The Impact of R&D Alliance on the Survival and Profitability of Newly Listed High Tech Firms

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Abstract

This paper investigates the extent to which R&D alliance participation affects the performance of newly listed high tech firms. The estimation strategy identifies the impact of R&D alliance through changes on a firm's alliance status. Using longitudinal data on 586 high tech firms that became public over the period 1990-2000, I find evidence suggesting that R&D collaborating firms experience significantly higher profits and enhanced survival, relative to non-R&D collaborating firms. R&D alliance participation raises the return on assets by 3.24% and Tobin's q by 2.83%. The hazard of poor performance and firm failure is attenuated by 10%, on average. The results are generally valid to model and sample specification and control for the potential endogeneity of alliance participation.

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1. Introduction

Firms are continually faced with the challenge to find ways to enhance their growth and survival. A key aspect of sustainable firm performance is to innovate – to develop new products that amplify market reach or to implement business methods and processes that reduce production costs. To do so, a firm must devote part of its resources to undertake research and development (R&D) activities. These can be as mundane, but fundamentally important, as appraising current technologies and capabilities, and as complicated as developing paradigm-shifting ideas. It is an established fact that research and development is a significant precursor to innovation (Hausman, et.al., 1984; Cohen and Levinthal, 1989; Griliches, 1990).

To perform R&D, a firm can decide to either do it alone, or to collaborate with other firms, in what is known as an R&D alliance. Essentially, an R&D alliance is a non-equity, contractual agreement among firms to jointly undertake R&D activities. The impetus for engaging in an alliance has economic merit: when firms collaborate, they share and concomitantly reduce the cost of R&D. More pertinently, participating firms can jointly manage the uncertainties associated with the innovation process and its eventual outcome (Mitchell and Singh, 1992), tap each other's core competencies to exploit synergies (Teece, 1992; Mody, 1993), and generate economies of scale and scope in R&D (Cohen and Klepper, 1996). From a welfare point of view, collaborative management of R&D enhances the incentive to innovate and deters wasteful duplication of research projects (Katz, 1986). The central theme for engaging in an alliance is that it benefits the firm. Hagedoorn (2002) documents remarkable increases in the number of R&D alliances formed worldwide that began during the 1960s. In 1980, there were about 200 cooperative R&D agreements established; by the middle of the 1990s, there were close to 700 alliances formed. High technology firms accounted for bulk of the alliances formed. Between 1980 and 1998, high tech R&D collaborations rose from 50% to over 80%.

The goal of this paper is to examine the extent to which participation in an R&D alliance affects firm performance. Of particular focus is its impact on the post-IPO (initial public offering) survival and profitability of high technology firms. Fama and French (2004) document high failure rates among newly listed firms, with more than 40% delisted within a decade due to poor performance. Firms operating in high technology industries, such as those in computers, machinery, and electronics, are not immune to this, posting sharp declines in earnings growth. The pronounced increase in high tech IPOs is correspondingly paralleled by significant attrition. Since high tech firms derive their competitive advantage mainly by innovating, examining the extent to which R&D alliances can help sustain their survival and profitability provides an important policy perspective for enhancing post-IPO performance. However, despite the acknowledged advantage and increasing trend towards collaborative R&D activities, there is scant evidence that characterizes the specific impact of alliances on survival and profitability.

Much of the empirical literature on R&D alliances analyzes its impact on the research productivity it confers to participating firms. The overwhelming consensus is that firms are generally better off collaborating with each other if they want to enhance their innovative performance. Branstetter and Sakakibara (1998, 2002) examine the impact of research consortia on the patenting behavior of Japanese firms and report an increase in registered patents among collaborating firms relative to stand-alone (non-collaborating) firms. Controlling for firm size and industry effects, they also find that collaborating firms generate higher levels of R&D expenditures. Sampson (2007) supports the finding that firms involved in an alliance report higher patent counts, particularly when participating firms exhibit diverse, but complementary skills and resources. Using patent citations as a measure of the extent to which firms share and promote technological knowledge, Gomes-Casseres, et.al., (2006) provide evidence that firms engaged in an R&D alliance show a higher degree of knowledge flow than those otherwise.

Theory posits a profit advantage for firms that participate in an R&D alliance. D'Aspremont and Jacquemin (1988), Kamien and Zang (1992, 2000), Bloch (1995), De Bondt (1997), and Deroin and Gannon (2006) exposit models that show higher profits for collaborating firms compared to their stand-alone counterparts. In these models, membership in an alliance confers higher profits to the firm mainly because of the reduction in the cost of production for high enough spillovers. The positive effect on profits extends to a model of unrestricted alliance membership and free entry, where Erkal and Piccinin (2007) show that collaborative R&D generally yields higher profits than R&D competition, in which firms independently perform R&D activities. The theory on firm survival emanates from Jovanovic (1982) who postulates a model of a firm learning its capabilities over time. Those that are able to discover and develop their capabilities increasingly become productive and survive, whereas those unable to do so fail. Learning also takes place in Klepper's (2002) model. Firms invest in R&D to reduce production costs. As firms become more experienced in conducting R&D activities, they consequently achieve higher profits and are less susceptible to exit-inducing shocks. The idea that a firm learns to raise productivity spurs the incentive to recognize its intrinsic capabilities, acknowledge deficiencies, and overcome constraints by collaborating with other firms. Interfirm collaborations provide a channel for efficient learning because the acquisition and development of capabilities for any firm acting alone can be lengthy and complicated.

