separate the competition mitigation effect. In addition, firms are more likely to compete with firms in the same industry. Therefore, in the multivariate analysis, I control for industry fixed effects. All the estimates are therefore driven by within-industry variation.

1.4.2 Descriptive Statistics: Firm Characteristics

Table 1.2 provides preliminary evidence that firms with higher levels of R&D tend to be more likely to go bankrupt. I present descriptive statistics for bankrupt firms as opposed to the firms that had not gone bankrupt. As indicated by the mean values reported in panel B, bankrupt firms are smaller (with assets of $0.16 billion vs. $1.08 billion per year), have a lower book to market ratio[4] (0.34 vs. 0.54), higher leverage (0.40 vs. 0.31), and a lower cash ratio (0.15 vs. 0.18) than firms that had not gone bankrupt. Importantly, bankrupt firms have higher levels of R&D intensity, both in R&D/assets (0.08 vs. 0.05 per year) and R&D/sales (0.53 vs. 0.30 per year) than surviving firms. The differences in various statistics between the two groups of firms are significant at the 1% level.

As shown in Table 1.2, there are 3,187 bankruptcies identified over the sample period, accounting for only 1.7% of the full sample. A concern therefore arises that the large number of zeros for the bankruptcy dummy may create a problem when the variable is used as a dependent variable. The lack of variation in the dependant variable might lead to inefficient estimates. To address this concern, I construct a matched sample for bankrupt firms.

1.4.3 Descriptive Statistics: Matched Sample

For each bankrupt firm, I first identify the set of all firms that had the same four-digit SIC code but did not go bankrupt over the sample period. Next, I choose the firm whose size is closest to that of the bankrupt firm and within its 30% size band as the matching firm, using total assets as the size measure. If there is no matching firm found in the associated four-digit SIC industry, I turn to matches based on three-digit SIC codes and then on two-digit SIC codes.

Using this matching methodology adopted in Bodnaruk et al. (2009), I find a matched sample of 2,662 firms for 2,743 bankrupt firms.[5] I match the sample based on size and industry since it is more likely that firms in the same industry and with the same size compete with each other. An alternative matching methodology is random sampling. Random sampling would give each firm in the sample an equal chance to be chosen. Random sampling is more efficient if the sample is sufficiently large. However, if we do random sampling when we

[4] I got 11.1% of data with negative book-value equity. One possible reason for negative book equity is that firms in financial distress typically accumulate negative retained earnings. It can also occur when high-tech firms use patents to raise capital, but the patents' value is not fully recorded on balance sheet. I can not discard those negative equity firms because they represent 22% of the bankrupt firms. However, the results are robustly similar while dropping all those negative book equity observations.

[5] The number of matching firms is not equal to the number of bankrupt firms since some matching firms are chosen more than once.

have a small sample, it is quite possible that the comparison group might differ systematically from the bankruptcy group. Any difference between the two groups could thus be due to the selection bias that is often incurred in a small sample. This bias can be reduced or eliminated if observations in the comparison group are selected to match the bankruptcy group on some variables. Based on the existing literature, such as Kupper et al. (1981) and Bodnaruk et al. (2009), selection of the comparison group by matching sampling is preferred in this case.

Table 1.3 presents the descriptive statistics for the matched sample. Compared to the matching firms, bankrupt firms have a higher R&D intensity in terms of R&D/assets and R&D/sales. The differences in R&D intensity are in line with my expectation.
Finally, in Table 1.4, I present the pairwise correlations between key explanatory variables. As is indicated in the table, there is little evidence of collinearity among my variables. Next I turn to multivariate analysis for more meaningful comparisons.

1.4.4 R&D and Likelihood of Going Bankrupt

In Table 1.5, I report the first set of regression results. I use a probit regression to relate R&D to the likelihood of going bankrupt, controlling for various firm characteristics. The dependent variable is a dummy equal to one if the firm went bankrupt in a given year, and zero otherwise. The key explanatory variables are two proxies for firms' R&D intensity: R&D/assets and R&D/sales. Columns (1)-(2) are regressions using a full sample. Columns (3)-(4) are restricted to the high-tech sample, while Columns (5)-(6) are based on the non-high-tech sample. Columns (7)-(8) are regressions using the matched sample. Columns (9)-(10) are for a positive R&D sample which eliminates zero R&D observations. All regressions in this table are estimated with year and industry fixed effects, and the reported standard errors are heteroskedastic consistent and clustered by firm.

My results demonstrate that R&D is positively associated with bankruptcy likelihood. Consistent with my prediction, I find that the estimated coefficients on R&D/assets and R&D/sales are positive and significant at the 1% level in all columns except for the non-high-tech sample. In Column (1), the coefficient of R&D/assets is 0.01, indicating that controlling for other factors at their mean levels, a one standard deviation increase in R&D/assets (0.14) is associated with an increased bankruptcy likelihood of 0.14% as compared to the average firm in its industry (the mean probability of bankruptcy in the full sample is 1.7%). Using R&D/sales as an alternative measure for R&D intensity in Column (2), I find similar results. The coefficient of R&D/sales is 0.001. A one standard deviation increase in R&D/sales (1.62) predicts a 0.16% increase in the probability of bankruptcy.

In Columns (3)-(4), I restrict attention only to innovative industries and find qualitatively similar though stronger results: e.g., the coefficient estimate on R&D/assets in Column (2) with the entire sample is 0.010 vs. 0.019 in Column (3). This suggests that the relationship might be more important for industries in which the firm needs to engage in R&D activity to differentiate its products from others. In other words, the innovation risk for firms in the high-tech sector is larger and more important. The coefficient of R&D/assets (R&D/sales) is 0.019 (0.001), implying that a one standard deviation increase in R&D/assets (R&D/sales) predicts an increased bankruptcy likelihood of 0.38% (0.26%). The mean probability of bankruptcy in the high-tech sample is 1.5%. Thus a standard deviation increase in R&D/assets is associated with a 25% increase in the bankruptcy likelihood as compared to the average firm in the high-tech sector.

In Columns (5)-(6), I run regression on the non-high-tech sample. Surprisingly, the estimated coefficient on R&D/assets in Column (5) is negative and significant. The estimate on R&D/sales in Column (6) is positive though insignificant. The results in Columns (5)-(6) show that firms that did more R&D in non-high-tech sectors are not more likely to go bankrupt. However, in interpreting these results we must consider two sources of potential endogeneity. First, firms in financial distress might be more likely to take risky R&D projects in anticipation of winning a big bet and turning the firm around. That could lead to a positive association between R&D and bankruptcy likelihood even if R&D itself did not increase bankruptcy risk. Second, successful firms might be more likely to do R&D since they have deep pockets and can more readily afford such investments. The non-high-tech sample suffers more from the second endogeneity problem. Since R&D is not necessary in the non-high-tech sector, only firms that can afford risky investment would do R&D to improve on perfection. I employ instrumental variable (IV) methods to address these concerns in next section.

Columns (7)-(8) show a positive association between R&D expenditures and bankruptcy likelihood based on the matched sample. Using a matched-pairs sample produces more efficient parameter estimates than using the full CRSP-Compustat population would, given the very small fraction of bankrupted firms in the population (Manski and Lerman, 1977). The coefficient of R&D/assets (R&D/sales) is 0.049 (0.003), implying that a one standard deviation increase in R&D/assets (R&D/sales) predicts an increased bankruptcy likelihood of 0.69% (0.49%). The mean probability of bankruptcy in the matched sample is 6.5%.
For Columns (9)-(10), I run regression on the positive R&D sample. The result that the estimates on R&D intensity variables remain to be positive and significant implies that the positive association between R&D and bankruptcy is not all driven by variation between zero R&D and non-zero R&D.

Table 1.5 also shows that the cash ratio is negatively related to bankruptcy likelihood, while leverage is positively correlated. In unreported results, without controlling for cash and leverage in the regression, the estimated effect of R&D on bankruptcy remains significant but smaller. It suggests that higher cash reserves and lower leverage could mitigate the effect of R&D on bankruptcy. The goal of this paper is to look at whether R&D increases risk for firms. It is interesting to see the extent to which R&D in itself affects bankruptcy risks when holding other factors, such as leverage and cash, constant— the partial or marginal effect of R&D. However, it is also of interest to consider the full effect that arises even when leverage and cash are allowed to vary.

1.4.5 Endogeneity Concerns

While the primary results as shown in Table 1.5 point to a positive relationship between R&D and bankruptcy likelihood, we have to be concerned about potential endogeneity issues. Perhaps, for example, the likelihood of bankruptcy affects R&D— endogeneity of the reverse causality type. Managers of firms in distress could be more risk-taking and thus more willing to undertake risky projects, like investments in R&D. If so, it would be wrong to interpret the coefficient on R&D as showing the effect of R&D on bankruptcy. On the other hand, it is also possible that financially safe companies ("blue chip" companies) are more likely to do R&D since they can more readily afford such risky investments. Such effects might cancel out any positive relationship between R&D and bankruptcy. In this case, the effect of R&D on bankruptcy would be underestimated. In this section, I address the endogneity issue by estimating an instrumental variables version of the model. The instruments are variables that affect firm's R&D intensity but that are not related to bankruptcy likelihood directly.

Instruments for R&D should explain the firm's R&D intensity and should be exogenous with respect to bankruptcy likelihood in the sense that they are uncorrelated with the error term in the primary regression. If these two conditions are met, using an instrumental variable allows identification of an exogenous probit component of R&D. I construct two such instrumental variables and run an IV- model[6] with a bankruptcy indicator variable as the dependent variable.

The first instrument is industry-median R&D. I construct the industry-median R&D intensity based on four-digit SIC codes for each firm, excluding the firm's own R&D. If there are only two firms within a four-digit SIC code, I use three- digit SIC codes instead. About 99% of firms in my sample use 4-digit SIC industry median as IVs, 0.6% of firms use three-digit SIC industry median, and 0.4% of firms are assigned missing value for the industry IV. I argue that industry R&D would affect a firm's R&D choice, but we do not have any theoretical argument or empirical evidence to show that it will change firms' idiosyncratic distress risk, except through their own R&D choice.

Similarly, I construct geographic-median R&D IVs as the second instrument based on county and state[7]. For each year, I calculate the median R&D intensity by each county and state and

[6] IV-Probit model is a probit model with continuous endogenous regressors.

[7] The county and state are where the "chief executive office" or "headquarters" of the company were located. Data is obtained from Compustat.

match with each firm. I first use county-median R&D as an IV for firm-level R&D. If there are only two firms in the county or the value for county variable is missing, I revert to a state-median R&D. If neither is available, I assign a missing value to the geographic IV. It turns out that 93% of firms use county-median as IVs and 6% of firms use state-median as IVs. Again, there is no reason for us to believe that this variable is related to a firm's bankruptcy likelihood directly.

Estimation results are provided in Table 1.6. I run the IV-Probit model for the full sample and all the sub-samples as in Table 1.5 which provides estimates for the probit model without R&D intensity being instrumented. A comparison of the estimates of Table 1.5 and Table 1.6 suggests that the estimates of R&D intensity are statistically significant and larger in magnitude when the R&D variables are instrumented. A Hausman test (unreported) comparing the estimates in each column in Table 1.5 and Table 1.6 suggests that all differences are significant. In particular, the point coefficient estimate for R&D/assets in Column (1) in Table 1.6 is almost twice that of the estimate in Column (1) in Table 1.5. Similarly, the point estimate for R&D/sales in Column (2) of Table 1.6 is twice that of the estimate in Column (2) of Table 1.5.

After using IVs in regressions, the estimated coefficients on R&D intensity based on non-high-tech sample in Column (5)-(6) are positive and significant. A comparison of the magnitudes of estimate in probit models and IV-Probit models suggests that failure to adjust for endogeneity of R&D leads to an underestimate of the effect of R&D on bankruptcy when using a simple probit model. In unreported results, I find that both the instruments are significant predictors of a firm's R&D. Importantly, the F-test rejects the null that the coefficients on both instruments are jointly zero. Moreover, the test of over-identifying restrictions fails to reject the joint null hypothesis that my instruments are uncorrelated with the error term and are correctly excluded from the second-stage regression. This downward bias suggests that the first endogeneity concern—that firms with high bankruptcy risk would do more R&D—is not a problem. On the contrary, there is some evidence that firms in a sound financial position would do more R&D.

1.4.6 Two Possible Channels through which R&D affects Bankruptcy

In this section, I examine empirically how R&D is positively related to bankruptcy. I propose two channels through which R&D could be related to bankruptcy: the firm-value volatility channel is related to the high intrinsic risk associated with R&D activities, and the second channel is related to information asymmetry arising from R&D.

The firm-value volatility channel is straightforward. High uncertainty in R&D leads to high uncertainty in firms' future prospects, thus contributing to greater volatility in firm value. For example, pharmaceutical firms' stock prices increase sharply if one of their R&D projects turns out to be a success, and plunge if there is a critical failure. Campbell et al. (2008) show that firms with more volatile past stock returns are more likely to file for bankruptcy. Volatility is a crucial variable in bankruptcy prediction because it captures the likelihood that the value of the firm's assets will decline to such an extent that the firm will be unable to pay its debts. The probability of bankruptcy is increasing with volatility. An important deficiency of accounting-based bankruptcy prediction models, such as the models in Altman (1968) and Ohlson(1980), is their failure to incorporate a measure of volatility. I use stock return volatility and cash flow volatility as measures of firm-value volatility in the empirical analysis.

The second channel I propose is the information asymmetry channel. Firms know more information about the R&D assets than do outsider investors. The reduced visibility of R&D assets would increase information costs and thus increase the cost of capital for R&D intensive firms. Given lower asset tangibility, R&D investment opportunities are costly to finance using external capital, so R&D intensive firms require a greater cash buffer against negative shocks. Once R&D is not productive and cash is used up, it is difficult for R&D intensive firms to survive negative shocks. Both Alam and Walton (1995) and Zantout (1997) find higher abnormal returns to firm shares following new debt issues when the firm is more R&D-intensive. The argument is that the market reacts positively to a firm obtaining new sources of financing when the firm has an asymmetric information problem because of its R&D strategy. In other words, R&D could limit firms' access to credit with information asymmetry arising from R&D. Without easy access to external financing, during a cash crunch following a negative shock, R&D intensive firms would be vulnerable to potential bankruptcy.

I use three different measures of information asymmetry in the empirical analysis. The first is the forecast error in earnings. Analysts' earnings forecasts are obtained from the Institutional Brokers Estimate Systems (IBES). I measure forecast error as the ratio of the absolute difference between the median forecast earnings and the actual earnings per share to the price per share at the end of the year. Firms with larger levels of information asymmetry between managers and the outside market about their cash flows and value are expected to have higher forecast errors.

The second measure of information asymmetry is the standard deviation of all earnings forecasts. This variable represents the dispersion among analysts about a consensus estimate of the forecast. Such disagreement among analysts could be an indication of the lack of available information about the firm, so it could be a metric of the level of information asymmetry about the firm.

Finally, following Dierkens (1991) and Krishnaswami et.al (1999), I use the volatility in three-day abnormal returns around quarterly earnings announcements as the third measure of information asymmetry about that firm and year. The quarterly earnings announcement dates are obtained from Compustat. I use the CRSP value-weighted index to compute the market-adjusted cumulative abnormal returns in a (-1, 1) window around the announcement dates. The market model is estimated within a (-200, -60) event window relative to the announcement date. A strong positive or negative reaction by the market around an information-revealing event such as an earnings announcement suggests that information asymmetry is high for these firms.

The correlation matrix in Table 1.7 shows that stock return volatility and cash flow volatility, the two firm-value volatility measures, and all three information asymmetry measures are positively related to bankruptcy likelihood and R&D intensity. Table 1.8 shows that stock return volatility measures explain a part of bankruptcy risk by increasing the explained variation from 16.2% to 17.3%. Controlling for information asymmetry measures increases the explained variation further to over 20%. The estimated coefficients on R&D intensity become much smaller, after controlling for stock return volatility and information asymmetry measures. However, R&D still remains a significant predictor of bankruptcy in all regressions. All these results provide support for the hypothesis that R&D may influence corporate bankruptcy through both of the volatility and information asymmetry channels.

To further identify the channels, I decompose volatility and information asymmetry into two components: one related to R&D and one unrelated to R&D. To deal with volatility, In a two-step process to deal with volatility, first I run regression of volatility on R&D and construct the component that is predicted by R&D. The residual is the unpredicted component. In the second step, I run a regression of the probability of bankruptcy on the two components related and unrelated to R&D to see how important R&D is. The results of the two-step process are reported in Table 1.9. It seems that both predicted volatility and unpredicted volatility have a significantly positive impact on the bankruptcy likelihood. The logic of the argument is that R&D contributes to volatility and, through this channel, increases the risk of bankruptcy. By isolating the part of volatility due to R&D, we identify this effect; other types of volatility also contributes to bankruptcy risk. The results are similar with the information asymmetry decomposition components.

1.4.7 Effects of R&D on a Firm's Long-Run Operation

To test how R&D would affect firms' long-run outcomes, I first extend the horizon of detecting bankruptcy from one year to three years. Then I examine the effect of R&D on the volatility of firms' future operating performance. I use return on assets (ROA) as a measure of firm's profitability. Table 1.10 shows that in all models, R&D is a significant predictor for firm risk. Its estimated coefficient in Column (1)) is even larger than those in short-run bankruptcy prediction models. It suggests that R&D effects could persist in the long run. In Column (2), I find that R&D has a significant and positive effect on the ROA volatility.

Furthermore, I use market beta as an additional measure of firm risk. Market beta is computed using a market model against the CRSP value-weighted index. I take the average of the next three years' market betas as a measure of the firm' market risk. Lev and Sougianris (1996) show that R&D is positively related to subsequent stock returns, suggesting either a mispricing of the shares of R&D-intensive firms or compensation for the extra-market risk associated with R&D. I empirically test whether R&D risk contains systematic risk. In Column (3) of Table 1.10, I find that R&D is positively associated with firms' market beta. The positive and significant association implies that R&D intensive firms could bear higher systematic risk. To further test this possibility, I investigate whether R&D intensive firms are associated with higher subsequent stock returns.

To assess long-term stock market performance, I calculate cumulative risk-adjusted abnormal returns (CARs) over one-year and three-year horizons using the Fama-French three-factor model. To avoid excluding delisting firm-years, I compound delisting returns with standard returns. A delisting return is the return on a security after it has been removed from a stock exchange. CRSP provides delisting returns computed from liquidation payments or from other information about the value of the security after delisting. CRSP allows up to ten years after the delisting to learn the delisting return and updates the records as needed. Following Beaver et al. (2007), I use multiple replacement values[8] for missing delisting returns. Table 1.10 indicates that, consistent with Lev and Sougianris (1996), high R&D firms exhibit abnormal excess returns. If the stock market is efficient, the higher subsequent return for R&D intensive firms might be, in effect, a risk premium for systematic risk. Thus this paper provides evidence that R&D risk entails a systematic risk component.

1.4.8 Evidence from Sub-samples

In this section, I conduct sub-sample analysis and compare the effect of R&D on bankruptcy for firms grouped by firm characteristics.

[8] I use the average daily delisting return for the corresponding 3-digit delisting code as the replacement value.

Brown et al. (2009) show that internal cash and stock issues are the primary sources of financing R&D expenditures. Relaxed financing constraints and increased finance supply would allow high-tech firms to raise R&D investment. Thus financially sound companies would do more R&D and have low bankruptcy likelihood. This effect might cancel out any positive relationship between R&D and bankruptcy likelihood. To overcome such endogeneity, I sort firms into groups based on their financial distress risk and run regressions separately by groups.

To measure the extent to which a firm is in financial distress, I use two proxies. The first proxy is firm size measured by the book value of total assets. I expect large firms to be less likely in financial distress. The second proxy is Altman's (1968) Z-score[9]. This Z-score is often used in literature to predict bankruptcy. It could be a good proxy for firm's financial distress risk. A low Z-score would indicate a high financial distress risk. For each year, I rank firms into quartiles according to their financial risk measures, and then estimate the model in each quartile. Controls include all the variables used in Table 1.5 and in each case, I estimate regressions with year and industry fixed effects.

Results reported in Table 1.11 demonstrate a positive and significant association between R&D and bankruptcy for each of the size quartiles and Z-score quartiles. For conciseness, I do not report the coefficients of the other control variables in the table. The estimates of these control variables are similar in sign and magnitude to those reported in the main table. The fact that we find a positive association between R&D and bankruptcy in all quartiles implies that the effect of R&D on bankruptcy likelihood is robust to firm's financial risk.

I further conduct sub-sample analysis by quartiles based on stock return volatility and announcement reaction. Table 1.11 shows that the positive and significant association between R&D and bankruptcy is mainly present in the quartiles consisting of firms with high information asymmetry or high stock return volatility. It suggests that stock return volatility and information asymmetry play an important role in explaining the effect of R&D on

[9] Following Altman(1968), I compute the Z-score based on the following model: Z-score =1.2*(working capital/total assets)+1.4*(retained earnings/total assets)+ 3.3* (earnings before interest and taxes/total assets) +0.6*(market value of equity/book value of total liabilities)+0.999*(sales/total assets).

bankruptcy likelihood. Without incurring acute information asymmetry or volatile stock returns, R&D has no effect on bankruptcy likelihood. This finding just provides support for the hypothesis that R&D could influence corporate bankruptcy through the pure volatility and information asymmetry channels.

1.4.9 Discussion

In the main specifications, besides the key variable of interest, I control for firm size, book-to-market ratio, leverage and cash ratio. I did not use profitability as a regressor even though it is often controlled in previous work on predicting bankruptcy. Profitability, if properly measured, must be almost a perfect predictor of bankruptcy. Bankrupty is, in essence, a failure of profitability. Everything should affect bankruptcy through profitability. R&D has an impact on bankruptcy because it affects profitability. R&D would increase the current costs and affect the expected future benefits. If the future benefits are not realized to compensate the past expenditure, firms are very likely to go out of business. In my model, I already controlled for book-to-market ratio, which is a good proxy for future profitability. If I control for current profitability as well and it is correctly measured, that would wipe out all the effects. We must allow for profitability to vary in some way to examine the effect of R&D on bankruptcy.

The definition of bankruptcy here is financial distress. I define a firm as bankrupt if it is delisted due to bad performance. I did not look at bankruptcy filing directly. First, it is difficult to get a complete database of bankruptcy filing over the sample period 1979-2009. Delisting is often an event that precedes bankruptcy. These delistings are closely correlated with bankruptcy filings. When I match my sample with the large firm bankruptcy filings database[10] over the same period, I find that all the bankruptcy filings are included in the sample. My sample covers 727 performance-related delistings with firms whose assets are over 100 million dollars, 93.1% of them filed for bankruptcy. Second, this operational definition of "bankruptcy" captures firms that perform so poorly that their stocks are delisted

[10] The Bankruptcy Research Database is provided by Lynn M. LoPucki who collected all Chapter 11 bankruptcy filings for firms with assets over 100 million in 1980 dollars from 1980 to 2006.

from the exchange even if they do not formally declare bankrutpcy. It might be a better measure of the general failure that I am trying to capture.

Leverage is used as a control in the main regressions. On the one hand, the goal of this paper is to look at the marginal effect of R&D, the extent to which R&D in itself affects bankruptcy risks when holding other factors, such as leverage and cash, constant. On the other hand, although lower leverage could mitigate the effect of R&D on bankruptcy, leverage may be not adjusted downwards by firms that plan to do a lot of R&D. There are substantial tax advantages associated with debt financing. At the very least, I control for industry fixed effects in the model. All the estimates are driven by variation within an industry. I assume there should not be big differences in industry peer firms' capital structure.

As to the functional form of R&D variable in the probit model, I use the linear form of R&D intensity. In unreported robustness checks, I test various nonlinear functions of R&D but the linear form seems to be a better fit. To address the endogenity of R&D, I estimate an instrument variable version of the model. The instrument variables should affect firms' R&D choice but not be related to firms' bankruptcy risk directly. Following Wooldridge (2002), Bergera et al. (2005) and Ortiz-Molina (2007), I use group (industry and geography) medians as instruments for R&D. Industry peer firms' R&D could stimulate more R&D from individual firms. Similarly, geographic neighboring R&D would also have a positive impact. However, in general the industry/geography medians should be influenced by the same industry/geographic shocks that influence the underlying firm-level R&D. If the underlying firm R&D is correlated with the error term, group medians would have the same property. Although group medians are not perfect instruments for individual R&D, they partially resolve the two endogenity problems of great concern— firms in financial distress or financially safe firms might be more likely to do R&D. The two possible endogeneities go in opposite directions, one leads to an overestimate of the effect of R&D on bankruptcy, and the other leads to an underestimate. Group medians could help identify R&D not caused by firms' idiosyncratic shocks. Furthermore, in unreported results, econometric tests fail to reject the hypothesis that the two group medians are valid instruments for R&D.

1.5 Conclusions

Prior research suggests that R&D is under-provided by the market because of well-understood market failures. A number of public policies have been implemented to stimulate R&D investment. The underlying rationale behind these policies suggests that the more R&D, the better. This paper demonstrates that R&D increases firm risk. The high stock return for R&D intensive firms could be a risk premium.

I find that R&D increases the probability of going bankrupt. The results are robust both in various sub-samples and after taking into account possible endogeneity problems. My analysis shows a previously unrecognized cost of R&D. Given the existence of bankruptcy costs, R&D might still be underprovided, on average, from a social point of view, but this study's findings suggest that this effect might have been overstated. Despite the various benefits of R&D (e.g. differentiating the firms' products and improving technological competence), the innovation risk and high uncertainty associated with R&D could also increase a firm's bankruptcy risk through volatile firm value and high information asymmetry. This paper does not mean to imply that R&D is value-destroying, but firms should take into account the potential negative impact of innovative activity when making their innovation and financing choices. Moreover, this paper helps to understand the trade-offs associated with R&D.

Chapter 2: Creative Destruction: Business Cycle Interactions with R&D and Bankruptcy

2.1 Introduction

There is growing empirical evidence suggesting that market economies are characterized by a continuous process of creative destruction——reallocation of resources and that this process play a major role in aggregate productivity and output growth (e.g. Olley and Pakes, 1996; Griliches and Regev, 1995; Bartelsman et al. 2004; and Aghion and Howitt, 2006). Creative destruction is usually envisioned as creative innovators displacing laggards utterly. However, in practice, the laggards may only be beaten back for a while and the exit rate of the innovators is much higher than that of the laggards. Only a few innovators can survive to achieve success. The innovation strategy is actually risky. And it might be more risky in recessions than in booms.

Recessions are periods in which the process of creative destruction is particularly strong. Innovators arise to dislodge unproductive established firms and depress their performance. Recessions have the effect of "winnowing the herd". This paper studies how the business cycle from the mid 1970s through the late 2000s affected the interactions between R&D and bankruptcy for US public firms in the high-tech sector. I find that R&D effects on bankruptcy increased during economic recessions. As exogneous shifts in costs or demand undermine profts, firms are more likely to have a liquidity crunch during an economic downturn. When firms have to obtain credit, it is more difficult to raise money based on R&D assets due to the associated high level of information asymmetry. R&D intensive firms would therefore be more negatively affected than other firms.

This paper also examines how high-tech firms respond to distress and how that response affects their future performance. Results show that firms tend to increase R&D intensity during downturns. Although part of the increase is due to the decline in asset values or sales, it also suggests that firms are reluctant to cut the innovation expenditures as sale or assets fall. The Wall Street Journal reported that in the dismal last quarter of 2008, US companies nudged down innovation spending by only 0.7% while seeing their revenues drop nearly 8%.

Booz & Company's Global Innovation 1000 Survey of the biggest R&D spenders showed an innovation investment growth rate of 5.7% in 2008, even though net incomes plummeted by 34%. My empirical results further show that the R&D leaders during recessions achieve higher sales growth and greater profitability after recessions than those R&D laggards. In other words, conditional on surviving recessions, innovators are more likely to achieve better operating performance than R&D laggards.

Innovation activities are often thought to be almost independent of fluctuations in the business cycle. Several reasons are offered. First, the duration of an innovation project often exceeds the duration of a business cycle phase. Second, firms may want to smooth their innovation expenditures and therefore try to continuously undertake innovation. Finally, innovation expenditures are often regarded as investments with sunk-cost characteristics and high adjustment costs. This paper considers the influence of business cycle fluctuations on the input factor of the innovation process: R&D. As markets have a limited capacity for absorbing new products, the introduction of a new product is most probable when market conditions are favorable. Firms might time their input of innovation just as they time the new products. Furthermore, since innovation takes time, R&D has to take place before boom periods come.

Furthermore, economic downturns might be a good time for beak-through innovations. It is easier for innovations to get wide adoption during economic downturns. When the economy is booming, little pressure is put on expenses, and large organizations often penalize innovators. Instead of looking for radical changes, companies are satisfied with spending more money on the same software, the same hardware, and the same advertising mix. But that changes quickly in hard times. Economic downturns force companies to reevaluate how they spend money and companies have to look for effective ways to cut costs. Therefore, economic downturns help innovators and companies generally have more innovation hunger. Moreover, in times of high sales there is a relatively high opportunity cost for a firm to devote resources to R&D projects. Firms rush to exploit economies of scale, set up distribution systems and launch marketing campaigns to create brand loyalty and lock in buyers in a variety of ways. It is only as the firm's production slows that it begins to devote more resources back into innovation development.

However, Seiler (1965) argues that there are no known relationships between optimum R&D expenditures and another single variable which can be used to establish a research budget with a sufficiently reliable degree of accuracy. The budgetary determination by top line officials in most cases is a matter of using broad gauges to see if the budget requests of research officers are reasonable. Among eight factors that were listed by Seiler as important influences on the budgeting decision, the top one is the short run availability of financial resources. Stiglitz (1993) also states that the volume of innovative activities undertaken by a firm is generally constrained by its cash flow and its ability to borrow. Brown, Fazzari and Petersen (2009) show that U.S. firms finance R&D from two main sources: cash flow and external equity. Since cash flow is generated by the actual activity of the firm, it responds pro-cyclically to variations in economic activity. Moreover, stock issues are greatly influenced by macroeconomic conditions. Therefore, even if investing in innovations during a recession is a good strategy, firms might be unable to achieve the strategy in light of financial constraints.

Kerr and Nanda (2009) evaluate how creative destruction follows from improved financial conditions after banking deregulation. This paper, on the other hand, focuses on the interaction in the context of worsening financial constraints during downturns. It seems that there are two forces acting on firms' R&D decision during recessions. One is the effect of creative destruction which would promote more R&D from firms which see an opportunity to move ahead of slow-moving rivals during the recession. The other is the financial constraints that become more severe during downturns. Firms need to balance these two forces. If firms have adequate internal funding then taking advantage of recessions to pursue innovation is more likely to be the favoured approach. On the other hand, if firms have to seek outside financing to invest in R&D, they might be forced to cut back in innovation during recessions.

Dugal and Morbey(1995) found that US companies that invested heavily in R&D in recessionary periods continue to grow, while competitors with only modest investments suffer sales declines. My empirical results confirm their finding and show that firms that chose to increase R&D during economic downturns had higher sales growth and greater profitability after the recession. One possibility is that firms that carry out more R&D in recessions do better than they otherwise would. Another possibility is that firms with good projects and good R&D opportunities choose to invest more in R&D. Thus R&D might be partially endogenous. However, the fact that R&D leaders have a greater chance of achieving better performance while they also have a greater chance of going bankrupt simply shows hat R&D is more risky in recessions than in booms.

2.2 Data

2.2.1 Sample Construction

I use the data from the COMPUSTAT-CRSP merged database (Fundamental Annual). The sample covers the period from 1976 to 2009. I choose 1976 as the earliest year for identifying R&D decisions over recessionary periods because U.S. GAAP was changed in 1974 to require firms to immediately expense their R&D expenditures[11] and there was one recession which started in 1973 and ended in 1975. The sample includes all U.S. public firms that have common shares traded on the NYSE, AMEX, or NASDAQ. Firms that incorporate outside the United States are excluded. I require that firms have positive assets to be included in a given year.

R&D has become highly concentrated in the high-tech industries. I follow Brown et al. (2009) and use the official definition of high-tech industries offered by the United States Department of Commerce.[12] More specifically, the high-tech sector consists of firms from the following seven industries defined by 3-digit SIC codes: drugs (SIC 283), office and computing equipment (SIC 357), communications equipment (SIC 366), electronic components (SIC

[11] Statement of Financial Accounting Standards, SFAS, No. 2, 1974
[12] "An Assessment of United States Competitiveness in High-Technology Industries," United States Department of Commerce, February 1983, International Trade Administration

367), scientific instruments (SIC 382), medical instruments (SIC 384), and software (SIC 737). R&D is not necessary in the non-high tech sector; only 26% of non-high tech firms report their R&D in the sample period, while 76% of firm-years in the high-tech sector have R&D expenditures. As shown in Figure 2.1, High-Tech R&D accounts for over half of total R&D investment for all publicly traded companies with coverage in Compustat (financial firms and utilities are excluded). Moreover, high-tech industries are responsible for virtually all of the cycle in R&D between 1976 and 2009. Non-high-tech R&D, measured as the distance between All Firms and High-Tech lines in Figure 2.1, seems to be constant over time. Therefore, in this paper, I use the high-tech sample to test the impact of business cycle on the relationship between R&D and bankruptcy. The high-tech sample includes 5,132 firms with 58,894 firm-year observations.

I further require firms to have at least six R&D observations to make sure firms are committed to R&D and we could have enough observations to examine how firms react to recessions. I also exclude firms if the sum of their cash flow-to-assets ratio over the sample is negative. These firms are almost always very small startup companies as just 32% of the cash flow observations are positive (compared to 79% in the rest of the sample). The small size of negative cash flow firms often leads to ratios that are highly variable and very large (in absolute value), which could give them disproportionate impact on the results. Moreover, these firms are responsible for a small fraction of aggregate R&D.

After imposing these restrictions, the regression sample consists of 1,948 firms that account for over 90% of the public-firm R&D in the high-tech sector. It is possible that such methodology would introduce survival bias. In robustness checks, I keep all the firms, but results do not change significantly.

Figure 2.1 shows that there is a time trend in R&D investment. During the 1990s there was an R&D boom which started in 1994 and ended in 2000. To examine the effect of the business cycle on R&D investment, I use R&D growth and R&D intensity as the main explanatory variables. Figure 2.2 presents time series of total R&D growth, firm asset growth and R&D intensity. These series can be compared with business cycle fluctuations. R&D

growth follows the movement of GDP, but recessions do not seem to discourage R&D investment very much. A noticeable negative R&D growth effect can only be clearly seen after the burst of the Internet bubble in 2001 and during the most recent financial crisis. This finding is consistent with the result in the literature that firms during distress often implement debt restructuring, asset sales and capital expenditures reduction, and only deep recessions cause firms to significantly cut their R&D expenditures.

Another variable I am interested in is R&D intensity. I measure R&D intensity using book asset values rather than market asset values or sales. Because there would be a large decline in market asset values or sales during downturns, the increase in intensity could be largely caused by the sharp reduction in the denominator and would not correspond to an increase in real R&D activity. However, even if we use book asset value, we can not avoid the cyclical fluctuation in asset values as shown in Figure 2.2.

From Figure 2.2, we can see that there is a small cyclical movement in R&D intensity, and the intensity increased over time. The R&D/assets ratio hovered around 0.04 in 1970s, increased to 0.06 in 1982, and continued to rise to 0.08 during the R&D boom and peaked at 0.12 in 1999. This consistent increase in R&D intensity could not be due to the slump in assets because firm asset value is also on the rise in the long run. It could be attributed to the simple fact that firms increased R&D spending. Possibly because more high tech firms went public to raise money over the last two decades they could afford much higher levels of R&D, as suggested in Brown et al. (2009).

2.2.2 Business Cycle Indicators

Fluctuations in economic activity are often represented by variation of GDP. GDP is an aggregation of several economic factors that together account for the business cycle. Any business cycle can be split up into different phases. Here I am concerned with that phase of a business cycle which is generally referred to as a recession. In the paper, I use three business cycle indicators to represent the state of the economy: the National Bureau of Economic

Research (NBER) recession indicator[13] dummy, GDP growth, and the default spread. The real GDP annual growth rate is taken from the Federal Reserve Bank of St. Louis's website. The default spread is the average yield on BAA less AAA Moody's rated corporate bonds with maturity of approximately 20-25 years, reported by the Federal Reserve. An increase in the default spread would imply an increase in default risk and would thus indicate a bad economic period. As can be seen in Figure 2.3, the NBER has identified four recessions over the sample period, including the recession arising from the financial crisis of 2007.

2.2.3 Descriptive Statistics

Over the sample period 1976-2009, according to the NBER's business cycle dating and GDP growth rate sorting, I identified four recession periods: 1980-1982, 1990-1991, 2001-2002, 2007-2009. Table 2.2 provides descriptive statistics for R&D and other spending ratios during recessions and non-recessionary periods. For firms in the sample, R&D far exceeds capital expenditures (capex) and advertising expenditures (ad). Moreover, firms did not cut R&D expenditures during recession periods, the differences between recession and non-recession groups in R&D are not significant. As the sales-to-assets ratio might reflect the magnitude of recession, we can see that sales ratio dropped sharply for the 2001-2002 Internet bubble burst period and the 2007-2009 most recent financial crisis. However, the mean R&D intensity over the 2001-2002 and 2007-2009 period was 0.139 and 0.133, respectively, while the mean R&D intensity over the non-recession periods was only 0.119. In contrast, there was a big cut in the ad and capex ratios in the last two big recessions. The differences between recession and non-recession groups in capital spending are statistically significant.

As indicated in Table 2.2, the mean of the cash flow ratio is 0.146, smaller than the sum of the R&D, advertising and capital spending ratio means. It implies that firm must obtain funds from an external source. This source is new stock issues. The final statistics in Table 2.2 report the share of finance from each source relative to total finance raised (the sum of internal cash flow, external public equity issues, and new debt). The mean share of cash flow

[13] http://www.nber.org/cycles.html

is 86.9%, the mean share of public equity issues is 10.6%, and the mean share of debt finance is just 2.3%. Clearly, internal cash flow accounts for a large fraction of financing. Firms also rely on public equity as their marginal source of financing, and debt finance is usually trivial for high tech firms. Thus, high tech firms should face binding financing constraints in recessions because the supply of both internal cash flow and external public equity finance would fall sharply during economic downturns.

Table 2.2 also shows that there is significant boom-bust variation in the financial ratios. The mean of the stock issues ratio over the non-recession periods is 0.064, while the mean of the stock ratio over the 2007-2009 period is -0.002. Rather than issuing new equity, some firms bought back their stock in recessions largely because management thought that the market had discounted the share price too steeply. With the slowdown in equity finance during recessions, firms have to resort to internal cash flow more significantly. The mean share of gross cash flow in total finance rises to 93% during downturns. In particular, the mean share of internal cash flow finance is 100% in the 2007-2009 financial crisis and some firms use extra cash to repurchase their stocks. The more stringent financial constraint in economic downturns should make a big difference to R&D, as it did for other spending. In section 4, I turn to multivariate analysis for more meaningful comparisons.

2.3 Empirical Results

2.3.1 Firm-Specific Characteristics

Table 2.1 provides descriptive statistics for the sample firms. As indicated in Table 2.1, the median book asset value is $74 billion, while the median market capitalization is $131 billion. The much higher market value captures the value of growth options in R&D resources which high-tech firms rely on to create innovation and differentiate their products from competitors. I define a firm as bankrupt if it was delisted from its stock exchange due to bad performance with delisting codes 400-599 and did not get relisted.[14] The delisting data are obtained from

[14] After the delisting year, data is not available for the delisted firm in Compustat.

CRSP. There are 159 bankruptcies identified over the sample period, accounting for 8.2 % of the full sample. However, the average annual bankruptcy rate is only 1%.

I control for firm size, market to book ratio, leverage and cash, both scaled by the book value of assets. Book measures of leverage are more appropriate for capturing the borrowing behavior of distressed firms than market measures, since large declines in the market value of equity prior to bankruptcy would drive up the market leverage even when the underling level of liabilities has not changed.

To control for industry effects on the likelihood of a firm going bankrupt, I add three-digit SIC dummies. And as regression relies on firm-level time series cross-sectional data, the standard errors are clustered by firm, to correct for heteroskedasticity and serial correlation. To ensure that outliers in the data are not driving my results, I winsorize[15] all the continuous variables at 1% tails in regressions. Finally, in Table 3, I present the pairwise correlations between key explanatory variables. As is indicated in the table, there is little evidence of collinearity among my variables.

2.3.2 Magnified Effect of R&D on Bankruptcy during Downturns

Chapter 1 shows that R&D increases the risk of bankruptcy for firms. In this section, I introduce an exogenous macroeconomic shock to examine the relationship between R&D and bankruptcy. I investigate whether, after a negative economic shock as compared to other periods without the negative shock, firms with high R&D intensity prior to the recessionary period are more likely to go bankrupt compared to firms that do less R&D. If R&D could induce bankruptcy, R&D intensive firms would have the greatest operating difficulties in an economic downturn. The reduced visibility surrounding R&D assets enhances a firm's information asymmetry and thus reduces a firm's ability to obtain external financing. Without easy access to credit, R&D-intensive firms are less likely to survive a negative

[15] To winsorized the data, tail values are set equal to some specified percentile of the data. For example, for a 90% winsorization, the bottom 5% of the values are set equal to the value corresponding to the 5th percentile while the upper 5% of the values are set equal to the value corresponding to the 95th percentile

shock. Therefore, I hypothesize that R&D effects on bankruptcy would be magnified during economic downturns.

I use three proxies to represent the magnitude of recession: the NBER recession dummy, real GDP growth[16] and the default spread. I add recession indicators to the model, as well as interaction terms between R&D intensity and recession indicators. In unreported results, when we do not control for the interaction terms, R&D is positively associated with bankruptcy likelihood in all models and the coefficients on the recession indicators are all significant and positive, which suggests that recession does increase a firm's chance of going bankrupt. Table 2.4 shows that when we run regressions on the full sample, the interaction terms between R&D and recession are all positive and significant. For example, in panel A of Table 2.4, recession is proxied by the NBER recession dummy. The coefficient on R&D is 0.011, and the coefficient on the interaction term between R&D and recession indicator is 0.006, indicating that one standard deviation increase in R&D/assets is associated with a 23.7%[17] increase in the bankruptcy likelihood as compared to the average firm in the industry during economic expansion and the effect of R&D on bankruptcy would be increased by 54.5% (0.006/0.011) if there is a recession. These results provide evidence for the hypothesis that the impact of R&D on the likelihood of bankruptcy is strengthened in economic downturns.

I further formulate an empirical test of the interplay between financial constraints and R&D effects. I compare the impact of recession on R&D's effects on bankruptcy across different measures of financial constraints. If the magnified marginal effect is due to the fact that R&D could increase the likelihood of bankruptcy by limiting the firm's access to credit as a result of high information asymmetry, financially constrained firms should have a larger increased effect than financially unconstrained firms.

The first constraint sorting criterion is based on dividend payout. I assign to the financially unconstrained group those firms which have made any cash dividend payments in the year.

[16] I took a negative sign of gdp growth so that it is increasing in the magnitude of recession.
[17] The mean probability of bankruptcy in the full sample is 0.65%.

The second financial constraint sorting is based on bond rating. Following Almeida and Campello (2007), I retrieve data on bond ratings assigned by Starndard & Poor's from Compustat and categorize those firms with a bond rating as financially unconstrained. Financially constrained firms are those whose bonds are not rated.

Table 2.4 shows that the interaction between R&D and recession attracts positive, statistically significant coefficients in all of the constrained firm estimations, while in unconstrained firms' estimations, the interaction terms between R&D and recession are negatively significant. The findings that R&D effects on bankruptcy increase in a downturn for financially constrained firms, but not for financially unconstrained firms are strongly consistent with the hypothesis that R&D could increase the likelihood of bankruptcy by limiting the firm's access to external capital with information asymmetry arising from R&D. R&D intensive firms with financial constrains suffer more from a negative economic shock, possibly because when firms have to obtain credits, it is more difficult to raise money on R&D assets during downturns. These results provide support for the view that R&D increases the cost of external financing, causing the firm to be less likely to survive negative shocks. On the other hand, there was some evidence that R&D effects on bankruptcy could decrease in a downturn for financially unconstrained firms. That might explain why firms were reluctant to cut their R&D expenditures during downturns—partly because of the high adjustment cost of R&D, bur primarily because firms want to take advantage of creative destruction opportunities.