Empirical support for the profit advantage R&D alliances confer on firms, in particular, high tech IPOs, is sparse, considerably more so for its likely effect on post-IPO survival. From a sample of American, European, and Japanese manufacturing firms, Hagedoorn and Schakenraad (1994) use path analysis to demonstrate that R&D cooperating firms are more profitable than non-R&D cooperating firms. Powell, et.al. (1999), report that R&D alliances formed in the biotechnology industry can help a firm achieve higher profits, conditional on how well-connected or active the firm is in the overall network. Using a worldwide sample of firms on the semiconductor industry, Stuart (2000) provide evidence of higher sales growth experienced by firms in an alliance. The higher revenue growth rate among collaborating firms is also supported by Baum, et.al., (2000). Much of the empirical literature on survival has recognized the importance of firm size (Klepper, 1996), firm age (Agarwal and Gort, 2002) and industry characteristics (Audretsch, 1995). While interfirm collaborations are becoming recognized as well, the specific impact of

R&D alliance merits investigation. Mitchell and Singh (1996), using logistic regression, find that alliances related to licensing, marketing, and distribution help firms survive longer. Capron and Mitchell (2007) examine survey data on executives from the telecommunications industry and report that firms survive longer by closing the capability gap. This means that alliances, such as R&D and marketing partnerships, enable firms to obtain and develop desired capabilities. However, Fosfuri and Giarratana (2004) find no support that alliances (which also broadly includes R&D, marketing, and distribution) raise firm survival rates. This is based from a hazard model of 270 startups in the security software industry.

There are essentially two main issues which these studies do not generally address that can potentially vitiate the causal linkage of profitability and survival to alliance participation. A key issue is the problem of selection on unobservables. Firms who self-select or are selected to participate in an alliance may differ from those that do not participate or get selected in ways that can also impact on their profitability and survival. Moreover, even if these unobservable factors are accounted for, there may be a feedback effect or reverse causation in that profitable, surviving firms may be the ones mainly involved in an alliance. If this possibility is valid but ignored, then parameter estimates of the alliance effect will provide misleading evidence of causality.

In this paper, I evaluate the specific impact of R&D alliance using information on the firm's listing duration and earnings profile. The estimation strategy identifies the impact through changes in the firm's alliance status. I employ Cox and piecewise duration models and an unobserved effects lag specification to ascertain the link between R&D alliance participation and the survival and profitability of high tech firms. Using a sample of 586 high tech firms newly listed in the United States over the period 1990-2000, I find evidence suggesting that R&D participating firms experience higher survival rates and generate higher profits. On average, alliances in R&D can help attenuate the risk of poor firm performance and eventual delistment by 10%. Profit valuations are higher by 2.83% using Tobin's q, and by 3.24%, using return on assets. These results are broadly impervious to model specification and sample selection. The alliance effect becomes more pronounced, even after controlling for firm age, when the sample includes well-established, older firms, suggesting that collaboration becomes even more important over time for sustainable performance.

This paper contributes to the literature along three strands. First, it provides empirical evidence for R&D alliance as a channel through which innovation can be pursued and developed that leads to sustainable firm performance. Second, it builds on studies that analyze IPO failure risk by highlighting the potential role of cooperative R&D agreements in deterring the hazards of poor performance. Finally, this paper reinforces insight from management and organizational studies that advocate development of capabilities through interfirm collaborations.

The rest of the paper is organized as follows. I review the literature espousing the hypothesized effect of R&D alliances on profitability and survival in section 2. I describe the construction of the data and variables used in the estimations in section 3. The empirical framework and the results are discussed in section 4. The paper concludes in section 5.

2 Hypothesis and Review of Literature

I posit that participation in an R&D alliance enhances the survival and profitability of newly listed high tech firms. I draw upon three essential advantages that R&D alliances confer to participating firms that provide salience to this hypothesis: (i) containment of uncertainty and tolerance for risk, (ii) complementarities, and (iii) economies of scale and scope in R&D.

Containment of uncertainty and tolerance for risk: High-tech firms mainly rely on new product development as a way to create, sustain, and boost brand recognition and market reach. Apart from the fact that production must be efficiently implemented to keep costs at bay, high tech firms attempt to introduce new products that not only meet consumer enthusiasm, but also generate market demand. The increasing complexity and vagaries of consumer tastes, coupled with the rapid obsolescence of technological capabilities and product innovations, create uncertainties and risks which necessitate firms to search for mechanisms that enable them to cope with competitive benchmarks. The creation of new products and technologies and the adoption of experimental processes are uncertainties and risks that firms face in order to succeed in the market (Mitchell and Singh, 1992). To create the seeds of innovation that can potentially generate profits and reinforce survival, firms must pass the hurdle of venturing into the unknown (uncertainties of whether or not the idea is implementable and novel enough to stimulate market interest) and the hazard of failure (risk that the idea gets shelved before, during, and after the innovation process because of, say, financial constraints or lack of sufficient expertise).