2.3.3 R&D Leaders and Laggards during Recessions

To examine how firms differ in their R&D strategies during downturns, I calculate the R&D arc growth rate for each firm and each year. The R&D arc growth rate[18] is defined as

$$\frac{RD_t - RD_{t-1}}{avg(RD_{t,} RD_{t-1})}.$$

Within each year and each 3-digit SIC industry, I group firms into quartiles according to their R&D growth. If firms are in the top quartile of R&D growth, I coded it as "lead" in R&D; if

[18] I used the arc growth rate to avoid excluding observations which had zero R&D for the previous year.

firms are in the bottom quartile, I coded it as "follow" in R&D. Here I look at the percentage change in R&D spending, rather than the level of R&D expense. The reasons I focus on the changes in R&D are as follows: First, firms with high levels of R&D in recessions maybe just because they do high R&D all the time. In that case, I can not disentangle the effect of R&D in recessions from R&D in non-recessionary periods. Second, percentage change in R&D could avoid using sales or assets which would suffer sharp decline in recessions as scaled measures.

For each of the four recession periods: 1980-1982, 1990-1991, 2001-2002 and 2007-2009, I identified firms that leaded and did not follow in R&D during the whole recession period as R&D leaders. In contrast, I categorized firms that followed in R&D and did not lead over the corresponding period as R&D laggards. Panel A of Table 2.5 shows that R&D leaders represent around 25% of all the firms. R&D leaders are firms that increased the most R&D spending by percentage in recessions, compared to R&D laggards that cut the most R&D spending in recessions. The purpose of the leader- laggard analysis is to look at how high-tech firms react to recession assuming that they can choose R&D quantity as a strategy choice and how different strategies affect their long-run corporate performance.

Panel B of Table 2.5 presents characteristics of R&D leaders and laggards before recessions. Compared to R&D laggards, R&D leaders are younger, smaller, have a higher market valuation, higher sales ratio, lower leverage and higher cash ratio. Moreover, R&D leaders have a higher return on assets (ROA). All the group differences at mean and median[19] are significant. Panel B also shows that R&D leaders seem to rely more on new stock issue as financing sources than R&D laggards, although the difference is not statistically significant at the mean level. Further, R&D leaders have a higher Tobin's q, indicating more growth opportunities. Moreover, R&D leaders are less likely to pay a dividend, only 10.3% of leaders paid out a dividend while 19.5% of laggards paid out the profits to shareholders.

[19] I conducted two-sided t test for means comparison and two-sided Wilcoxon-Mann-Whitney test for median comparison.

Panel C in Table 2.5 reports the spending ratios changes of R&D leaders in recessions. R&D leaders have a higher advertising ratio than R&D laggards during recessions, while the ad ratio differences are not statistically significant before and after recessions. As to capital investment, R&D leaders always have a higher capital spending ratio than R&D laggards, but both types of firms cut their capital investment during recessions. R&D leaders and laggards have opposite R&D strategy during downturns, one group increased the R&D ratio while the other group decreased it. From panel C, we can see that R&D leaders have a lower R&D intensity than R&D laggards before recessions, but the position is reversed during recessions. R&D leaders then keep a higher R&D ratio than R&D laggards after recessions.

2.3.4 R&D Strategy in Downturns and Long-Run Performance

In this section, I examine whether firms' R&D strategies during downturns appear to affect their long-run performance. I use sales growth and ROA as measures of firm performance, and compare the performance between R&D leaders and R&D laggards. Industry adjustment is carried out by subtracting the 3-digit SIC industry median from the firm's performance. Although my sample covers four recession periods: 1980-1982, 1990-1991, 2001-2002 and 2007-2009, the post-recession performance data is not available for the most recent recession and thus I can only do the analysis based on the first three recessions.

Table 2.6 shows that R&D leaders have a significantly higher sales growth during recessions and after recessions, compared to R&D laggards. The average sales growth within five years after recessions for R&D laggards is 8.2%, but the mean sales growth rate for R&D leaders is 19.3%. The industry adjusted measure comparison is qualitatively similar. From Table 2.6, we can also see that R&D leaders achieved a higher ROA than laggards after recessions. The group differences at the median are all statistically significant. The group differences at the mean are statistically significant when we compare the post-recession performance over the five years horizon. Overall, Table 2.6 provides preliminary evidence that R&D leaders had a better post-recession performance than R&D laggards.

Moreover, R&D leaders seem to have a higher variance of performance than R&D laggards. The last column reports the p-value of F-test which tests whether the variances of the two groups are equal. For the sales growth measures, R&D leaders always have a higher standard deviation, and the difference is significant at the 5% level. For the ROA measures, the difference between the two groups is not all statistically significant. The higher performance variance associated with R&D leaders indicates that of R&D could reinforce the high uncertainty of firm's future prospects. However, Table 2.6 also shows that R&D leaders have a lower bankruptcy rate during recessions, compared to R&D laggards. The difference in bankruptcy rates disappears after the firms survived the recession. It is consistent with the creative destruction theory that during recessions, new innovative firms would replace old, less innovative ones.

Next I examine whether there is a positive relationship between increasing R&D during recessions and future firm performance using multivariate regression analysis.

Again, I measure firm performance by sales growth and ROA. For each firm, I calculate the mean of sales growth and ROA over the five years period after the recession as long-run performance measure. The key explanatory variable is average R&D growth during the recessionary period. I also control for firm's R&D intensity and other firm characteristics variables, measured one year prior to the recession. I control for 3-digit SIC industry fixed effect,[20] thus the estimate is driven by variation within 3-digit SIC industry.

In Table 2.7, models (1)-(4) are estimated with sales growth during the recession as the dependent variable. Models (5)-(8) are estimated with long-run sales growth as the dependent variable. I run regressions on the full sample and subsamples for each recession period separately. Table 2.7 shows that a higher R&D is always associated with a greater sales growth during recessions. The coefficient on R&D growth is 0.23, suggesting that a 1% increase in R&D growth during recessions would increase sales growth over the recessionary period by 0.23%. Moreover, the coefficients on R&D growth are positive and significant in almost all the long-run sales growth models, except in model (6) for period 1980-1982. In model (5), when we run regression on the full sample, the coefficient on R&D growth is 0.07,

[J]The same as I conduct industry adjustment for the dependent variable and independent variables.

indicating a 1% change in R&D growth during recessions would be associated with a 0.07%. change in the long-run sales growth.

Table 2.8 reports regression results prediction long-run ROA. We can see that the coefficients on R&D growth are always significantly positive in models predicting ROA during recessions. The coefficient on R&D growth is 0.06, suggesting that a 1% increase in R&D growth during recessions would increase ROA over the recessionary period by 0.06%. However, the significance disappears when we estimate models for long-run ROA. R&D growth in recessions does not seem to affect the long-run ROA. One possible explanation is the quality of R&D is just as important if not more important than the amount of R&D. Furthermore, R&D intensity is negatively associated with both ROA in recessions and long-run ROA after recessions. Its estimated coefficients are significant in all models. Since the conservative accounting principles require firms to immediately expense their R&D expenditures, R&D would negatively affect firm's profitability measure in some sense.

Overall, Table 2.7 and Table 2.8 show that firms that chose to increase R&D during recessions had greater sales growth and higher ROA during recessions, than firms that chose to do less R&D. In addition, R&D growth over the recessionary period positively affects firms' long-run sales growth. Those empirical results provide support for the creative destruction theory that more innovative firms would be winners in recessions.

2.3.5 Discussion

In this paper, I show that R&D has a magnified effect on bankruptcy during economic downturns. This result is also economically significant: a one standard deviation increase in R&D/assets is associated with a 36.6% increase in the bankruptcy likelihood as compared to the average firm in the industry during economic downturns. The effect of R&D on bankruptcy during downturns was 54.5% more than during economic expansion. Furthermore, I present empirical results that firms taking a more aggressive posture in increasing R&D during downturns enjoy stronger sustained operating performance. It is consistent with the creative destruction theory that more innovative firms would be winners in recessions.

There are potential endogeneity issues associated with the finding that R&D leaders during recessions have significantly better post-recession performance. High performing firms might be more likely to invest in R&D during recessions. I compare the pre-recession characteristics of R&D leaders and R&D laggards. I find that R&D laggards had a lower sales ratio and a lower ROA before recessions. It seems that R&D laggards were poorly performing firms, compared to R&D leaders. But I also find that R&D laggards are more likely to pay dividends than R&D leaders, before recessions and even during recessions, suggesting that R&D laggards were not financially constrained firms. Those firms chose to cut their R&D spending in recessions. This decision might be due to the fact that they didn't have good growth opportunities, since I find that R&D laggards are on average three years older and have a much lower Tobin's q than R&D leaders.

To minimize the problem of reverse causality or other forms of endogeneity, I measure ex ante financial performance one year before the recession started and control for the lagged variables in the model to examine whether R&D strategies during recessions could make a difference holding the firm fundamental characteristics constant. Results are robust to controlling for firms' pre-recession performance. The increase in R&D during the recessionary period still has a significantly positive impact on the future corporate performance, though the magnitude of the effect becomes smaller. These results suggest that R&D decisions during recessions appear to play an important role in explaining the differences in post-recession performance. R&D could be used as a business strategy to take advantage of creative destruction opportunities in recessions.

2.4 Conclusions

In this paper, I find that R&D's effect on bankruptcy increased during recessions. After a negative economic shock, many firms face binding financial constraints. R&D-intensive

firms might be particularly affected by such constraints due to the high information asymmetry associated with R&D activities. This would further restrict their financing sources.

However, I find that firms are reluctant to decrease their R&D spending during economic downturns. Firms that increase their commitment to innovation do best from a recession. The only way for firms to emerge stronger from a recessionary period is by having new products, new technologies, and new innovation capabilities. Therefore, while companies that do find themselves financially pinched have to pull back on R&D investment in tough times, the strongest companies-those with strong balance sheets-- need to focus in maintaining innovation activities.

This paper gives support for the creative destruction hypothesis, which posits that new innovative firms will replace old ones that fail to innovate. Innovation could bring an end to the recession. Temporary economic distress can be caused by creative destruction since established enterprises with obsolete technologies would layoff workers at first, more creative and productive enterprises would generate new opportunities for workers and provide jobs later.

During economic downturns, innovation is perhaps the single most important condition for transforming the crisis into an opportunity. While many businesses simply won't be able to afford further investment in innovation, governments should recognize that innovation systems, with all their academic and industrial components, are strategic national assets.

Chapter 3: Patent Citations and M&A Transactions

3.1 Introduction

This paper examines the role of patent citation links between acquirer and target firms in M&A transactions and presents evidence that M&A deals between two firms with a citation link generate better performance. First, I find that post-merger performance is superior when the merging firms are linked by patent citations. Second, I find that acquirer announcement returns are positively related to citation links between acquirer and target firms.

Researchers have shown that acquiring firms generally fail to realize positive returns from acquisitions, while target firms capture most, if not all of the total gains. Nevertheless, Higgins and Rodriguez (2006) find that the acquiring firm's pre-acquisition information gathering of the true underlying value of the target firm increases acquirer returns. They hypothesize that an acquirer can obtain significant additional information through pre-acquisition alliances with the target firm. The primary question this paper asks is whether patent citation links prior to M&A transactions could increase acquirer returns.

Patent citations are often used as a measure of knowledge spillovers. When inventors apply for a patent, they must demonstrate that the invention is novel, useful, and not obvious to someone with average expertise in the same industry. To do so, the inventor cites earlier patents and explains how the new patent improves upon earlier inventions. Patents cited by many subsequent patents tend to contain important ideas upon which later inventors build. I focus on two types of citation links between acquirers and targets. The first link is where the acquirer makes at least one patent citation to the target firm's patents before they undertake an M&A transaction, and I refer to this type of link as "AciteT". The second type is where the target cites the acquirer's patents before the deal announcement, and I refer to this type of link as "TciteA".

Patent citations indicate a knowledge flow. Jaffe et al. (2000) undertook a survey in which they asked inventors about citations to previous patents made in their patent applications.

Results show that half of the citing inventor respondents indicate great familiarity with the cited invention. The inventor survey results suggest that patent citations do provide an indication of communication between inventors. This paper argues that patent citation links could reduce information asymmetry between two firms and thus, increase the likelihood of a subsequent M&A deal.

Heeley et al. (2006) show that R&D expenditures are systematically related to a target firm's likelihood of being acquired. The authors propose that cumulative R&D expenditures create technology resources that have value to acquirers. This paper asks whether patent citations could create information resources that are valuable to the acquirers and thus, increase acquisition likelihood. I find that a patent citation link between two firms has a positive impact on the probability of a subsequent M&A transaction between them. In addition, the positive citation link effect becomes stronger when the two firms are not in the same state or the target candidate is not a public firm. These results are consistent with the argument that patent citation links would increase the likelihood of acquisition due to decreased information asymmetry between citation linked firms.

Patent citation links between acquirer and target firms can affect acquirer's returns through two channels. Investors holding the stocks of acquiring firms have two important concerns about entering into an M&A transaction: (1) the acquirer might overbid for the target firm (the "winner's curse"), or (2) the acquirer might have an unsuccessful post-merger integration. First, if the existence of a patent citation link reduces the level of asymmetrical information between the two firms, the acquirer could be more able to assess the true value of the target firm and hence, avoid overpaying for the target firm. Second, having a patent citation link prior to an M&A transaction could give the acquirers an information advantage about the profitability and the quality of a match between two firms. This is because having a citation link between two firms indicates more familiarity with each other. Hence, the deal may be expected to lead to a more successful integration of the two firms and the realization of expected synergies. My empirical results, indicating that acquirer announcement returns are positively related to patent citation links between acquirer and target firms, are consistent with both hypotheses. In various tests in the paper, I aim to distinguish between these two possible explanations.

The two hypotheses differ in terms of why acquirers obtain better returns. One suggests that acquirers in citation-linked deals might avoid overpayment and thus, extract a greater portion from the value created by the deal. The other hypothesis states that citation-linked deals are associated with greater value creation. Acquirers can receive a higher return even given the allocation of the surplus between the acquirer and the target. I empirically evaluate these hypotheses by studying announcement returns, bidder premiums, and the long-run operating performance of the new firm after deal completion. I find that citation links are positively related to the combined announcement returns and operating performance of the new firm in the long run. Interestingly, when I analyze the AciteT and TciteA links separately, I find that the positive association between citations links and the performance of the deal is significant only in AciteT links. This is probably because acquirers have an information advantage about the profitability and the quality of a match between two firms only when playing the active citing part. These findings are consistent with the hypothesis that the existence of a citation link indicates more synergy gain and increases the likelihood of the two firms representing a better quality match and having a greater chance for a smooth post-deal integration.

When I analyze bidder premiums, I find a sharp difference between how each type of citation link affects the premiums. AciteT links are positively related to bidder premium, while TciteA links are negatively related to bidder premium. Moreover, when I analyze acquirer and target announcement returns, I only find significance in AciteT links. Acquirer and target announcement returns are not significantly related to the presence of TciteA links. These findings are not consistent with the hypothesis that patent citation links could increase acquirers' returns due to avoiding overpayment.

Taken together, I find evidence consistent with the hypothesis that acquirer's returns increase in citation links as a result of high synergy gain involved, rather than as a greater portion of surplus reallocated due to avoiding overpayment. Moreover, the finding that synergy gains are associated with AciteT links but not with TciteA links suggests that greater value is created when the citing firm buys the cited party.

3.2 Hypothesis and Empirical Predictions

In this section, I develop testable predictions to investigate the role of patent citations in M&A deals.

Frequent citation links suggest mutual familiarity. Thus, citations would reduce the information asymmetry between the target and acquiring firms. Motivated by the adverse selection argument of Myers and Majluf (1984) and the associated financing “pecking order” suggested by Myers (1984), acquiring firms would be more willing to acquire a target when citation links are present due to low information cost. Hence, my first empirical prediction is:

Prediction 1: Ceteris paribus, the patent citation link between two firms would increase the likelihood of the two entering an M&A transaction.

Patent citation links between the target and acquiring firm will ease the concerns of investors and therefore, generate a higher return at the acquisition announcement. First, investors are typically concerned that acquirers will overbid for target firms. If patent citations reduce information asymmetry between the bidder and the target firm, the bidder in the transaction with citation links is less asymmetrically informed about the true value of the target share and thus, is less likely to overbid. Second, investors are often concerned about the execution of the post-merger integration process. Acquirers in citation-linked deals might have an information advantage about the quality of match. Thus, the presence of a citation link between the two firms before the transaction increases the likelihood of a relatively smooth knowledge flow and thus, a successful integration process. Accordingly, my next prediction is:

Prediction 2: Ceteris paribus, acquiring firm announcement returns are positively related to the citation link between the acquiring firm and target firm.

I hypothesize that acquirers in citation-linked deals have an information advantage about the profitability and the quality of a match between two firms. The presence of citation link prior to an M&A transaction indicates high quality deals. Thus:

Prediction 3: Ceteris paribus, synergy gain of the deal is positively related to the citation link between the acquiring firm and the target firm.

I hypothesize that patent citation links reduce information asymmetry between the acquirer and target firms about the true value of the target firm. The presence of a citation link prior to the M&A transaction indicates less chance of overpayment. Thus:

Prediction 4: Ceteris paribus, bidder premium is negatively related to the citation link between the acquiring firm and the target firm.

Positive support for Predictions 3 and 4 would imply that acquirers in M&A transactions with citation links possess certain pre-announcement informational advantages about the true value of the target firms or the quality of a match between the two firms.

3.3 Data

My sample of acquisitions is from Securities Data Company's (SDC) US Mergers and Acquisitions database. I begin with all M&A transactions with an announcement date between 1981 and 2003. I choose 1981 to 2002 as my time period because SDC's M&A data is complete since 1981 and the latest patent citation data available is through 2002. The patent citation data is obtained from the NBER US patent citation data file over the period between 1975 and 2002, including all patent citations for US utility patents[21] granted in the period 1-Jan-75 to 31-Dec-03. I used the name-matching software[22] that matches M&A firm names with patent assignee names, such that 13.8% of acquiring firms and 8.7% target firms

[21] A utility patent protects any new invention or functional improvements on existing inventions. This can be a patent on a product, machine, process, or even the composition of matter.
[22] Ed Egan provided the software. It cleans the firm names by removing punctuation marks, such as dashes and commas, and removes suffixes, such as "inc." and "ltd."

are matched. The matched sample has 5,180 transactions for which both target and acquiring firms are matched with the patent database.

I identify all deals in which the acquirer is a public firm, and the acquirer controls less than 50% of the target before the acquisition announcement and owns 100% of the target after the transaction. I further eliminate small transactions in which the deal value disclosed in the SDC is less than 5 million USD, or less than 1% of the acquirer's market capitalization measured on the 11th trading day prior to the announcement date. My final sample consists of 2,487 M&A transactions that meet these criteria.

For each M&A transaction, I count the number of citations between the target and acquiring firms prior to the year of acquisition announcement. If the acquirer's patents ever cited the target's patents, the deal is classified as a transaction with an AciteT link. Similarly, if the target's patents made any citations to the acquirer's patents, the deal is classified as a transaction with a TciteA link. I combine these two types of citation links and create a dummy variable, *Cite Dummy*, which equals one if there is a citation link between the acquirer and the target firm, and zero otherwise. Among the 2,487 M&A deals announced between 1981 and 2002, 340 are classified as a citation-linked transaction and the rest 2,147 as non-linked transactions. In 216 out of 340 citation-linked transactions, we have an AciteT link. In 250 out of 340 citation-linked transactions, we have a TciteA link. In 126 out of 340 citation-linked transactions, we have both AciteT and TciteA links.

Table 3.1 presents the distribution of my M&A sample by announcement year. Consistent with Moeller et al. (2004), I find that the number of acquisitions does not increase monotonically through time; it increases slowly and reaches its highest level in 1999, and then drops significantly in the early 2000s. In Table 3.1, I also report the distribution by announcement year for citation-linked transactions and non-linked transactions, respectively. These two subsamples present a similar time trend as the full sample.

Table 3.2 presents the distribution of the M&A sample by 2-digit SIC industry. We can see that the top 10 industries are mostly high technology sectors since firms have to own patents to be included in the sample. Citation-linked transactions account for 5–17% of those high technology deals. This paper focuses on acquisitions in R&D intensive industries since the motivation for acquisition in R&D intensive industries is straightforward. Blonigen and Taylor (2000) find a substantial negative correlation between R&D intensity and a firm's propensity to acquire. A negative correlation between R&D intensity and acquisition activity may exist because firms are choosing between an internal growth strategy with relatively high R&D intensity versus an external growth strategy with acquisitions. This is traditionally known as 'make or buy' strategy, in which an acquisition can be considered a substitute for internal R&D effort.

Table 3.3 presents the summary statistics for each key citation variable. The percentage of citation-linked transactions in my sample is 14%. In citation linked deals, the acquirers make, on average, 14.9 citations to the target firms with an average citing lag of 5.7 years. The target firms make, on average, 13.5 citations to the acquirers, with an average citing lag of 6.3 years. Table 3.3 also reports the summary statistics for various acquirer, target and deal characteristics. I describe the variable construction in more detail in the Appendix 3. Table 3.3 presents the means for the full sample, and then for two subsamples based on the existence of a citation link between the acquirer and the target. Acquirers are, on average, larger and tend to acquire bigger target and public targets in citation-linked transactions than in non-linked transactions. Furthermore, citation-linked transactions are more likely to be all-stock deals and within-industry deals. Citation-linked transactions also have more competing bidders for the target. I control for these differences when I analyze the role of citation links in M&A transactions in my subsequent analysis.

3.4 Empirical Results

3.4.1 Univariate Analysis

I measure abnormal announcement returns with the standard event study method developed by Brown and Warner (1985). I use the CRSP value-weighted return as the market return and estimate the market model parameters over the period from event day -200 to event day -60. I follow Bradley et al. (1988) and form a value-weighted portfolio of the acquirer and the target, with the weights based on their market capitalization at the 11th trading day prior to the acquisition announcement date. I adjust for toeholds by subtracting the target equity held by the acquirer from the target's market capitalization. Table 1.4 presents the cumulative abnormal returns (CARs) for the acquirer (ACARs) and the target (TCARs), as well as for the combined portfolio of acquirer and target firms (PCARs) around acquisition announcements. I report mean and median CARs over three different windows: the standard three-day event window (-1, +1), the five-day event window (-2, +2), and the seven-day event window (-3, +3).

Table 3.3 shows that the full sample mean abnormal returns for acquirers range from -0.11% to 0.03% and are not significantly different from zero. Target firms have a positive mean CAR of 20.38–23.06%. Average PCARs vary from 1.55 to 1.8%. Median CARs show a similar pattern as the means. I next split the entire M&A sample into two groups based on the existence of a citation link between the acquirer and the target, and summarize the subsample CAR results.

Table 3.4 shows that mean ACARs are lower in citation-linked transactions and the difference between the two subsamples is significant. However, the lower announcement returns in transactions between citation-linked firms might be attributed to the fact that such deals involve larger acquirers, more public targets, and are more likely to use stock deals, three factors shown by earlier research to affect acquirer returns negatively: Moeller et al.(2004) find that larger acquirers experience lower announcement returns, Fuller et al. (2002) show that acquirer shareholders lose when purchasing a public target, and Travlos (1987) shows that acquisitions paid with equity are accompanied by lower announcement returns. In my subsequent multivariate analysis, I control for all those relevant factors.

In contrast to acquirer announcement returns, target announcement returns in citation-linked transactions are not significantly different from those in non-linked transactions. However, portfolio combined returns are higher in citation-linked transactions and the difference between the two subsamples is statistically significant. This result is consistent with the view that the deal profitability is positively related to the existence of a citation link due to the acquirers' pre-announcement information advantage about the deal quality.

In Table 3.4, I proceed with the analysis of bidder premiums. I obtain a measure of bidder premium, PREM4WK, defined as the ratio of the offer price to the target-trading price 4 weeks prior to the announcement date. Table 3.4 compares PREM4WK across citation-linked and non-linked transactions and shows that the premiums are higher in citation-linked transactions and that the difference between the two subsamples is significant. I continue with an alternative measure of bidder premium proposed in work by Baker et al. (2009). This paper argues that the target's 52-week high price represents a reference price to investors and managers and displays a strong effect on the determination of the offer price for the target firm. The paper finds that offer prices in M&A transactions are often biased toward the 52-week high price of the target. In addition, acquirer firm shareholders interpret offer prices over the target's 52-week high as overpayment and show a greater negative reaction at the announcement of the transaction.

Following Baker et al. (2009), I define the 52-week target high as the 52-week high stock price of the target firm over the 365 calendar days ending 30 days prior to the announcement date, and define a measure of bidder premium, PREM52WKH, as the ratio of the offer price to the 52-week high price of the target. Table 3.4 shows that the mean premium in citation-linked transactions is 1.19 and is significantly different from zero at the 5% level. In contrast, the mean premium in non-connected transactions is 1.13 and not significantly different from zero. In addition, the mean premium is significantly higher in citation-linked transactions than in non-linked transactions. These univariate analysis results are not consistent with the view that the ability to avoid overpaying is greater in citation-linked transactions. Next, I turn to multivariate analysis for more meaningful comparisons.

3.4.2 Patent Citations and the Probability of a Subsequent M&A Transaction

Having a citation link could reduce the information asymmetry between two firms and may facilitate an M&A transaction between them. Prediction 1 states that the existence of a citation link between two firms could be positively related to observing a subsequent M&A transaction between them. I test this prediction following a similar method used in Bodnaruk et al. (2009).

Similar to the methodology adopted in Bodnaruk et al. (2009), for the actual acquirer of each deal in my sample, I define the set of all potential acquirer firms as the acquirers included in my sample, which made a M&A transaction within the same 2-digit SIC industry and in the same year. I perform the procedure for each target firm and find its corresponding set of potential acquiring firms. The final dataset has 26,079 matched observations, with 2,096 realized and 23,983 unrealized M&A transactions.

For each pair of firms, I then use the patent citation database to identify whether there has been a citation link between them prior to the announcement of the actual M&A transaction I consider. I estimate a probit model, where the dependent variable equals one if there is an M&A transaction taking place between each pair of firms, and zero otherwise. The key explanatory variable is the cite dummy. I also include a number of control variables, such as the same-state dummy, same-industry dummy, public-target dummy, and difference in the number of patents. Since the citation link could also be a proxy for technological proximity, I control technological proximity in the regression to estimate the marginal effect of the citation link attributed to information asymmetry. Jaffe (1986) proposed the measure of technological proximity I use:

$$\Pr ox_{ij} = \frac{\sum_{k=1}^{K} P_{ik} P_{jk}}{\sqrt{(\sum_{k=1}^{K} P_{ik}^2)(\sum_{k=1}^{K} P_{jk}^2)}}$$

where $P_{ik,} P_{jk}$ are the number of patents held by firm i and firm j in patent class k, respectively. Thus $\Pr ox_{ij}$ is a measure of the extent of overlap in distribution of patents across firms.

I also include an interaction term between the cite dummy and the same-state dummy and an interaction term between the cite dummy and the public-target dummy to test if the citation-link plays a role because of decreasing information asymmetry. If such effect is due to a reduction in information asymmetry, the effect would decrease if the target and acquiring firm are in the same state or if the target firm is a public firm. In either case, it is easier for the acquirer to track the target and thus, the deal is associated with less information asymmetry.

In Regression (1) of Table 3.5, the coefficient on cite dummy is positive and significant at the 1% level, indicating that firms with citation links are more likely to engage in future acquisitions. The coefficient on the interaction term between cite dummy and same-state dummy is negative but not significant. The coefficient on the interaction term between cite dummy and public-target dummy is significantly negative. In Regression (2), where I separate citation links as AciteT and TciteA links, I find that both types of citation links are positively related to observing a subsequent M&A deal between the linked firms. Furthermore, both interaction terms with AciteT dummy are negatively significant. For TciteA dummy, only the interaction term with public-target dummy is significantly negative. I find similar results in Regression (3). Table 3.5 also shows that if the two firms are in the same state or stay in different industries, there is a greater likelihood of reaching an M&A deal. Overall, the results in Table 3.5 provide support for my first prediction.

3.4.3 Patent Citations and Announcement Returns

I further explore the univariate results in a multivariate setting, including factors, which have been shown to affect announcement results by earlier work. Following Moeller et al. (2004), I control for acquirer firm size; relative deal size; method of payment; deal attitude; deal competition; whether the acquisition is within 2-digit SIC industry; whether the acquirer and the target share the same state; whether the deal involves a tender offer; and a firm's Tobin's Q, lagged return, and leverage. All regressions include year and industry dummies to control for year and industry fixed effects.

Table 3.6 presents the OLS regression results of acquirer CARs over the (-1, +1) window surrounding the acquisition announcement. My key independent variable is the cite dummy, which equals one if at least one patent citation between the acquirer and the target firm is existing prior to announcement date, and zero otherwise. In regression (1), I regress ACAR on the cite dummy and other control variables. The cite dummy has a positive and significant effect on acquirer abnormal returns: having a citation link between acquirer and target firms increases the 3-day ACAR by 0.852 percentage points. For the control variables, most of the parameter estimates are consistent with the findings of previous literature. Consistent with Moeller et al. (2004), I find a strong negative correlation between acquirer size and ACAR. I also find that deals involving public targets are associated with lower acquirer abnormal returns, confirming earlier evidence in Fuller et al. (2002).

In Regression (2), I separate citation link as AciteT link and TciteA link and repeat the baseline regression. I define AciteT dummy equal to one if the acquirer ever cited the target's patents, and zero otherwise. Similarly, TciteA dummy is an indicator variable, which equals one if the target firm ever cited the acquirer's patents, and zero otherwise. The coefficient on the AciteT dummy is positive and significant; having an AciteT link between acquirer and target firms increases the 3-day ACAR by 1.157 percentage points. However, the coefficient on the TciteA dummy is insignificant, implying that a TciteA link between acquirer and target firms is not associated with higher acquirer returns. In Regression (3), I use a continuous variable for citation links and repeat the baseline regression. I define AciteT as the number of citations the acquirer made to the target's patents scaled by the total number of patent citations made by the acquirer. Similarly, TciteA is defined as the number of citations the target firm made to acquirer's patents scaled by the total number of patent citations made by the target firm. The result is similar to that in Regression (2). The coefficient on AciteT is positive and significant, but the coefficient on TciteA is insignificant.

Table 3.7 presents the results on target returns where the dependent variable is the 3-day TCAR. I include the same set of control variables as in the ACAR regressions. In Regression (1), I regress TCAR on the cite dummy and other control variables, and find that the citation link has no significant relation with target returns. However, when I separate citation links into the AciteT link and TciteA link in Regression (2), I find that AciteT link is associated with significantly a higher TCAR, while TciteA link is not related to TCAR. The result in

Regression (3) is similar to that in Regression (2). Since the main factor affecting TCAR is bidder premium, I will elaborate more on this point in Section 4.4, where I analyze the relation between citation links and bidder premiums. I did not use bidder premium as a control in the models of ACAR and TCAR since I hypothesize citation links would affect announcement returns through the bidder premium.

I examine the announcement returns for the acquirer and the target as a combined portfolio in Table 1.8, where the dependent variable is the 3-day PCAR. In Regression (1), I use the same control variables as before and find a significant and positive coefficient on the cite dummy. In Regression (2), the estimated coefficient on AciteT dummy is positive and significant, but the estimate on TciteA dummy is insignificant. In Regression (3), both AciteT and TciteA have a significant and positive effect on the combined portfolio returns. These results support Prediction 3 that there is a positive relationship between patent citation links and deal quality.

3.4.4 Patent Citations and Bidder Premiums

To investigate further whether patent citations links help acquirers avoid overpayment, I proceed with the multivariate analysis of bidder premiums. I use the two bidder premium measures PREM4WK and PREM52WKH. If acquirers in citation-linked deals have informational advantage about the true stand-alone value of the target, they may have a greater ability to price the deal accurately and a lower tendency to engage in psychology pricing by setting the offer price above the 52-week high price of the target. In addition, they may use their information advantage to reduce the extent of overpayment for the target and to allocate the surplus created in the deal more evenly between the acquirer and the target.

Table 3.9 reports my results on the relation between patent citations and bidder premiums after controlling for firm and deal characteristics shown to affect the level of premiums, such as method of payment; industry relatedness of the acquisition; deal attitude; deal competition; whether the deal involves a tender offer; whether the acquirer and target firms are in the same state; and acquirer and target firm size and Tobin's Q. In regressions (1) and (4), I regress takeover premiums (PREM4WK and PREM52WKH) on the cite dummy and the set of control variables. Although the cite dummy has no significant effect on PREM4WK, it is positively related to PREM52WKH. In regressions (2) and (5), I separate citation links into AciteT link and TciteA link. I find that AciteT link is positively related to PREM4WK and PREM52WKH, while TciteA link is negatively related to both premium measures. Both correlations are statistically significant. In regressions (3) and (6), in which I use the continuous citation variables, I still find that AciteT is positively related to both premium measures, while TciteA is negatively related to both premium measures. The significance in the different directions of the two types of citation links might explain why I did not find significance for the cite dummy.

Overall, these results are not consistent with the interpretation that the presence of a citation link appears to lead to an increase in acquired returns by limiting the extent of overpayment for the target. AciteT links, which are associated with higher bidder premiums, generate higher acquirer announcement returns, while TciteA links associated with lower bidder premiums generate no significance in acquirer announcement returns.

In Table 3.10, I run probit regressions of the probability of completing the deal. The dependent variable is a dummy, which equals one if the M&A transaction is completed, and zero otherwise. Results show that there is no significant association between the cite dummy and the probability of completing the deal. However, in Regression (2), when I split citation links into AciteT link and TciteA link, I find a positive and significant association between AciteT link and the probability of completing the deal: having an AciteT link increases the likelihood of completing the deal by 3.3%.

Overall, my findings are consistent with Prediction 3 that patent citations links are positively related to the success and profitability of an M&A transaction between the linked firms. However, the results do not provide support for Prediction 4 that bidder premium is negatively related to the citation link between the acquiring firm and the target firm. Even if acquirers in citation-linked deals might have informational advantage about the true stand-alone value of the target, they also know more about the amount of synergies from the deal. Thus, it is not surprising that acquirers are willing to pay premiums for citation-linked targets, especially with AciteT links, and that they are more likely to complete such M&A transactions.

3.4.5 Patent Citations and Post-Acquisition Long-Run Performance

My findings on combined portfolio returns support Prediction 3 in those citation-linked transactions are associated with greater wealth creation from the acquisition. In this section, I complement this finding by examining the long-run performance of citation-linked transactions after deal completion. If citation-linked firms have superior knowledge about each company, they may have a positive effect on the success of the post-merger integration process and on the probability of realizing expected synergies from the deal. Hence, one can expect that citation-linked transactions exhibit better operating performance than non-linked transactions.

Following Chen et al. (2007) and Kang and Kim (2008), I use the ratio of earnings before interest and taxes to total assets (ROA) as the first measure of operating performance of the new firm. I subtract the 2-digit SIC industry median ROA from the new firm's ROA to account for industry-specific factors. To control for the time-series predictability of operating performance, I estimate an AR(1) model, where I regress the post-acquisition industry-adjusted 5-year average ROA of the new firm on the pre-acquisition industry-adjusted ROA of the acquirer firm. I use the residual from this AR(1) regression as my measure of abnormal change in ROA, denoted by ΔROA. The second measure of operating performance I use is sales growth. Similar to ROA, I calculate industry-adjusted sales growth and then estimate an AR (1) model to get residual as the measure of abnormal change in sales growth, denoted by ΔSaleGrowth.

I run the regression of long-run performance using the same set of explanatory variables as in the CAR regressions. Table 3.11 presents the results. Regression (1) and (4) shows that cite dummy has a positive and significant effect on the operating performance measures ΔROA and ΔSaleGrowth. In Regression (2) and (5), where I separate citation links into AciteT link and TciteA link, I find that that only the AciteT dummy has a positive and significant effect on ΔROA and ΔSaleGrowth. In Regression (3) and (6), the significance also only appears on the coefficient of AciteT. These results combined with my earlier finding that combined announcement returns are positively related to AciteT links are supportive of Prediction 3 that the synergy gain of the deal is positively related to the citation link between the acquiring firm and the target firm.

3.5 Conclusions

This paper demonstrates that the existence of a patent citation link between two firms has a positive impact on the probability of a subsequent M&A deal between them. I further find M&A transactions where the acquirer and the target have a patent citation link before the acquisition announcement generate better performance in the long run. In AciteT-linked transactions, acquirers pay significantly higher premiums and generate higher announcement returns for both of the acquirer and target firms. In TciteA-linked transactions, acquirers pay significantly lower premiums but generate no significant returns for either acquirer or target firm. Overall, these results are consistent with the view that patent citations indicate high quality deals. Furthermore, this paper suggests that the positive association between acquirer returns and citation links is not attributed to addressing the overbidding problem.

Table 1.1 Bankruptcy Rates over 1979-2009

The table reports the probability of bankruptcy over time. The sample consists of all US public firms that had common shares traded on the NYSE, AMEX, or NASDAQ from 1979 to 2009. Firms that incorporated outside the United States are excluded. Financial firms (SIC codes 6000-6999) and utility firms (SIC codes 4900-4999) are also excluded. I require that firms have positive assets to be included in a given year. I also construct a high-tech sample by following the high-tech definitions offered by the United States Department of Commerce by seven three-digit SIC codes: SIC 283, SIC 357, SIC 366, SIC 367, SIC 382, SIC 384 and SIC 737. A firm is defined as bankrupt if it is delisted due to bad performance. Delistings are obtained from CRSP. I group firms into two groups: zero-R&D and R&D firms. Firms that did not have any R&D expenditures in the previous three years are classified as zero-R&D firms. Firms that reported positive R&D during the previous three years are classified as R&D firms. The probability of bankruptcy is denoted in percentages.

Year	Full Sample						High-Tech Sample					
	Number of firms			Prob of bankruptcy			Number of firms			Prob of bankruptcy		
	All firms	Zero-R&D firms	R&D firms	All firms	Zero-R&D firms	R&D firms	All firms	Zero-R&D firms	R&D firms	All firms	Zero-R&D firms	R&D firms
1979	5084	62%	38%	0.61	0.64	0.48	744	27%	73%	0.4	0.5	0.19
1980	5060	63%	37%	0.83	0.85	0.67	772	29%	71%	0.65	0.45	0.6
1981	5174	63%	37%	0.91	0.98	0.8	844	28%	72%	0.83	0.42	1.2
1982	5291	63%	37%	1.46	1.64	0.98	909	28%	72%	1.54	0.77	1.88
1983	5513	62%	38%	1.05	1.1	1.11	1058	23%	77%	0.57	0.84	0.63
1984	5716	61%	39%	3.05	3.29	1.69	1180	20%	80%	1.95	1.67	3.38
1985	5758	61%	39%	3.59	3.69	3.25	1263	21%	79%	3.69	0.76	3
1986	5967	59%	41%	3.16	3.42	1.64	1371	18%	82%	1.82	3.37	1.54
1987	6092	59%	41%	1.77	1.83	1.52	1440	18%	82%	3.01	3.29	1.87
1988	6064	59%	41%	3.39	3.58	3.18	1460	19%	81%	3.81	3.23	3.69
1989	5986	60%	40%	3.21	3.09	3.44	1467	22%	78%	1.98	0.93	3.37
1990	5893	60%	40%	3.34	3.17	3.69	1473	23%	77%	3.72	1.49	3.29
1991	5995	61%	39%	3.54	3.97	1.97	1566	24%	76%	3.04	1.57	3.42
1992	6214	61%	39%	1.63	1.6	1.88	1702	25%	75%	1.41	0.72	1.91
1993	6556	60%	40%	0.9	0.78	1.23	1852	26%	74%	0.92	0	1.44
1994	6876	60%	40%	1.08	1.14	1.07	2000	26%	74%	0.85	0.57	1.01
1995	7124	59%	41%	1.01	1.2	0.81	2167	25%	75%	0.55	0.18	0.71
1996	7597	56%	44%	0.92	1.01	0.97	2450	21%	79%	0.45	0.2	0.64
1997	7704	55%	45%	1.21	1.38	1.09	2564	20%	80%	0.7	0.38	0.95
1998	7602	55%	45%	1.89	1.97	1.86	2635	22%	78%	1.52	0.7	1.86
1999	7519	51%	49%	1.62	3.1	1.28	2723	16%	84%	1.03	0.9	1.22
2000	7519	52%	48%	3.11	3.45	1.91	2751	19%	81%	1.31	1.15	1.5
2001	7197	53%	47%	3.9	3.11	3.85	2593	20%	80%	3.97	4.25	3.8
2002	6762	52%	48%	3.38	3.11	3.81	2468	21%	79%	3.55	1.76	3.87
2003	6358	52%	48%	1.68	1.72	1.71	2354	20%	80%	1.53	1.25	1.67
2004	6031	52%	48%	0.83	0.93	0.75	2216	19%	81%	0.5	0.24	0.58
2005	5774	50%	50%	0.92	1	0.87	2157	17%	83%	0.79	0.54	0.87
2006	5441	49%	51%	0.7	0.72	0.71	2050	14%	86%	0.93	1.39	0.9
2007	5111	47%	53%	1.06	1.33	0.85	1912	12%	88%	0.84	0.86	0.88
2008	4681	47%	53%	3.33	3.3	3.39	1736	11%	89%	3.28	1.56	3.49
2009	4010	46%	54%	3.49	3.01	3.95	1454	10%	90%	3.65	3.01	3.86
				1.70	1.78	1.63				1.54	1.16	1.72

Table 1.2 Sample Characteristics

The table reports summary statistics at the firm-year level for full sample and high-tech sample. Samples are defined in Table 1.1. All variable definitions are provided in Appendix 1.

Panel A: Firm-year Characteristics for Full Sample

	N	Mean	SD	P5	Median	P95
Bankrupt	189669	0.017	0.129	0	0	0
R&D/assets	189669	0.056	0.138	0	0	0.294
R&D/sales	181835	0.307	1.620	0	0	0.712
Total assets($M)	189669	1061	8537	0.951	51.00	3344
B/M	147821	0.531	1.262	-0.322	0.485	3.073
Leverage	177405	0.314	0.415	0	0.225	0.866
Cash	177919	0.174	0.225	0.002	0.075	0.713

Panel B: Firm-year Characteristics and Bankruptcy for Full Sample

	Bankrupt=0			Bankrupt=1		
	N	Mean	Median	N	Mean	Median
R&D/assets	186482	0.054	0	3187	0.076	0
R&D/sales	178806	0.303	0	3029	0.530	0
Total assets($M)	186482	1077	51.90	3187	158.4	16.86
B/M	144690	0.535	0.487	3131	0.337	0.354
Leverage	174238	0.312	0.224	3167	0.402	0.348
Cash	174737	0.175	0.075	3182	0.154	0.050

Panel C: Firm-year Characteristics for High-Tech Sample

	N	Mean	SD	P5	Median	P95
Bankrupt	55331	0.015	0.122	0	0	0
R&D/assets	55331	0.146	0.197	0	0.082	0.600
R&D/sales	52307	0.842	3.626	0	0.084	5.439
Total assets($M)	55331	483.2	3516	0.686	25.19	1303
B/M	43970	0.372	1.000	-0.286	0.339	1.464
Leverage	50997	0.247	0.458	0	0.097	0.901
Cash	51153	0.301	0.273	0.007	0.221	0.855

Panel D: Firm-year Characteristics and Bankruptcy for High-Tech Sample

	Bankrupt=0			Bankrupt=1		
	N	Mean	Median	N	Mean	Median
R&D/assets	54491	0.145	0.081	840	0.226	0.135
R&D/sales	51516	0.832	0.083	791	1.527	0.149
Total assets($M)	54491	489.7	25.65	840	60.42	10.66
B/M	43146	0.376	0.341	824	0.171	0.193
Leverage	50159	0.245	0.095	838	0.351	0.216
Cash	50314	0.302	0.222	839	0.260	0.146

Table 1.3 Sample Characteristics for the Matched Sample

The table reports summary statistics for the matched sample. For each bankrupt firm in sample defined in Table 1.1, I choose the single matching firm to be the firm that is in the same 4-digit-SIC industry but did not go bankrupt over the sample period and is the closest in size conditional on being within its 30% size band of the bankrupt firm, using total assets as the size measure. All variable definitions are provided in Appendix 1. All the variables are taken an average over the period from the year appearing on Compustat to the year of bankruptcy.

Bankrupt Firms:

Variable	N	Mean	SD	P5	Median	P95
R&D/assets	2743	0.074	0.170	0	0	0.414
R&D/sales	2679	1.000	4.459	0	0	4.040
Total assets($M)	2743	123.3	305.4	3.575	27.50	553.1
B/M	2715	0.560	1.007	-0.415	0.468	3.117
Leverage	2738	0.337	0.272	0.016	0.293	0.788
Cash	2741	0.199	0.199	0.013	0.127	0.638

Matching Firms:

Variable	N	Mean	SD	P5	Median	P95
R&D/assets	2662	0.061	0.143	0	0	0.345
R&D/sales	2598	0.617	3.443	0	0	1.601
Total assets($M)	2662	119.7	306.3	3.577	26.20	531.1
B/M	2139	0.581	0.940	-0.237	0.516	1.940
Leverage	2486	0.298	0.281	0.001	0.235	0.803
Cash	2488	0.208	0.208	0.013	0.132	0.672

Table 1.4 Correlation Matrix of Firm Fundamental Characteristics

The sample is defined in Table 1.1. All variable definitions are provided in Appendix 1. The corresponding p-value is reported in the brackets below each correlation coefficient.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Bankrupt	1.000						
(2)	R&D/assets	0.019	1.000					
		(0.000)						
(3)	R&D/sales	0.018	0.565	1.000				
		(0.000)	(0.000)					
(4)	Firm size	-0.054	-0.237	-0.133	1.000			
		(0.000)	(0.000)	(0.000)				
(5)	B/M	-0.023	-0.136	-0.064	0.133	1.000		
		(0.000)	(0.000)	(0.000)	(0.000)			
(6)	Leverage	0.029	0.056	0.003	-0.174	-0.367	1.000	
		(0.000)	(0.000)	(0.247)	(0.000)	(0.000)		
(7)	Cash	-0.012	0.395	0.351	-0.253	-0.059	-0.216	1.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Table 1.5 Probit Regression of the Likelihood of Going Bankrupt

The table reports marginal effects estimates from probit models. The dependent variable is a dummy indicating whether a firm went bankrupt in a given year. Columns (1)-(2) report the results using the full sample defined in Table 1.1. The unit of observation is firm-year. Columns (3)-(4) report the results using the high-tech sample. I construct the high-tech sample by following the high-tech definitions offered by the United States Department of Commerce by seven three-digit SIC codes: SIC 283, SIC 357, SIC 366, SIC 367, SIC 382, SIC 384 and SIC 737. Columns (5)-(6) report the results using the non-high-tech sample. Columns (6)-(7) report the results using the matched sample. For each bankrupt firm in sample defined in Table 1.1, I choose the single matching firm to be the firm that is in the same 4-digit-SIC industry but did not go bankrupt over the sample period and is the closest in size conditional on being within its 30% size band of the bankrupt firm, using total assets as the size measure. Columns (9)-(10) report the results using the positive R&D sample. The positive R&D sample includes only firm-year observations with at least one year of positive R&D over the previous three years. All variable definitions are provided in Appendix 1. All the accounting and financial variables are taken at time T-1 to explain bankruptcy at time T, and winsorized at 99% to address outlier problems. Two-digit SIC industry and year fixed effects are controlled. Robust p-values based on standard errors clustered by firm are in parentheses. The symbols *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) Full Sample	(2) Full Sample	(3) High-tech	(4) High-tech	(5) Non-high-tech	(6) Non-high-tech	(7) Matching Sample	(8) Matching Sample	(9) Positive R&D	(10) Positive R&D
R&D/assets	0.010***		0.019***		-0.012**		0.049***		0.007***	
	[0.000]		[0.000]		[0.011]		[0.000]		[0.002]	
R&D/sales		0.001***		0.001***		0.0004		0.003***		0.001***
		[0.000]		[0.000]		[0.306]		[0.000]		[0.000]
Firm size	-0.004***	-0.005***	-0.003***	-0.004***	-0.005***	-0.005***	-0.015***	-0.016***	-0.004***	-0.004***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
B/M	-0.040	-0.040	-0.036	-0.043	-0.036	-0.036	-0.496***	-0.475***	-0.070*	-0.069*
	[0.145]	[0.133]	[0.516]	[0.415]	[0.250]	[0.248]	[0.000]	[0.000]	[0.055]	[0.054]
Cash	-0.017***	-0.020***	-0.014***	-0.014***	-0.020***	-0.024***	-0.065***	-0.065***	-0.013***	-0.015***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Leverage	0.001	0.002***	-0.001	0.000	0.003***	0.003***	0.054***	0.061***	-0.001	-0.001
	[0.101]	[0.003]	[0.287]	[0.936]	[0.002]	[0.000]	[0.000]	[0.000]	[0.122]	[0.446]
Observations	147,339	144,643	43,839	42,823	103,500	101,820	32,478	31,842	71,014	69,820
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.066	0.074	0.079	0.081	0.067	0.075	0.094	0.094	0.087	0.092

Table 1.6 IV-Probit Regression of the Likelihood of Going Bankrupt

The table reports marginal effects estimates from IV-Probit models. The dependent variable is a dummy indicating whether a firm went bankrupt in a given year. Firm's R&D intensity is instrumented by industry-median and geographic-median R&D intensity. The industry-median R&D intensity is constructed by four- digit SIC code. Geographic-median R&D intensity is constructed by county. The unit of observation is firm-year. Columns (1)-(2) report the results using the full sample defined in Table 1.1. Columns (3)-(4) report the results using the high-tech sample. I construct the high-tech sample by following the high-tech definitions offered by the United States Department of Commerce by seven three-digit SIC codes: SIC 283, SIC 357, SIC 366, SIC 367, SIC 382, SIC 384 and SIC 737. Columns (5)-(6) report the results using the non-high-tech sample. Columns (6)-(7) report the results using the matched sample. For each bankrupt firm in sample defined in Table 1.1, I choose the single matching firm to be the firm that is in the same 4-digit-SIC industry but did not go bankrupt over the sample period and is the closest in size conditional on being within its 30% size band of the bankrupt firm, using total assets as the size measure. Columns (9)-(10) report the results using the positive R&D sample. The positive R&D sample includes only firm-year observations with at least one year of positive R&D over the previous three years. All variable definitions are provided in Appendix 1. All the accounting and financial variables are taken at time T-1 to explain bankruptcy at time T, and winsorized at 99% to address outlier problems. Two-digit SIC industry and year fixed effects are controlled. Robust p-values based on standard errors clustered by firm are in parentheses. The symbols *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) Full Sample	(2) Full Sample	(3) High-tech	(4) High-tech	(5) Non-high-tech	(6) Non-high-tech	(7) Matching Sample	(8) Matching Sample	(9) Positive R&D	(10) Positive R&D
R&D/assets	0.019**		0.020**		0.027*		0.056*		0.017***	
	[0.020]		[0.012]		[0.080]		[0.088]		[0.002]	
R&D/sales		0.002*		0.002*		0.004*		0.005***		0.002***
		[0.065]		[0.059]		[0.076]		[0.000]		[0.000]
Firm size	-0.004***	-0.005***	-0.003***	-0.004***	-0.005***	-0.005***	-0.015***	-0.015***	-0.004***	-0.004***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
B/M	-0.035	-0.033	-0.034	-0.041	-0.029	-0.029	-0.489***	-0.485***	-0.069**	-0.068**
	[0.204]	[0.235]	[0.555]	[0.448]	[0.363]	[0.371]	[0.000]	[0.000]	[0.045]	[0.045]
Cash	-0.019***	-0.021***	-0.013***	-0.018***	-0.023***	-0.028***	-0.064***	-0.066***	-0.014***	-0.015***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Leverage	0.001	0.003***	-0.001	0.001	0.002**	0.004***	0.055***	0.062***	-0.001	-0.001
	[0.209]	[0.003]	[0.381]	[0.893]	[0.044]	[0.000]	[0.000]	[0.000]	[0.133]	[0.336]
Observations	146,158	143,043	43,472	41,630	102,686	99,201	32,257	31,142	69,814	68,520
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 1.7 Correlation across Information Asymmetry, Volatility and Bankruptcy

Sample is defined in Table 1.1. All variable definitions are provided in Appendix 1. The corresponding p-value is reported in the brackets below each correlation coefficient.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	Bankrupt	1.000							
(2)	Stock return volatility	0.135	1.000						
		(0.000)							
(3)	Cash flow volatility	0.019	0.250	1.000					
		(0.000)	(0.000)						
(4)	Forecast error	0.195	0.205	0.144	1.000				
		(0.000)	(0.000)	(0.000)					
(5)	Forecast dispersion	0.044	0.029	0.041	0.337	1.000			
		(0.000)	(0.000)	(0.000)	(0.000)				
(6)	Announcement reaction	0.094	0.487	0.169	0.166	0.014	1.000		
		(0.000)	(0.000)	(0.000)	(0.000)	(0.002)			
(7)	R&D/assets	0.019	0.255	0.387	0.054	0.026	0.189	1.000	
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
(8)	R&D/sales	0.018	0.143	0.224	0.019	0.008	0.055	0.565	1.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.062)	(0.000)	(0.000)	

Table 1.8 Bankrupt Regression Controlling for Volatility and Information Asymmetry

The table reports marginal effects estimates from probit models. The dependent variable is a dummy indicating whether a firm went bankrupt in a given year. Sample is defined in Table 1.1. The unit of observation is firm-year. All variable definitions are provided in Appendix 1. All the accounting and financial variables are taken at time T-1 to explain bankruptcy at time T, and winsorized at 99% to address outlier problems. Two-digit SIC industry and year fixed effects are controlled. Robust p-values based on standard errors clustered by firm are in parentheses. The symbols *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	bankrupt	bankrupt	bankrupt	bankrupt	bankrupt	bankrupt	bankrupt	bankrupt	bankrupt
R&D/assets	0.009***	0.005**	0.007**	0.005***	0.004***	0.005**	0.004***	0.003**	0.004**
	[0.001]	[0.036]	[0.039]	[0.002]	[0.003]	[0.012]	[0.008]	[0.030]	[0.030]
Firm size	-0.009***	-0.008***	-0.008***	-0.001***	-0.001***	-0.002***	-0.001***	-0.001***	-0.002***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
B/M	-0.057*	-0.013	-0.067**	0.049**	0.086***	0.127***	0.055**	0.089***	0.147***
	[0.073]	[0.664]	[0.035]	[0.021]	[0.002]	[0.000]	[0.012]	[0.001]	[0.000]
Cash	-0.014***	-0.013***	-0.017***	-0.003***	-0.003***	-0.003**	-0.004***	-0.004***	-0.004***
	[0.000]	[0.000]	[0.000]	[0.002]	[0.001]	[0.017]	[0.000]	[0.000]	[0.006]
Leverage	0.021***	0.019***	0.020***	0.007***	0.007***	0.013***	0.007***	0.007***	0.014***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Stock return volatility		0.046***					0.011***	0.012***	0.016***
		[0.000]					[0.000]	[0.000]	[0.000]
Cash flow volatility			0.003**						
			[0.029]						
Forecast error				0.017***			0.017***		
				[0.000]			[0.000]		
Forecast dispersion					0.004***			0.003***	
					[0.000]			[0.000]	
Announcement reaction						0.030***			0.024***
						[0.000]			[0.000]
Observations	113,990	113,990	106,717	53,464	45,269	78,339	49,901	42,391	71,922
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.162	0.173	0.161	0.244	0.198	0.183	0.265	0.220	0.195

Table 1.9 Decomposition of Volatility and Information Asymmetry

The table reports marginal effects estimates from probit models. The dependent variable is a dummy indicating whether a firm went bankrupt in a given year. Volatility and information asymmetry measures are decomposed into two parts: the part predicted by R&D and the other part unpredicted by R&D. In the first step, I run regression of volatility and information asymmetry measures on R&D and form the part that is predicted by R&D. The residual is the unpredicted part. In the second step, I run regression of the probability of bankruptcy on the predicted part and the unpredicted part while controlling for other variables. Sample is defined in Table 1.1. The unit of observation is firm-year. All variable definitions are provided in Appendix 1. All the accounting and financial variables are taken at time T-1 to explain bankruptcy at time T, and winsorized at 99% to address outlier problems. Two-digit SIC industry and year fixed effects are controlled. Robust p-values based on standard errors clustered by firm are in parentheses. The symbols *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	bankrupt	bankrupt	bankrupt	bankrupt	bankrupt
Stock return volatility predicted	0.072***				
	[0.000]				
Stock return volatility unpredicted	0.046***				
	[0.000]				
Cash flow volatility predicted		0.007***			
		[0.000]			
Cash flow volatility unpredicted		0.003**			
		[0.029]			
Forecast error predicted			0.133***		
			[0.000]		
Forecast error unpredicted			0.017***		
			[0.000]		
Forecast dispersion predicted				-0.069***	
				[0.004]	
Forecast dispersion unpredicted				0.004***	
				[0.000]	
Announcement reaction predicted					0.079***
					[0.000]
Announcement reaction unpredicted					0.030***
					[0.000]
Firm size	-0.008***	-0.008***	-0.001***	-0.001***	-0.002***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
B/M	-0.013	-0.067**	0.049**	0.086***	0.127***
	[0.664]	[0.035]	[0.021]	[0.002]	[0.000]
Cash	-0.013***	-0.017***	-0.003***	-0.003***	-0.003**
	[0.000]	[0.000]	[0.002]	[0.001]	[0.017]
Leverage	0.019***	0.020***	0.007***	0.007***	0.013***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	113,990	106,717	53,464	45,269	78,339
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.173	0.161	0.244	0.198	0.183

Table 1.10 R&D Effects on Firm's Long-run Outcome

The table reports estimates from regressions using the sample defined in Table 1.1. The unit of observation is firm-year. Model (1) is probit regression. The dependent variable Bankrupt3year is a dummy indicating whether a firm went bankrupt in the next three years. Model (2)-(5) are OLS regressions. ROA volatility is the standard deviation of ROA (return on assets) over the next three years. Market beta is computed using a market model against the CRSP value-weighted index over the next three years. Car1year and car3year are the cumulative abnormal return (CAR) over the next one year and three years. CAR is computed using the Fama-French three-factor model. All variable definitions are provided in Appendix 1. All the accounting and financial variables are winsorized at 99% to address outlier problems. Two-digit SIC industry and year fixed effects are controlled. Robust p-values based on standard errors clustered by firm are in parentheses. The symbols *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) Bankrupt3year	(2) ROA volatility	(3) Market beta	(4) CAR1year	(5) CAR3year
R&D/assets	0.025***	0.704***	0.610***	0.200***	0.523***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Firm size	-0.011***	-0.074***	0.115***	-0.023***	-0.057***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
B/M	0.368***	-0.732***	-7.519***	13.739***	30.509***
	[0.000]	[0.009]	[0.000]	[0.000]	[0.000]
Cash	-0.022***	0.106***	0.405***	-0.034*	-0.222***
	[0.000]	[0.000]	[0.000]	[0.084]	[0.000]
Leverage	0.002	0.392***	-0.106***	0.112***	0.344***
	[0.241]	[0.000]	[0.000]	[0.000]	[0.000]
Constant		0.325***	0.141***	0.007	0.107
		[0.000]	[0.001]	[0.883]	[0.317]
Observations	147,339	131,966	117,487	106,103	106,239
R-squared	0.058	0.330	0.282	0.028	0.040
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes

Table 1.11 Quartile Analysis

The table reports marginal effects estimates from probit models. The dependent variable is a dummy indicating whether a firm went bankrupt in a given year. Sample is defined in Table 1.1. The unit of observation is firm-year. I sort all the firm years into quartiles according to firm characteristics. For each characteristic quartile, I estimate a probit model. Panel A, B, C and D present coefficient estimates with firms sorted into quartiles based on firm size at time T-1, z-score at time T-3, stock return volatility at T-1 and announcement reaction at time T-1, respectively. All variable definitions are provided in Appendix 1. Other controls (including size, B/M, cash, leverage) are taken at time T-1 to explain bankruptcy at time T and not reported in the table. Two-digit SIC industry and year fixed effects are controlled. Robust p-values based on standard errors clustered by firm are in parentheses. The symbols *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Q1 Low	Q2	Q3	Q4 High
	Panel A: Size Quartiles			
R&D/assets	0.034***	0.038***	0.014*	0.010*
	[0.000]	[0.000]	[0.056]	[0.064]
Mean quartile value	3.6	25.2	130.9	4086
Bankruptcy rate	0.025	0.023	0.013	0.006
Observations	33,165	30,724	34,546	36,369
	Panel B: Z-Score Quartiles			
R&D/assets	0.026*	0.024**	0.017***	0.012***
	[0.053]	[0.033]	[0.009]	[0.000]
Mean quartile value	-44	3.6	4.3	24.8
Bankruptcy rate	0.025	0.020	0.015	0.014
Observations	21,553	22,853	23,199	22,509
	Panel C: Stock Return Volatility Quartiles			
R&D/assets	-0.001	-0.001	0.014**	0.034***
	[0.544]	[0.983]	[0.024]	[0.000]
Mean quartile value	0.067	0.11	0.159	0.297
Bankruptcy rate	0.010	0.014	0.025	0.061
Observations	27,262	27,861	27,920	27,961
	Panel D: Announcement Reaction Quartiles			
R&D/assets	0.003	-0.001	0.005	0.017**
	[0.233]	[0.810]	[0.162]	[0.011]
Mean quartile value	0.022	0.043	0.071	0.146
Bankruptcy rate	0.004	0.005	0.009	0.023
Observations	13,230	13,802	18,775	18,967
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Table 2.1 High-Tech Firm Characteristics

The table reports the summary statistics for high-tech firms in the sample. The sample is constructed from publicly traded with coverage in the Compustat database during 1976 to 2009. I construct the high-tech sample by following the high-tech definitions offered by the United States Department of Commerce by seven three-digit SIC codes: SIC 283, SIC 357, SIC 366, SIC 367, SIC 382, SIC 384 and SIC 737. I exclude firms incorporated outside of the United States, firms with no stock price data, and firms without at least six R&D observations. I also exclude firms if the sum of their cash flow-to-assets ratio over the sample period is less than or equal to zero. I require that firms have positive assets to be included in a given year. All variable definitions are provided in Appendix 2.

Variable	N	Mean	SD	P5	Median	P95
R&D/Assets	31595	0.12	0.14	0.00	0.09	0.38
R&D/Sales	31595	0.30	1.00	0.00	0.09	0.98
Total Assets(M$)	31595	794.20	2694.19	4.11	74.22	3555.79
Market CAP(M$)	27952	1776.85	6935.62	4.81	130.74	7242.29
Sale ratio	30005	1.24	0.78	0.21	1.11	2.74
B/M	27946	0.52	0.52	0.05	0.41	1.45
Leverage	30735	0.17	0.22	0.00	0.09	0.57
Cash	30839	0.27	0.24	0.01	0.20	0.75
bankrupt	31595	0.01	0.08	0.00	0.00	0.00

Table 2.2 Sample Descriptive Statistics

The sample is defined in Table 2.1. All variable definitions are provided in Appendix 2. Outliers in all variables are trimmed at the 1% level. According to the NBER's business cycle dating and GDP growth rate sorting, I identified four recession periods: 1980-1982, 1990-1991, 2001-2002, 2007-2009. The table reports the summary statistics for the full sample and each recession-period subsample. The final column reports p-values for tests that the mean and median values differ across recession and non-recession periods.

Variable and Statistics	Full Sample	1980-1982	1990-1991	2001-2002	2007-2009	Recession	Non-Recession	Differences (p-values)
rd								
Mean	0.119	0.073	0.115	0.139	0.133	0.118	0.119	0.453
Median	0.085	0.058	0.088	0.102	0.091	0.084	0.086	0.123
STD	0.126	0.077	0.120	0.138	0.144	0.127	0.126	0.107
ad								
Mean	0.010	0.014	0.015	0.007	0.006	0.010	0.010	0.583
Median	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.000
STD	0.023	0.024	0.027	0.019	0.018	0.022	0.023	0.002
capex								
Mean	0.056	0.093	0.056	0.040	0.029	0.052	0.058	0.000
Median	0.041	0.074	0.045	0.029	0.020	0.035	0.043	0.000
STD	0.052	0.069	0.046	0.038	0.030	0.052	0.053	0.298
sale								
Mean	1.083	1.287	1.227	0.928	0.863	1.058	1.092	0.000
Median	1.024	1.238	1.173	0.842	0.744	0.985	1.037	0.000
STD	0.583	0.513	0.605	0.605	0.531	0.595	0.578	0.002
Cash flow								
Mean	0.146	0.163	0.152	0.096	0.123	0.131	0.152	0.000
Median	0.159	0.169	0.166	0.122	0.143	0.150	0.162	0.000
STD	0.169	0.125	0.175	0.196	0.182	0.176	0.166	0.000
New debt issuance								
Mean	0.007	0.015	-0.005	-0.003	0.003	0.002	0.009	0.000
Median	0.000	0.000	-0.003	0.000	0.000	0.000	0.000	0.000
STD	0.086	0.089	0.081	0.079	0.079	0.082	0.087	0.000
New stock issuance								
Mean	0.058	0.083	0.067	0.024	-0.002	0.040	0.064	0.000
Median	0.004	0.005	0.002	0.004	0.000	0.002	0.004	0.000
STD	0.175	0.179	0.187	0.115	0.109	0.153	0.182	0.000
Cash flow/net finance								
Mean	0.869	0.802	0.876	0.928	1.077	0.930	0.846	0.000
Median	0.956	0.889	0.984	0.973	1.000	0.975	0.949	0.000
STD	1.095	0.949	1.166	1.235	1.389	1.213	1.047	0.000
New debt/net finance								
Mean	0.023	0.031	-0.020	0.022	0.013	0.012	0.028	0.125
Median	0.000	0.000	-0.002	0.000	0.000	0.000	0.000	0.153
STD	0.710	0.701	0.812	0.762	0.757	0.759	0.691	0.000
New stock/net finance								
Mean	0.106	0.170	0.131	0.062	-0.058	0.069	0.121	0.000
Median	0.018	0.022	0.007	0.017	0.000	0.010	0.020	0.000
STD	0.631	0.472	0.540	0.699	0.816	0.664	0.618	0.000

Table 2.3 Correlation Matrix

The sample is defined in Table 2.1. All variable definitions are provided in Appendix 2. The corresponding p-value is reported in the brackets below each correlation coefficient.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Bankrupt	1.000						
(2)	R&D/Assets	0.061	1.000					
		(0.000)						
(3)	R&D/Sales	0.013	0.465	1.000				
		(0.023)	(0.000)					
(4)	Firm size	-0.044	-0.204	-0.054	1.000			
		(0.000)	(0.000)	(0.000)				
(5)	B/M	-0.015	-0.219	-0.096	-0.046	1.000		
		(0.011)	(0.000)	(0.000)	(0.000)			
(6)	Leverage	0.050	-0.010	-0.018	-0.051	-0.235	1.000	
		(0.000)	(0.075)	(0.001)	(0.000)	(0.000)		
(7)	Cash	-0.014	0.305	0.379	-0.045	-0.118	-0.355	1.000
		(0.017)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Table 2.4 Economic Downturn Effect

The table reports marginal effects estimates from probit models. The dependent variable is a dummy indicating whether a firm went bankrupt in a given year. A firm is defined as bankrupt if it is delisted due to bad performance. Delistings are obtained from CRSP. The table first reports the results using the full sample defined in Table 2.1. The unit of observation is firm-year. Then firms are assigned to “financially constrained” and “financially unconstrained” categories based on firm dividend payout and bond rating. Results using the subsamples are presented in the last four columns. All variable definitions are provided in Appendix 2. All the accounting and financial variables are winsorized at 99% to address outlier problems. Three-digit SIC industry fixed effects are controlled. Robust p-values based on standard errors clustered by firm are in parentheses. The symbols *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Recession Proxied by NBER Recession Dummy

		Dividend Payout		Bond Rating	
VARIABLES	Full Sample	Unconstrained firms	Constrained firms	Unconstrained firms	Constrained firms
R&D/assets	0.011***	0.003	0.013***	0.000*	0.012***
	[0.000]	[0.251]	[0.000]	[0.071]	[0.000]
Firm size	-0.001***	-0.000	-0.001***	-0.000	-0.001***
	[0.000]	[0.224]	[0.000]	[0.561]	[0.000]
B/M	0.130**	0.099***	0.138*	-0.000	0.114
	[0.047]	[0.001]	[0.083]	[0.268]	[0.191]
Cash	-0.003**	0.001	-0.006***	0.000	-0.008***
	[0.046]	[0.110]	[0.008]	[0.309]	[0.002]
Leverage	0.008***	-0.001	0.009***	0.000***	0.009***
	[0.000]	[0.286]	[0.000]	[0.000]	[0.000]
Recession	0.000	0.000	0.001	0.000	0.000
	[0.823]	[0.954]	[0.478]	[0.836]	[0.929]
Recession × R&D/assets	0.006*	-0.027***	0.007*	0.000	0.007
	[0.063]	[0.001]	[0.090]	[0.455]	[0.101]
Observations	27,846	3,924	22,704	1,775	19,243
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No	No
Pseudo R2	0.126	0.203	0.120	0.380	0.118

Panel B: Recession Proxied by GDP Growth

VARIABLES	Full Sample	Dividend Payout Unconstrained firms	Dividend Payout Constrained firms	Bond Rating Unconstrained firms	Bond Rating Constrained firms
R&D/assets	0.017***	-0.000	0.019***	0.000	0.019***
	[0.000]	[0.962]	[0.000]	[0.153]	[0.000]
Firm size	-0.001***	-0.000	-0.001***	-0.000	-0.001***
	[0.000]	[0.273]	[0.000]	[0.499]	[0.000]
B/M	0.113*	0.165***	0.115	-0.000	0.098
	[0.073]	[0.000]	[0.131]	[0.547]	[0.244]
Cash	-0.004**	0.003*	-0.006***	0.000	-0.008***
	[0.030]	[0.067]	[0.005]	[0.480]	[0.002]
Leverage	0.007***	-0.002	0.008***	0.000***	0.008***
	[0.000]	[0.313]	[0.000]	[0.001]	[0.000]
Recession	0.025	-0.025	0.051**	0.000	0.033
	[0.221]	[0.323]	[0.030]	[0.890]	[0.199]
Recession × R&D/assets	0.216***	-0.081	0.226***	0.000	0.248***
	[0.002]	[0.620]	[0.007]	[0.563]	[0.007]
Observations	27,846	3,924	22,704	1,775	19,243
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No	No
Pseudo R2	0.133	0.209	0.129	0.355	0.125

Panel C: Recession Proxied by Default Spread

VARIABLES	Full Sample	Dividend Payout Unconstrained firms	Dividend Payout Constrained firms	Bond Rating Unconstrained firms	Bond Rating Constrained firms
R&D/assets	-0.001	0.020**	-0.002	-0.000	-0.001
	[0.750]	[0.018]	[0.661]	[0.167]	[0.853]
Firm size	-0.001***	-0.000	-0.001***	-0.000	-0.001***
	[0.000]	[0.214]	[0.000]	[0.779]	[0.000]
B/M	0.130**	0.159***	0.139*	-0.000	0.117
	[0.046]	[0.001]	[0.081]	[0.804]	[0.179]
Cash	-0.004**	0.003	-0.006***	0.000	-0.008***
	[0.036]	[0.123]	[0.005]	[0.498]	[0.002]
Leverage	0.008***	-0.003*	0.009***	0.000***	0.009***
	[0.000]	[0.086]	[0.000]	[0.000]	[0.000]
Recession	-0.144	0.135*	-0.191	-0.000**	-0.190
	[0.171]	[0.077]	[0.147]	[0.026]	[0.172]
Recession × R&D/assets	1.305***	-1.598**	1.647***	0.000**	1.393***
	[0.000]	[0.040]	[0.000]	[0.028]	[0.005]
Observations	27,846	3,924	22,704	1,775	19,243
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No	No
Pseudo R2	0.129	0.193	0.123	0.378	0.120

Table 2.5 Characteristics of R&D Leaders and Laggards

The sample is defined in Table 2.1 According to the NBER's business cycle dating and GDP growth rate sorting, I identified four recession periods: 1980-1982, 1990-1991, 2001-2002, 2007-2009. I require firms to have data available one year prior to the recession and during the recession period. I identified firms that leaded in R&D growth (top quartile) during the whole recession period as R&D leaders, and firms that followed in R&D growth (bottom quartile) over the recession period as R&D laggards. Panel A presents the breakdown of firms for each recession period; Panel B shows the key characteristics of R&D leaders and laggards in the year prior to the recession; Panel C shows the spending ratios changes of R&D leaders and laggards during recessions and five years after recessions. All variable definitions are provided in Appendix 2. Outliers in all variables are trimmed at the 1% level.

Panel A: Decomposition of Firms

NBER Recession period	Leaders	Laggards	Others	Leaders percent
1980-1982	107	127	247	22.25%
1990-1991	246	231	465	26.11%
2001-2002	355	236	658	28.42%
2007-2009	225	218	465	24.78%

Panel B: Key Characteristics of R&D Leaders and Laggards before Recessions

	Mean			Median		
Variables	Laggards	Leaders	Differences (p-values)	Laggards	Leaders	Differences (p-values)
Firm age	14.022	10.535	0.000	11.000	8.000	0.000
Total assets($m)	951.473	611.287	0.011	82.803	79.216	0.553
MCAP($m)	1918.148	2374.841	0.350	79.293	200.169	0.000
Tobin's q	1.870	3.071	0.000	1.375	2.153	0.000
Sale	1.094	1.369	0.000	1.022	1.201	0.000
Leverage	0.206	0.145	0.000	0.132	0.059	0.000
Cash	0.225	0.305	0.000	0.146	0.238	0.000
Return on assets	-0.019	0.091	0.000	0.061	0.123	0.000
Cash flow/net finance	0.830	0.742	0.192	0.941	0.902	0.025
New stock/net finance	0.118	0.168	0.263	0.009	0.044	0.000
Dividend dummy	0.195	0.103	0.000	0.000	0.000	0.000

Panel C: Spending Ratios of R&D Leaders and Laggards during Recessions

	Mean			Median		
Variables	Laggards	Leaders	Differences (p-values)	Laggards	Leaders	Differences (p-values)
Advertising spending						
Before recession	0.011	0.012	0.332	0.000	0.000	0.711
During recession	0.010	0.012	0.072	0.000	0.000	0.017
After recession	0.009	0.011	0.235	0.000	0.001	0.160
Capital spending						
Before recession	0.056	0.079	0.000	0.036	0.046	0.000
During recession	0.040	0.065	0.000	0.024	0.044	0.000
After recession	0.049	0.058	0.002	0.038	0.044	0.000
R&D spending						
Before recession	0.158	0.139	0.034	0.111	0.083	0.000
During recession	0.118	0.144	0.000	0.083	0.102	0.000
After recession	0.116	0.141	0.000	0.081	0.111	0.000

Table 2.6 Post-Recession Performance Comparison

The table reports the post-recession performance comparison between R&D leaders and R&D laggards in the sample. The sample is defined in Table 2.1.According to the NBER's business cycle dating and GDP growth rate sorting, I identified four recession periods: 1980-1982, 1990-1991, 2001-2002, 2007-2009. I require firms to have data available one year prior to the recession and during the recession period. I identified firms that leaded in R&D growth (top quartile) during the whole recession period as R&D leaders, and firms that followed in R&D growth (bottom quartile) over the recession period as R&D laggards. Performance is measured during the recession and five years after the recession. Industry adjustment is carried out by subtracting the 3-digit SIC industry median from the firm's performance. All variable definitions are provided in Appendix 2. Outliers in all variables are trimmed at the 1% level.

	Mean			Median			STD		
	Laggard	Leader	p_value	Laggard	Leader	p_value	Laggard	Leader	p_value
Level sales growth:									
During recession	-0.025	0.217	0.000	-0.062	0.121	0.000	0.379	0.449	0.000
One year after	0.048	0.204	0.000	0.017	0.109	0.000	0.330	0.459	0.000
Two years after	0.076	0.210	0.000	0.049	0.144	0.000	0.330	0.395	0.000
Three years after	0.038	0.131	0.000	0.026	0.086	0.000	0.301	0.341	0.003
After recession	0.082	0.193	0.000	0.044	0.121	0.000	0.315	0.344	0.030
Industry adjusted sales growth:									
During recession	-0.047	0.204	0.000	-0.091	0.107	0.000	0.369	0.440	0.000
One year after	-0.046	0.120	0.000	-0.077	0.032	0.000	0.335	0.459	0.000
Two years after	-0.052	0.084	0.000	-0.084	0.014	0.000	0.328	0.396	0.000
Three years after	-0.062	0.029	0.000	-0.056	-0.009	0.000	0.304	0.338	0.012
After recession	-0.029	0.083	0.000	-0.058	0.018	0.000	0.312	0.338	0.045
Level return on assets:									
During recession	-0.027	0.062	0.000	0.046	0.102	0.000	0.265	0.204	0.000
One year after	0.048	0.065	0.126	0.089	0.100	0.062	0.197	0.189	0.324
Two years after	0.047	0.070	0.046	0.093	0.107	0.052	0.202	0.184	0.020
Three years after	0.050	0.067	0.141	0.094	0.103	0.072	0.196	0.185	0.188
After recession	0.033	0.058	0.024	0.079	0.095	0.020	0.200	0.179	0.006
Industry adjusted return on assets:									
During recession	-0.045	0.061	0.000	-0.013	0.067	0.000	0.244	0.197	0.000
One year after	0.009	0.029	0.082	0.024	0.052	0.008	0.206	0.187	0.016
Two years after	0.015	0.035	0.086	0.028	0.043	0.036	0.214	0.182	0.000
Three years after	0.021	0.038	0.156	0.024	0.045	0.043	0.219	0.189	0.001
After recession	0.004	0.030	0.022	0.019	0.038	0.010	0.208	0.177	0.000
Bankruptcy rate:									
During recession	0.031	0.010	0.000						
One year after	0.010	0.003	0.139						
Two years after	0.007	0.006	0.892						
Three years after	0.006	0.003	0.577						
After recession	0.030	0.030	0.982						

Table 2.7 Regressions Predicting Long-Run Sales Growth

The table reports estimates from regressions using the sample defined in Table 2.1. According to the NBER's business cycle dating and GDP growth rate sorting, I identified four recession periods: 1980-1982, 1990-1991, 2001-2002, 2007-2009. I require firms to have data available one year prior to the recession and during the recession period. All models are OLS regressions. The dependent variable is the mean of sales growth over a period. Long-run sales growth is measured as the mean of sales growth over the five years period after the recession. R&D growth is calculated as the mean of growth rate of R&D over the recession period. All the other firm characteristics variables are measured one year prior to the recession. Outliers in all variables are trimmed at the 1% level. Three-digit SIC industry fixed effects are controlled. Robust p-values based on standard errors clustered by firm are in parentheses. The symbols *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Dep= Sales growth during recession				Dep= Long-run sales growth			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Full Sample	1980-1982	1990-1991	2001-2002	Full Sample	1980-1982	1990-1991	2001-2002
R&D growth during recession	0.230***	0.157***	0.219***	0.234***	0.069***	-0.007	0.065*	0.070*
	[0.000]	[0.000]	[0.000]	[0.000]	[0.003]	[0.804]	[0.069]	[0.079]
Firm size	-0.009***	-0.007	-0.020***	-0.011*	-0.007*	-0.009**	-0.005	-0.007
	[0.008]	[0.103]	[0.002]	[0.054]	[0.056]	[0.042]	[0.327]	[0.260]
R&D/Asset	0.453***	0.647***	0.475*	0.280*	0.343**	0.080	0.716***	0.149
	[0.000]	[0.002]	[0.059]	[0.078]	[0.020]	[0.674]	[0.009]	[0.363]
B/M	-2.832*	-6.704***	-8.142***	-0.588	-1.279	-6.582***	-2.118	0.335
	[0.062]	[0.001]	[0.001]	[0.819]	[0.405]	[0.000]	[0.397]	[0.891]
Leverage	0.147***	0.003	-0.148**	0.237**	0.072	-0.057	-0.106*	0.186**
	[0.003]	[0.971]	[0.021]	[0.017]	[0.169]	[0.398]	[0.082]	[0.028]
Cash	0.218***	0.236	0.103	0.269***	0.275***	0.137	0.141**	0.342***
	[0.000]	[0.101]	[0.290]	[0.000]	[0.000]	[0.124]	[0.049]	[0.000]
Constant	0.142***	0.046	0.275***	0.054	0.164***	0.161***	0.178***	0.181***
	[0.000]	[0.465]	[0.001]	[0.419]	[0.000]	[0.000]	[0.003]	[0.007]
Observations	2,979	364	750	1,065	2,005	349	711	945
R-squared	0.170	0.266	0.189	0.157	0.145	0.085	0.152	0.177
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	NO	NO	NO	Yes	NO	NO	NO

Table 2.8 Regressions Predicting Long-Run ROA

The table reports estimates from regressions using the sample defined in Table 2.1. According to the NBER's business cycle dating and GDP growth rate sorting, I identified four recession periods: 1980-1982, 1990-1991, 2001-2002, 2007-2009. I require firms to have data available one year prior to the recession and during the recession period. All models are OLS regressions. The dependent variable is the mean of ROA over a period. Long-run ROA is measured as the mean of ROA over the five years period after the recession. R&D growth is calculated as the mean of growth rate of R&D over the recession period. All the other firm characteristics variables are measured one year prior to the recession. Outliers in all variables are trimmed at the 1% level. Three-digit SIC industry fixed effects are controlled. Robust p-values based on standard errors clustered by firm are in parentheses. The symbols *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Dep=ROA during recession				Dep= Long-run ROA			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Full Sample	1980-1982	1990-1991	2001-2002	Full Sample	1980-1982	1990-1991	2001-2002
R&D growth during recession	0.060***	0.048**	0.086***	0.048**	0.002	-0.008	0.002	0.005
	[0.000]	[0.038]	[0.000]	[0.035]	[0.864]	[0.757]	[0.903]	[0.821]
Firm size	0.021***	0.013***	0.025***	0.020***	0.018***	0.019***	0.022***	0.015***
	[0.000]	[0.004]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
R&D/Asset	-0.589***	-0.038	-0.379***	-0.561***	-0.369***	-0.452***	-0.365***	-0.366***
	[0.000]	[0.771]	[0.000]	[0.000]	[0.000]	[0.004]	[0.001]	[0.000]
B/M	-4.385***	-1.761	-3.438**	-4.011***	-2.542***	-2.363*	-4.083**	-2.447**
	[0.000]	[0.264]	[0.038]	[0.005]	[0.002]	[0.079]	[0.012]	[0.034]
Leverage	-0.091***	-0.217***	-0.099**	-0.087*	-0.031	-0.070	-0.064	0.012
	[0.001]	[0.001]	[0.026]	[0.062]	[0.240]	[0.162]	[0.101]	[0.777]
Cash	-0.237***	-0.137	-0.131***	-0.289***	-0.181***	-0.030	-0.144***	-0.193***
	[0.000]	[0.282]	[0.000]	[0.000]	[0.000]	[0.650]	[0.001]	[0.000]
Constant	0.107***	0.162***	0.012	0.044	0.038	0.076*	0.069**	-0.000
	[0.000]	[0.003]	[0.745]	[0.330]	[0.101]	[0.052]	[0.033]	[0.998]
Observations	2,975	364	752	1,060	2,003	349	711	943
R-squared	0.385	0.163	0.278	0.331	0.227	0.188	0.190	0.257
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	NO	NO	NO	Yes	NO	NO	NO

Table 3.1 Corporate Acquisitions by Announcement Year

The table reports the number of corporate acquisitions by the year of bid announcement. The sample consists of 2,487 M&A between a US target and a US public acquiring firm in the period 1981–2002. Deals are identified from Securities Data Company's (SDC) M&A database, and both target and acquiring firms have patents matched with the NBER patent citation database prior to the acquisition announcement year. The table first presents the number and percentage of acquisitions for each year for the full sample and then for the two subsamples based on the existence of a patent citation link between the acquirer and the target. Citation-linked transactions refer to M&A transactions where there is a patent citation link between the acquirer and the target. Non-linked transactions refer to M&A transactions where there is no patent citation link between the acquirer and the target.

Year	Full Sample		Citation-Linked Transactions		Non-Linked Transactions	
	Number	Percentage	Number	Percentage	Number	Percentage
1981	44	1.77	4	1.18	40	1.86
1982	52	2.09	5	1.47	47	2.19
1983	70	2.81	2	0.59	68	3.17
1984	68	2.73	7	2.06	61	2.84
1985	55	2.21	7	2.06	48	2.24
1986	90	3.62	10	2.94	80	3.73
1987	55	2.21	9	2.65	46	2.14
1988	77	3.1	11	3.24	66	3.07
1989	83	3.34	17	5	66	3.07
1990	66	2.65	9	2.65	57	2.65
1991	58	2.33	4	1.18	54	2.52
1992	91	3.66	8	2.35	83	3.87
1993	88	3.54	11	3.24	77	3.59
1994	130	5.23	21	6.18	109	5.08
1995	141	5.67	22	6.47	119	5.54
1996	166	6.67	27	7.94	139	6.47
1997	212	8.52	25	7.35	187	8.71
1998	230	9.25	27	7.94	203	9.46
1999	230	9.25	40	11.76	190	8.85
2000	222	8.93	26	7.65	196	9.13
2001	137	5.51	36	10.59	101	4.7
2002	122	4.91	12	3.53	110	5.12
Total	2,487	100	340	100	2,147	100

Table 3.2 Corporate Acquisitions by Industry

The table reports the number of corporate acquisitions for the top 10 two-digit SIC industry in the sample. Sample is defined in Table 3.1.

Two digit-SIC Industry	Transactions	Citation-Linked Transactions	Percentage
Industrial Machinery and Equipment	404	65	0.16
Instruments and Related Products	404	70	0.17
Electronic & Other Electric Equipment	397	66	0.17
Chemicals and Allied Products	255	35	0.14
Business Services	178	18	0.10
Transportation Equipment	159	18	0.11
Fabricated Metal Products	76	4	0.05
Paper and Allied Products	70	10	0.14
Misc. Manufacturing Industries	55	8	0.15
Primary Metal Industries	49	6	0.12
	2047	300	0.15

Table 3.3 Summary Statistics

The table reports the summary statistics for citation links between acquirer and target firms in the sample in Panel A. Sample is defined in Table 3.1. Panel B first presents the means for the full sample and then for the two subsamples based on the existence of a patent citation link between the acquirer and the target. Citation-linked transactions refer to M&A transactions where there is a patent citation link between the acquirer and the target. Non-linked transactions refer to M&A transactions where there is no patent citation link between the acquirer and the target. All variable definitions are provided in the Appendix 3. The symbols *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Citation Links

Variable	N	Mean	SD	Median	P75	P95	P99	Max
Cite dummy	2487	0.14	0.34	0	0	1	1	1
AciteT dummy	2487	0.09	0.28	0	0	1	1	1
TciteA dummy	2487	0.1	0.3	0	0	1	1	1
AciteT_citations	216	14.92	39.11	2	9	81	210	295
AciteT_citinglag	216	5.65	3.54	5.16	7.29	12.13	19.31	24.01
AciteT_citingpatents	216	11.12	29.49	2	7	73	152	229
TciteA_citations	250	12.41	35.34	3	8	56	198	382
TciteA_citinglag	250	6.32	4.12	5.67	8.00	13.87	20.71	22.61
TciteA_citingpatents	250	8.5	25.68	2	5	34	143	285

Panel B: Acquirer, Target and Deal Characteristics

	N	Full Sample	Citation-Linked Transactions	Non-Linked Transactions	Diff. b/w Linked and Non-Linked
Acquirer Characteristics					
Acquirer Mkt cap($M)	2261	6461.16	10341.49	5814.44	***
Acquirer Tobin's q	2261	2.42	2.6	2.39	
Acquirer Leverage	2282	0.19	0.18	0.2	*
Acquirer Patents	2487	698.63	1883.12	511.05	***
Target Characteristics					
Public Target	2487	0.34	0.52	0.31	***
Target Mkt cap ($M)	639	1609.46	2413.56	1362.8	***
Target Tobin's q	639	2.24	2.33	2.22	
Target Leverage	641	0.21	0.22	0.2	
Target Patents	2487	52.94	214.96	27.28	***
Deal Characteristics					
Transaction value ($M)	1479	1034.199	2465.169	767.972	***
Relative deal size	1385	0.335	0.359	0.331	
All stock	2487	0.189	0.262	0.177	***
All cash	2487	0.135	0.135	0.135	
Tender offer	2487	0.076	0.103	0.072	**
Same industry	2487	0.468	0.579	0.45	***
Same state	2487	0.223	0.25	0.219	
Compete	2487	0.039	0.079	0.033	***
Completed	2487	0.843	0.815	0.847	

Table 3.4 Univariate Comparisons of CARs and Bidder Premiums

This table presents the mean and median of acquirer return (ACAR), target return (TCAR), and combined portfolio return (PCAR) over the 3-day, 5-day, and 7-day event windows around acquisition announcement dates, as well as takeover premiums based on target's previous 4-week stock price (PREM4WK) and previous 52-week high stock price (PREM52WK). The table first presents for the full sample and then for the two subsamples based on the existence of a patent citation link between the acquirer and the target. Sample is defined in Table 3.1. The symbols *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Full Sample			Citation-Linked Transactions		Non-Linked Transactions		Diff. b/w Linked and Non-linked	
	N	Mean	Median	Mean	Median	Mean	Median	Mean	Median
ACAR									
[-1,+1]	2350	0.03	-0.13	-0.34	-0.14	0.11	-0.1	*	
[-2,+2]	2350	0.08	-0.2	-0.69	-0.51	0.19	-0.12	*	*
[-3,+3]	2350	-0.11	-0.52	-0.6	-0.92	-0.05	-0.45		
TCAR									
[-1,+1]	780	20.38	15.55	21.19	17.86	20.19	15.1		
[-2,+2]	780	21.49	17.25	21.9	19.11	21.43	16.71		
[-3,+3]	780	22.06	18.2	22.81	20.08	21.93	18.02		
PCAR									
[-1,+1]	593	1.55	0.86	2.45	1.79	1.26	0.65	*	***
[-2,+2]	593	1.8	1.07	2.44	1.54	1.61	0.9		
[-3,+3]	593	1.59	0.86	2.76	2.46	1.25	0.45	*	**
PREMIUM									
PREM4WK	567	1.72	1.55	1.85	1.62	1.67	1.53	**	
PREM52WKH	568	1.15	1.12	1.19	1.2	1.13	1.08	*	***

Table 3.5 Probit Regression of the Likelihood of Being Acquired

This table reports marginal effects estimates from probit regressions for estimating the probability of M&A transactions. The dependent variable is a dummy, which equals to one if there is an M&A transaction taking place between potential acquirers and potential targets, and zero otherwise. For each target, we define the set of all potential acquirer firms as the ones that were involved in a deal in the same 2-digit SIC target industry in the same year. P-value based on standard errors adjusted for heteroskedasticity and firm clustering are reported in parentheses. The symbols *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Acquired		
	(1)	(2)	(3)
Same state	0.065***	0.065***	0.065***
	[0.000]	[0.000]	[0.000]
Same industry	-0.010***	-0.010***	-0.010***
	[0.000]	[0.000]	[0.000]
Diff_patents	-0.001	-0.000	-0.000
	[0.139]	[0.268]	[0.665]
Technological proximity	0.066***	0.067***	0.067***
	[0.000]	[0.000]	[0.000]
Public target	-0.012***	-0.013***	-0.013***
	[0.000]	[0.000]	[0.000]
Cite dummy	0.200***		
	[0.000]		
Same state X Cite dummy	-0.011		
	[0.440]		
Public target X Cite dummy	-0.022***		
	[0.008]		
AciteT dummy		0.151***	
		[0.000]	
TciteA dummy		0.111***	
		[0.000]	
Same state X AciteT dummy		-0.024*	
		[0.093]	
Public target X AciteT dummy		-0.002**	
		[0.033]	
Same state X TciteA dummy		0.018	
		[0.426]	
Public target X TciteA dummy		-0.023**	
		[0.020]	
AciteT			187.332***
			[0.000]
TciteA			3.524***
			[0.000]
Same state X AciteT			-54.128*
			[0.059]
Public target X AciteT			-3.761***
			[0.000]
Same state X TciteA			-0.001
			[0.999]
Public target X TciteA			-0.569
			[0.414]
Observations	26,024	26,024	24,742
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Pseudo R2	0.188	0.188	0.190

Table 3.6 OLS Regressions of Acquirer Announcement Returns

The table reports estimates from OLS regressions of acquirer announcement returns. The dependent variable is ACAR, the 3-day cumulative abnormal return of acquiring firms. Sample is defined in Table 3.1. All variable definitions are provided in Appendix 3. All regressions control for calendar year-fixed effects and 2-digit SIC industry fixed effects whose coefficients are suppressed for brevity. P-value based on standard errors adjusted for heteroskedasticity and firm clustering are reported in parentheses. The symbols *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) ACAR	(2) ACAR	(3) ACAR
Cite dummy	0.852*		
	[0.059]		
AciteT dummy		1.157*	
		[0.050]	
TciteA dummy		-0.243	
		[0.667]	
AciteT			65.816*
			[0.097]
TciteA			4.320
			[0.651]
Same state	0.815	0.856*	0.855*
	[0.101]	[0.081]	[0.078]
Same industry	0.471	0.541	0.532
	[0.227]	[0.159]	[0.191]
Tender offer	1.932***	1.866***	1.941***
	[0.001]	[0.002]	[0.001]
hostile	-0.917	-0.643	-0.735
	[0.383]	[0.538]	[0.493]
All stock	-0.448	-0.420	-0.372
	[0.416]	[0.433]	[0.484]
All cash	0.423	0.364	0.346
	[0.370]	[0.441]	[0.463]
Public Target	-2.210***	-2.075***	-2.090***
	[0.000]	[0.000]	[0.000]
Compete	-0.641	-0.699	-0.702
	[0.386]	[0.346]	[0.348]
Relative deal size	-0.475**	-0.467**	-0.459**
	[0.011]	[0.012]	[0.013]
Acquirer size	-0.664***	-0.664***	-0.637***
	[0.000]	[0.000]	[0.000]
Acquirer Tobin's q	-0.004	0.015	0.007
	[0.973]	[0.906]	[0.961]
Acquirer Leverage	-0.174	-0.231	-0.311
	[0.908]	[0.880]	[0.841]
Acquirer lagged return	-1.109**	-1.109**	-1.119**
	[0.044]	[0.045]	[0.048]
Constant	15.070***	13.142***	12.641***
	[0.000]	[0.000]	[0.000]
Observations	1,340	1,340	1,340
R-squared	0.106	0.114	0.114
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes

Table 3.7 OLS Regressions of Target Announcement Returns

The table reports estimates from OLS regressions of target announcement returns. The dependent variable is TCAR, the 3-day cumulative abnormal return of target firms. Sample is defined in Table 3.1. All variable definitions are provided in Appendix 3. All regressions control for calendar year-fixed effects and 2-digit SIC industry fixed effects whose coefficients are suppressed for brevity. P-value based on standard errors adjusted for heteroskedasticity and firm clustering are reported in parentheses. The symbols *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) TCAR	(2) TCAR	(3) TCAR
Cite dummy	0.975		
	[0.712]		
AciteT dummy		0.382**	
		[0.028]	
TciteA dummy		-3.492	
		[0.588]	
AciteT			71.896*
			[0.082]
TciteA			-14.808
			[0.631]
Same state	1.001	1.056	0.982
	[0.732]	[0.716]	[0.735]
Same industry	0.770	0.911	0.822
	[0.758]	[0.715]	[0.744]
Tender offer	9.333***	9.105***	9.351***
	[0.008]	[0.009]	[0.009]
hostile	12.471***	12.713***	12.349***
	[0.001]	[0.001]	[0.001]
All stock	0.472	0.305	0.418
	[0.872]	[0.918]	[0.887]
All cash	8.069**	7.801**	7.933**
	[0.036]	[0.041]	[0.039]
Public Target	1.404	1.304	1.536
	[0.752]	[0.765]	[0.732]
Compete	-8.435***	-8.118***	-8.365***
	[0.002]	[0.003]	[0.002]
Relative deal size	-0.952	-0.884	-0.961
	[0.363]	[0.395]	[0.361]
Acquirer size	0.856	1.134	0.906
	[0.236]	[0.119]	[0.213]
Target Tobin's q	-0.776	-0.787	-0.772
	[0.167]	[0.164]	[0.169]
Target Leverage	-4.489	-4.527	-4.743
	[0.528]	[0.519]	[0.511]
Target lagged return	-4.574*	-4.694*	-4.608*
	[0.081]	[0.076]	[0.080]
Constant	-42.042***	-47.495***	-43.122***
	[0.007]	[0.002]	[0.006]
Observations	516	516	516
R-squared	0.232	0.234	0.232
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes

Table 3.8 OLS Regressions of Combined Portfolio Announcement Returns

The table reports estimates from OLS regressions of combined portfolio announcement returns. The dependent variable is PCAR, the 3-day cumulative abnormal return of combined portfolio of acquirers and targets. Sample is defined in Table 3.1. All variable definitions are provided in the Appendix 3. All regressions control for calendar year-fixed effects and 2-digit SIC industry fixed effects whose coefficients are suppressed for brevity. P-value based on standard errors adjusted for heteroskedasticity and firm clustering are reported in parentheses. The symbols *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) PCAR	(2) PCAR	(3) PCAR
Cite dummy	2.219***		
	[0.006]		
AciteT dummy		2.557**	
		[0.044]	
TciteA dummy		-0.822	
		[0.479]	
AciteT			172.763*
			[0.064]
TciteA			30.751*
			[0.070]
Same state	0.403	0.438	0.342
	[0.655]	[0.627]	[0.701]
Same industry	0.477	0.473	0.443
	[0.537]	[0.540]	[0.568]
Tender offer	3.127***	2.982***	3.381***
	[0.004]	[0.006]	[0.001]
hostile	3.275	3.235	3.060
	[0.103]	[0.102]	[0.116]
All stock	0.118	-0.137	0.225
	[0.897]	[0.883]	[0.807]
All cash	3.960***	3.865***	3.782***
	[0.000]	[0.000]	[0.000]
Public Target	-5.322*	-5.089*	-5.245*
	[0.055]	[0.068]	[0.058]
Compete	-2.916***	-2.760***	-2.825***
	[0.006]	[0.010]	[0.007]
Relative deal size	1.085***	1.091***	1.086***
	[0.001]	[0.001]	[0.001]
Acquirer size	-0.362	-0.326	-0.294
	[0.175]	[0.223]	[0.260]
Acquirer Leverage	0.053	-0.196	-0.061
	[0.987]	[0.952]	[0.985]
Acquirer lagged return	-1.130	-1.132	-1.022
	[0.268]	[0.269]	[0.316]
Target Leverage	5.101**	5.098**	4.736*
	[0.041]	[0.042]	[0.058]
Target lagged return	-1.064	-1.176	-1.183
	[0.197]	[0.153]	[0.149]
Constant	7.239	6.432	6.078
	[0.236]	[0.296]	[0.316]
Observations	511	511	511
R-squared	0.312	0.310	0.313
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes

Table 3.9 OLS Regressions of Bidder Premiums

The table reports estimates from OLS regressions of bidder premiums. The dependent variable for regression (1)–(3) is PREM4WK. The dependent variable for regression (4)–(6) is PREM52WKH. Sample is defined in Table 3.1. All variable definitions are provided in Appendix 3. All regressions control for calendar year-fixed effects and 2-digit SIC industry fixed effects whose coefficients are suppressed for brevity. P-value based on standard errors adjusted for heteroskedasticity and firm clustering are reported in parentheses. The symbols *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	PREM4WK			PREM52WKH		
	(1)	(2)	(3)	(4)	(5)	(6)
Cite dummy	0.095			0.002		
	[0.364]			[0.969]		
AciteT dummy		0.247*			0.121*	
		[0.090]			[0.084]	
TciteA dummy		-0.244*			-0.150**	
		[0.067]			[0.044]	
AciteT			11.3348**			1.130**
			[0.048]			[0.021]
TciteA			-2.050			-0.762
			[0.032]**			[0.151]
Same state	-0.105	-0.103	-0.107	-0.115*	-0.115*	-0.115*
	[0.281]	[0.292]	[0.279]	[0.059]	[0.056]	[0.058]
Same industry	0.108	0.107	0.114	0.069	0.067	0.070
	[0.166]	[0.161]	[0.145]	[0.205]	[0.218]	[0.196]
Tender offer	0.390***	0.368***	0.393***	0.055	0.043	0.054
	[0.007]	[0.009]	[0.007]	[0.402]	[0.510]	[0.416]
hostile	0.112	0.113	0.093	0.153*	0.152*	0.150*
	[0.428]	[0.421]	[0.522]	[0.055]	[0.061]	[0.063]
All stock	-0.359***	-0.388***	-0.362***	-0.244***	-0.259***	-0.246***
	[0.003]	[0.001]	[0.003]	[0.000]	[0.000]	[0.000]
All cash	-0.718***	-0.721***	-0.729***	-0.336***	-0.334***	-0.337***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Compete	0.087	0.098	0.092	0.106	0.109	0.107
	[0.496]	[0.444]	[0.479]	[0.140]	[0.126]	[0.141]
tsize	-0.180***	-0.178***	-0.183***	-0.085***	-0.084***	-0.085***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Acquirer size	0.104***	0.108***	0.111***	0.099***	0.100***	0.100***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Acquirer Tobin's q	-0.019	-0.020	-0.020	-0.019	-0.020	-0.019
	[0.286]	[0.225]	[0.238]	[0.194]	[0.158]	[0.184]
Target Tobin's q	-0.006	-0.000	-0.004	-0.011	-0.007	-0.010
	[0.774]	[0.983]	[0.841]	[0.532]	[0.673]	[0.553]
Constant	2.188***	2.103***	2.116***	0.105	0.083	0.096
	[0.000]	[0.001]	[0.000]	[0.776]	[0.822]	[0.790]
Observations	521	521	521	522	522	522
R-squared	0.276	0.282	0.278	0.269	0.276	0.270
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 3.10 Probit Regression of the Likelihood of Completing Deal

This table report marginal effects estimates from probit regressions for estimating the probability of M&A transaction being competed. The dependent variable is a dummy, which equals one if the deal is completed with an effective date in SDC, and zero otherwise. Sample is defined in Table 3.1. All variable definitions are provided in the Appendix 3. All regressions control for calendar year-fixed effects and 2-digit SIC industry fixed effects whose coefficients are suppressed for brevity. P-value based on standard errors adjusted for heteroskedasticity and firm clustering are reported in parentheses. The symbols *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) Completed	(2) Completed	(3) Completed
Cite dummy	-0.006		
	[0.794]		
AciteT dummy		0.023**	
		[0.032]	
TciteA dummy		-0.021	
		[0.412]	
AciteT			3.290*
			[0.065]
TciteA			-0.548
			[0.198]
Same state	0.033**	0.033**	0.034**
	[0.039]	[0.034]	[0.031]
Same industry	-0.021	-0.021	-0.021
	[0.186]	[0.194]	[0.191]
Tender offer	0.043**	0.042**	0.041*
	[0.038]	[0.042]	[0.052]
hostile	-0.239***	-0.233***	-0.229***
	[0.000]	[0.000]	[0.000]
All stock	-0.011	-0.010	-0.012
	[0.624]	[0.633]	[0.577]
All cash	-0.008	-0.008	-0.008
	[0.708]	[0.709]	[0.705]
Public Target	-0.088***	-0.087***	-0.087***
	[0.000]	[0.000]	[0.000]
Compete	-0.256***	-0.256***	-0.255***
	[0.000]	[0.000]	[0.000]
Acquirer size	0.016***	0.016***	0.016***
	[0.007]	[0.005]	[0.004]
Acquirer Tobin's q	-0.006	-0.006	-0.006
	[0.172]	[0.159]	[0.158]
Acquirer Leverage	-0.069	-0.071	-0.072
	[0.162]	[0.152]	[0.145]
Relative deal size	-0.015**	-0.015**	-0.015**
	[0.035]	[0.039]	[0.032]
Observations	1,316	1,316	1,316
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Pseudo R2	0.224	0.225	0.225

Table 3.11 OLS Regression of Long-Run Operating Performance

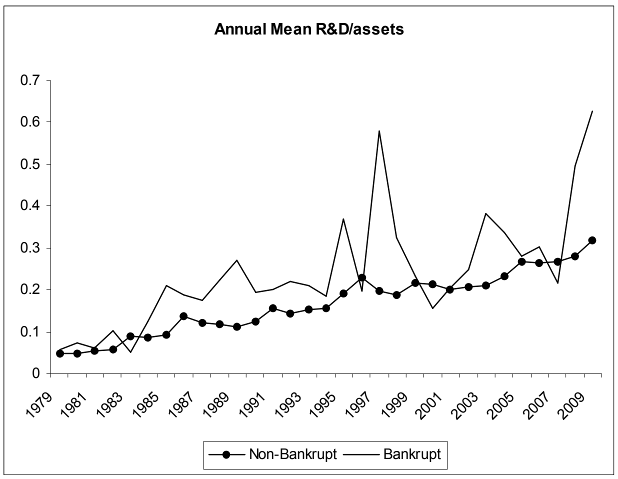
The table reports estimates from OLS regressions of long-run operation performance of the acquiring firms. The dependent variable for regression (1)–(3) is ΔROA, defined as the residual from a cross section regression of the post-acquisition 5-year average industry-adjusted ROA on the pre-merger measure. The dependent variable for regression (4)–(6) is ΔSaleGrowth, defined as the residual from a cross section regression of the post-acquisition 5-year average industry-adjusted sales growth on the pre-merger measure. Sample is defined in Table 3.1. All variable definitions are provided in the Appendix 3. All regressions control for calendar year-fixed effects and 2-digit SIC industry fixed effects whose coefficients are suppressed for brevity. P-value based on standard errors adjusted for heteroskedasticity and firm clustering are reported in parentheses. The symbols *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

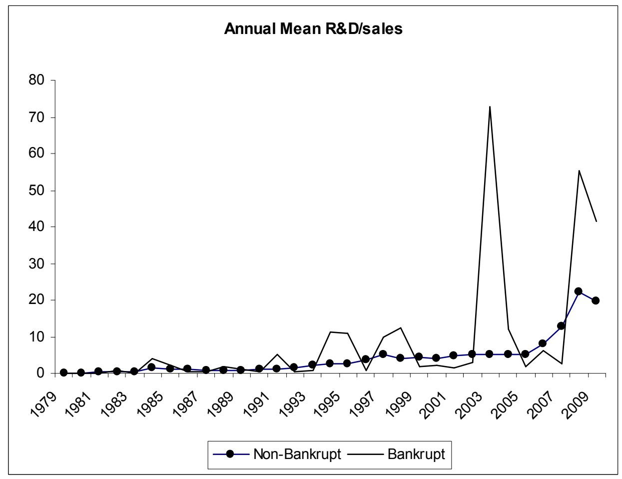
	△ROA			△SaleGrowth		
	(1)	(2)	(3)	(4)	(5)	(6)
Cite dummy	0.012*			0.101***		
	[0.095]			[0.004]		
AciteT dummy		0.013*			0.106**	
		[0.098]			[0.026]	
TciteA dummy		-0.001			0.035	
		[0.987]			[0.400]	
AciteT			0.787			10.304**
			[0.157]			[0.034]
TciteA			0.144			0.211
			[0.502]			[0.804]
Same state	0.001	0.001	0.000	0.058	0.061	0.063*
	[0.923]	[0.916]	[0.958]	[0.118]	[0.106]	[0.070]
Same industry	0.006	0.007	0.007	0.024	0.025	0.023
	[0.406]	[0.400]	[0.386]	[0.401]	[0.388]	[0.459]
Tender offer	0.010	0.010	0.010	-0.040	-0.042	-0.034
	[0.249]	[0.252]	[0.272]	[0.300]	[0.280]	[0.389]
hostile	-0.012	-0.012	-0.010	-0.039	-0.048	-0.048
	[0.588]	[0.594]	[0.609]	[0.789]	[0.740]	[0.744]
All stock	0.014	0.014	0.014	-0.147***	-0.149***	-0.143***
	[0.160]	[0.166]	[0.147]	[0.001]	[0.001]	[0.001]
All cash	-0.003	-0.003	-0.003	0.042	0.042	0.038
	[0.747]	[0.747]	[0.721]	[0.165]	[0.172]	[0.198]
Public Target	0.001	0.001	0.001	0.008	0.007	0.010
	[0.942]	[0.924]	[0.923]	[0.824]	[0.832]	[0.783]
Compete		-0.003	-0.003	-0.149**	-0.147**	-0.138
		[0.816]	[0.804]	[0.032]	[0.037]	[0.104]
Relative deal size	0.000	0.000	0.001	0.019*	0.019	0.018
	[0.943]	[0.936]	[0.826]	[0.100]	[0.105]	[0.186]
Acquirer size	-0.005*	-0.005	-0.005*	0.011	0.011	0.015
	[0.092]	[0.101]	[0.085]	[0.273]	[0.305]	[0.159]
Acquirer Tobin's q	-0.005	-0.005	-0.005*	-0.039***	-0.039***	-0.041***
	[0.106]	[0.107]	[0.088]	[0.004]	[0.003]	[0.001]
Acquirer Leverage	0.103***	0.103***	0.105***	-0.037	-0.042	-0.060
	[0.000]	[0.000]	[0.000]	[0.778]	[0.749]	[0.658]
Constant	0.006	0.004	0.003	0.370*	0.381*	0.283
	[0.916]	[0.939]	[0.960]	[0.057]	[0.054]	[0.149]
Observations	929	929	929	926	926	926
R-squared	0.203	0.203	0.204	0.206	0.207	0.207
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Figure 1.1 High-Tech R&D Intensity (Bankrupt vs. Non-bankrupt Firms)

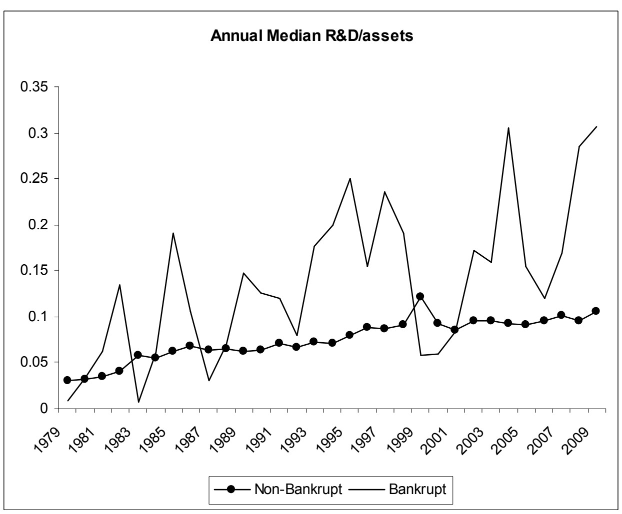
These figures depict the annual mean and median in the R&D/assets and R&D/sales of the high-tech sector over the period 1979-2009. I construct the high-tech sample by following the high-tech definitions offered by the United States Department of Commerce by seven 3-digit SIC codes: SIC 283, SIC 357, SIC 366, SIC 367, SIC 382, SIC 384 and SIC 737. The solid line plots the annual mean (median) of R&D intensity for bankrupt firms. The dot-marked line plots the annual mean (median) of R&D intensity for non-bankrupt firms.

Panel A: Annual Mean of R&D Intensity over 1979-2009





Panel B: Annual Median of R&D Intensity over 1979-2009



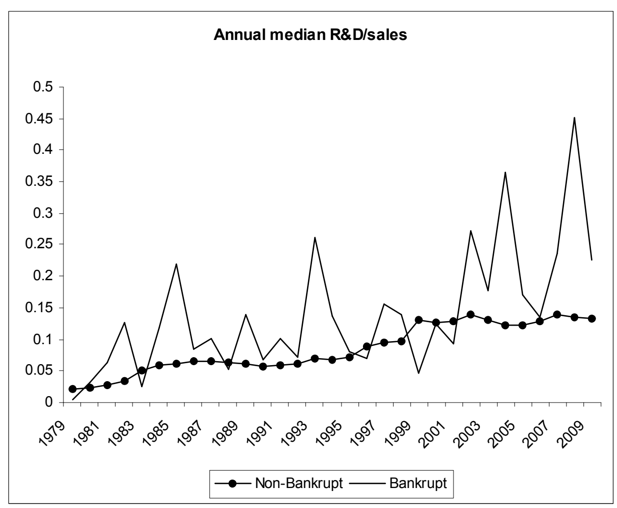


Figure 2.1 R&D Investment

The solid line plots the sum of R&D for all publicly traded companies with coverage in Compustat(financial firms and utilities are excluded) over time. The dashed line plots the sum of R&D for firms in the seven high-tech industries with SIC codes 283,357,366,367,382,384,737.

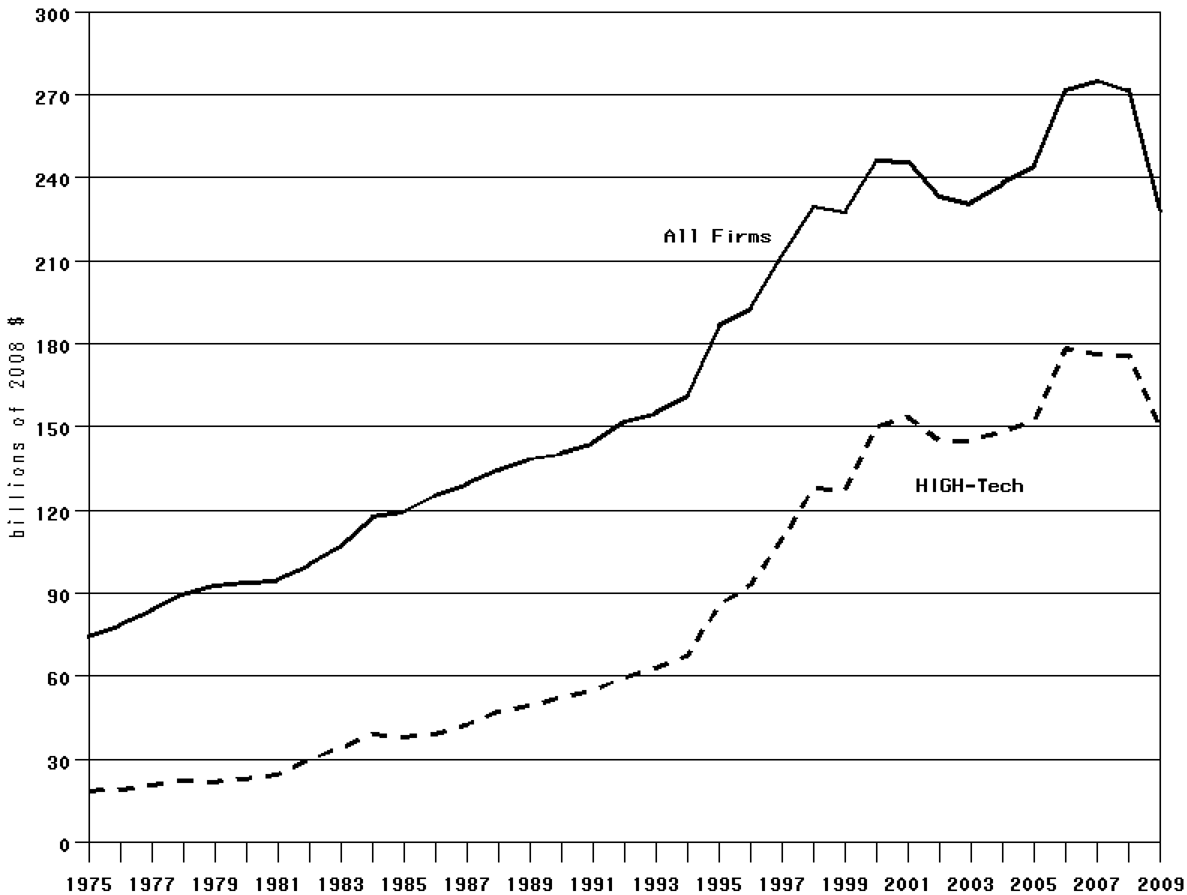
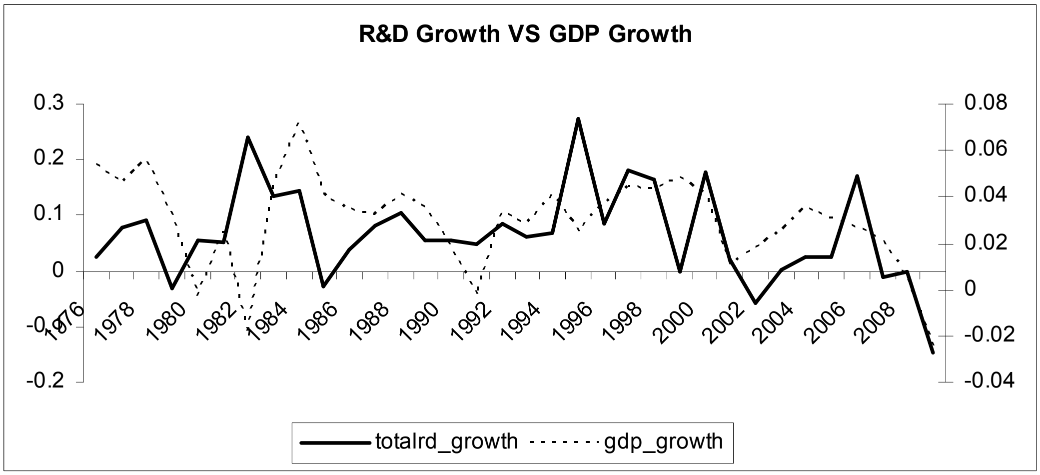
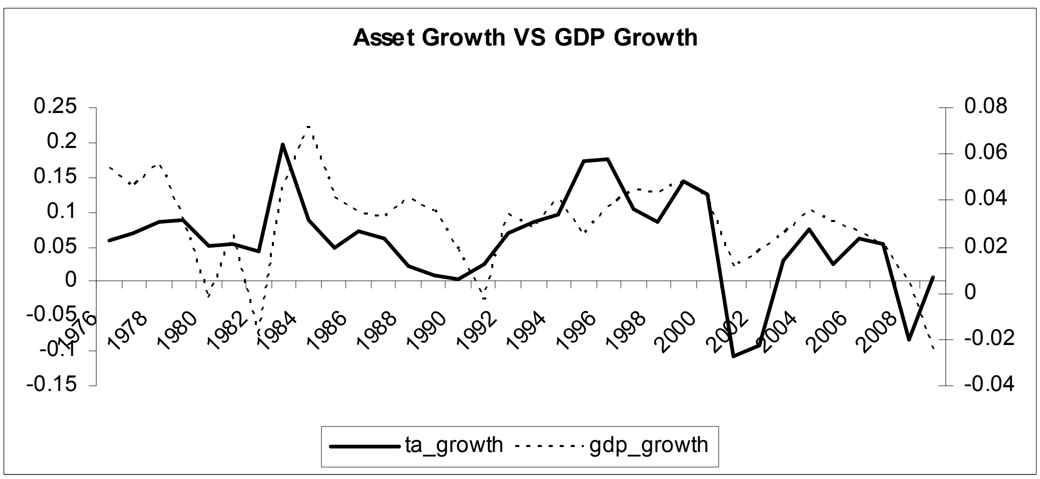


Figure 2.2 Time Series of R&D Growth, Asset Growth and R&D Intensity





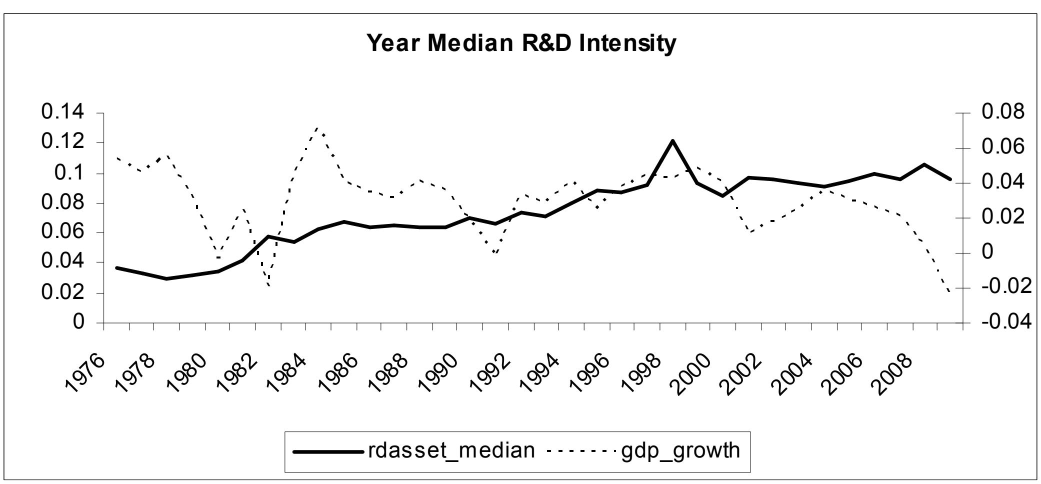
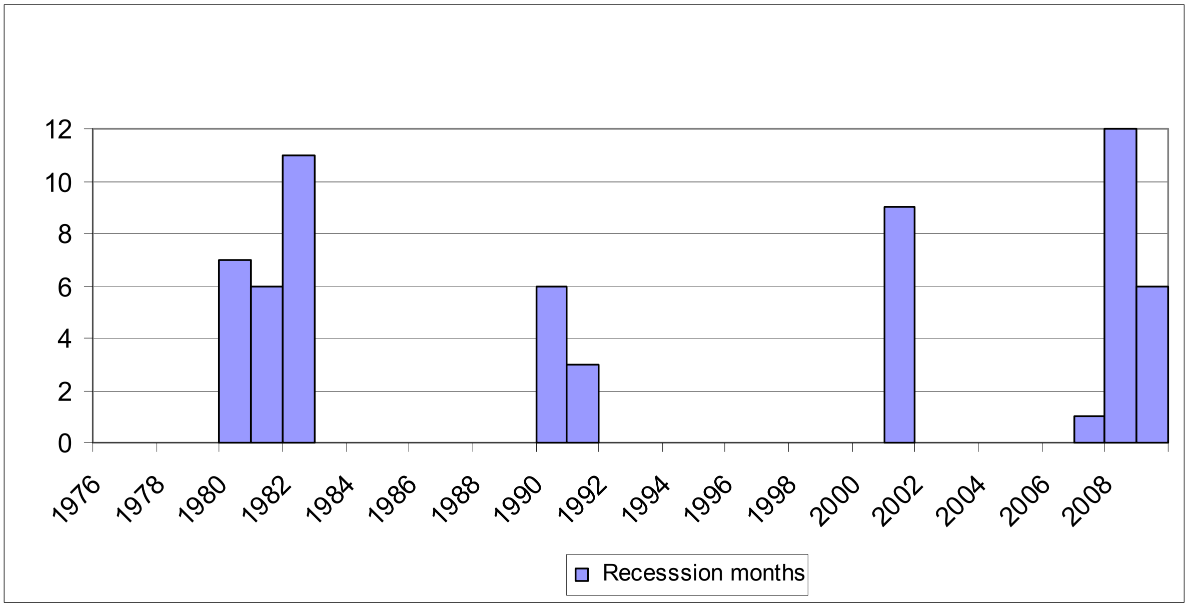


Figure 2.3 Business Cycles Identified by NBER from 1976-2009

The figure shows the recession periods over 1979-2009. Recession months represents the number of months in a year identified by NBER as in a contraction period.



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Appendices

Appendix 1: Variable Definitions for Chapter 1

Variable	Definition
Announcement reaction	Calculated as the standard deviation of cumulative abnormal returns in [-1, 1] window around quarterly earnings announcements dates over a year.
Bankrupt	Dummy variable equal to one if the firm went bankrupt in a given year, and zero otherwise. A firm is defined as bankrupt if it is delisted due to bad performance.
Book-to-Market (B/M)	Measured as book value of total assets/ (book value of total assets-book value of equity+ market value of equity).
Delisting return	Calculated by comparing a value after delisting against the price on the security's last trading date. It is obtained from CRSP.
CAR-1YEAR	Calculated as the cumulative abnormal monthly returns over the next year using the Fama-French three-factor model.
CAR-3YEAR	Calculated as the cumulative abnormal monthly returns over the next three years using the Fama-French three-factor model.
Cash	The ratio of cash and marketable securities to the book value of total assets.
Cash flow volatility	Calculated as the standard deviation of cash flow over assets for the previous three years. Cash flow is defined as operating income before depreciation, less interest and taxes.
Firm size	The natural log of the book value of total assets in 2008 dollars.
Forecast dispersion	Calculated as the dispersion in the analysts' earnings forecasts. Analysts' earnings forecasts are obtained from the Institutional Brokers Estimate Systems (IBES).
Forecast error	Calculated as the ratio of the absolute value of the difference between the actual earnings and the forecast earnings to the price per share at the end of year.
Leverage	The ratio of total debt to the book value of total assets, where debt includes long-term debt and debt in current liabilities.
Market beta	Computed using a market model against the CRSP value-weighted index.
R&D/assets	The ratio of R&D expenditures to the book value of total assets. For each firm-year, I compute the mean of R&D intensity in terms of R&D expenditures over assets for the previous three years. If R&D expenditures variable is missing, I follow the tradition to set the missing value to zero.
R&D/sales	The ratio of R&D expenditures to sales. For each firm-year, I compute the mean of R&D intensity in terms of R&D expenditures over sales for the previous three years.
ROA volatility	Calculated as the standard deviation of ROA (return on assets) over the next three years. ROA is measured as the ratio of operating income to the book value of total assets.
Stock return volatility	Calculated as the standard deviation of monthly stock returns within a year.
Z-score	Constructed following Altman's (1968) as a measure of financial condition. A high Z-score indicates a low financial distress risk.

Appendix 2: Variable Definitions for Chapter 2

All names in parentheses refer to the Compustat (XPF version, Fundamental Annual) item names.

Variable	Definition
Advertising expenditures (ad)	AD is the ratio of advertising expenditures (XAD) to the book value of total assets (AT). If advertising expenditures variable(XRD) is missing, I follow the tradition to set the missing value to zero.
Capital expenditures (capex)	capex is the ratio of capital expenditures (CAPX) to the book value of total assets (AT).
Cash flow	Cash flow is gross cash flow divided by the book value of total assets, where gross cash flow is defined as (after-tax) income before extraordinary items (IB) plus depreciation and amortization (DP) plus research and development expense (XRD).
Firm age	The number of years (plus one) elapsed since the year in which the firm was included in Compustat.
Net sales(sale)	Sale is the ratio of net sales (SALE) to the book value of total assets.
New debt issuance	New debt issuance is equal to long-term debt issuance (DLTIS) minus long-term debt reduction (DLTR), scaled by the book value of total assets(AT).
New stock issuance	New stock issuance is equal to the sale o f common and preferred stock(SSTK) minus the purchase of common and preferred stock(PRSTKC), scaled by the book value of total assets(AT).
Return on assets	ROA is the ratio of operating income (OIBDP) to the book value of total assets (AT).
R&D/assets(rd)	R&D/assets is the ratio of R&D expenditures (XRD) to the book value of total assets (AT). If R&D expenditures (XRD) is missing, I follow the tradition to set the missing value to zero.
R&D growth	R&D growth is measured by the arc growth rate, defined as $\frac{RD_t - RD_{t-1}}{avg(RD_{t,} RD_{t-1})}$. Here R&D is real R&D adjusted using consumer price index.
Tobin's Q	Tobin's q is the ratio of market value of assets to book value of assets. The market value of assets is equal to total assets (AT) minus book value of common equity (CEQ) plus the market value of common equity (fiscal year end price (PRCC_F) times shares outstanding (CSHO)).

Appendix 3: Variable Definitions for Chapter 3

Variable	Definition
Panel A: Patent Citation Links	
Cite dummy	Dummy variable: equal to one if there is a citation link between the acquirer and the target, and zero otherwise.
AciteT dummy	Dummy variable: equal to one if the acquirer ever cited the target firm's patents prior to the announcement year of the deal, and zero otherwise.
TciteA dummy	Dummy variable: equal to one if the target firm ever cited the acquirer's patents prior to the announcement year of the deal, and zero otherwise.
AciteT	The number of citations the acquirer made to the target firm's patents prior to the announcement year of the deal scaled by the total number of patent citations made by the acquirer.
TciteA	The number of citations the target made to the acquirer's patents prior to the announcement year of the deal scaled by the total number of patent citations made by the target.
AciteT_citationlag	The average difference between the grant year of the acquirer's citing patent and that of the target's cited patent.
AciteT_citingpatent	The number of the acquirer's patents that made citations to the target prior to the announcement year of the deal.
TciteA_citationlag	The average difference between the grant year of the target's citing patent and that of the acquirer's cited patent.
TciteA_citingpatent	The number of the target's patents that made citations to the acquirer prior to the announcement year of the deal.
Panel B: Acquisition Performance Measures	
ACAR	The 3-day cumulative abnormal percentage return for the acquirer using the market model estimated using the return for the period (-200,-60).
TCAR	The 3-day cumulative abnormal percentage return for the target using the market model estimated using the return for the period (-200,-60).
PCAR	The 3-day cumulative abnormal percentage return for a value-weighted portfolio of the acquirer and the target using the market model estimated using the return for the period (-200,-60). The weights are based on the market capitalizations of the acquirer and the target at the 11th trading day prior to the announcement date. The target's weight is adjusted for the acquirer's toehold.
ΔSales growth	Residual from a cross-sectional regression of post-acquisition 5-year average industry-adjusted sales growth on the pre-merger industry-adjusted measure.
ΔROA	Residual from a cross-sectional regression of post-acquisition 5-year average industry-adjusted ROA(return on assets) on the pre-merger industry-adjusted measure.
Panel C: Acquirer and Target Characteristics	
Firm size	The natural log of market value of equity calculated as the number of shares outstanding multiplied by the stock price at the 11th trading day prior to the acquisition announcement in 2002 US dollars.
Tobin's Q	Market value of assets over book value of assets.

Appendix 3: Variable Definitions for Chapter 3 Continued

Variable	Definition
Leverage	The ratio of total debt to the book value of total assets, where debt includes long-term debt and debt in current liabilities.
Lagged return	Stock return over the year before the announcement using CRSP monthly data.
Patents	The natural log of one plus the number of patents granted before the announcement year.
Diff_patents	The difference between target's and acquirer's patents.
Technological proximity	Measure of the extent of overlap in distribution of patents across the target and acquirer. It is proposed by Jaffe (1986).
Panel D: Deal Characteristics	
All cash	Dummy variable: equal to one for deals involving all cash financing, and zero otherwise.
All stock	Dummy variable: equal to one for deals involving all stock financing, and zero otherwise.
Completed	Dummy variable: equal to one if deal is completed with a non-missing effective date in SDC, and zero other wise.
Same state	Dummy variable: equal to one if acquirer and target are in the same state, and zero otherwise.
Same industry	Dummy variable: equal to one if acquirer and target share a 2-digit SIC code, and zero otherwise.
Relative deal size	The natural log of deal value divided by acquirer's market value of equity.
Tender offer	Dummy variable: equal to one for tender offers, and zero otherwise.
Hostile	Dummy variable: equal to one for a bid is hostile, and zero otherwise.
Compete	Dummy variable: equal to one if a deal has competing bidders, and zero otherwise.
Public target	Dummy variable: equal to one if the target is a public firm, and zero otherwise.
PREM4WK	Premium calculated as the ratio of the offer price to the target-trading price 4 weeks prior to the announcement date.
PREM52WKH	Premium calculated as the ratio of the offer price to the target's 52-week highest stock price over the 365 calendar days ending 30 days prior to the announcement date.