Participation in an alliance provides a mechanism or structure that allows firms to jointly manage the uncertainty of the innovation process and tolerate the risks involved. Unlike their stand-alone counterparts, those involved in an alliance are able to open up mixed options of jointly creating, designing, testing, and implementing products and processes that would have otherwise been constrained or suppressed because of the uncertainties and risks. Collaboration acts as an enabling mechanism in that firms can realize uncertain technologies with limited individual risk exposures.

Robertson and Gatignon (1998) find empirical support for this: firms that face greater technological uncertainty, such as those in high technology industries, are more likely to (i) engage in an alliance than to develop the innovation single-handedly, (ii) pursue paradigm-shifting ideas, and (iii) introduce innovations at a faster rate. Robinson (2007) similarly report that alliances are commonly established in inherently riskier industries (in particular, high tech) and that the risk of the alliance activity is comparably greater than the risk of individual firm projects, suggesting that the alliance as a whole can tolerate greater risk for expectations of greater reward, despite limited investment exposures by participating firms. Erkal and Minehart (2006) point out that because uncertainties are highest at the beginning of any research venture, the incentive to collaborate is correspondingly highest at this stage. Dittrich and Duysters (2007) document an interesting case study of Nokia, which is currently one of the top mobile phone companies in the world. To test its technological capabilities and set the standards for an untapped market, Nokia collaborates with other mobile companies such as Ericsson, Siemens, and Motorola. The view is that a strategic technological alliance with other firms creates an innovation network that relaxes market access through joint product development and technology standardization.

Complementarities: Interfirm R&D agreements are established to collaboratively discover and develop technologies that result in profitable ventures for the firm. While the set of firm responsibilities and group tasks in which R&D activities are organized and outcomes are achieved may broadly differ across alliances, the aim of successful innovative performance among participating firms is a common thread that forges alliances. This implies that alliances are not random collections of firms. Alliances evolve through a grouping together of firms with dissimilar, but complementary skills, knowledge, and expertise. Because alliances are mainly driven by project-specific goals, participating firms learn each other's distinct capabilities and create a pool of knowledge from which they can draw and harness the skill necessary to implement research ventures. Rothaermel and Boeker (2008) report evidence that projects aimed at discovering and developing human therapeutic drugs have involved alliances between pharmaceutical and biotechnology firms. These collaborations were forged mainly on the basis of accessing each other's complementary capabilities to ensure drug success.

Access to complementarities is the operative word for R&D alliances (Teece, 1992; Mody, 1993; Grant and Baden-Fuller, 2004). The pursuit of a successful innovative outcome that elevates firm survival and profitability necessitates a high tech firm to have a considerable amount of multi-disciplinary knowledge and expert capabilities. Singularly obtaining and learning these can be costly, inefficient, and unwieldy for any particular firm. Participation in an alliance provides an avenue for firms to focus on their core competencies and to access each other's specialized knowledge. Doz, et.al. (2000) report that collaborating firms undergo an interactive cycle of learning, reevaluation, and readjustment in the course of delineating alliance tasks and expectations. Using a sample of over 2,000 German manufacturing firms that were asked about their innovation activities over the period 1990-1992, Becker and Dietz (2004) find that firms collaborate in order to complement existing R&D capabilities and that this results in higher research productivity and more product innovations.

Economies of scale and scope in R&D: Fundamentally, firms invest resources in R&D in order to generate innovative products and processes that bolster market demand, create niches, or streamline production to make it cost-efficient. This enables firms to realize higher profits and lower susceptibility to the hazards of failure and market exit. While it is acknowledged that R&D is a key input to the innovation process, resources spent on discovering novel ideas and implementing these into commercial ventures do not, by themselves, necessarily translate to a successful innovation outcome. Such success entails a high intensity of quality research and development principally driven through economies of scale and scope. This distinction is important. Henderson and Cockburn (1996) and Cockburn and Henderson (2001) provide empirical evidence that while the research aspect of R&D is successfully initiated through economies of scale, its development phase is successfully implemented through economies of scope.

This generally imbues large firms an advantage in R&D in that their size enables them to reduce the unit cost required for these activities (Cohen and Klepper, 1996; Macher and Boerner, 2006) and to exploit the synergy of having different functional groupings inherent in their organizational structure (Henderson and Cockburn, 1996; Zollo and Winter, 2002). But not all firms are large, and large firms do not necessarily possess a limitless amount of resources and the skill and experience needed to successfully conduct R&D.

It is in this context that R&D alliances play a central role as the bridge or mechanism that enables participating firms to achieve economies of scale and scope in R&D. Collaboration engenders (i) economies of scale in the sense that it creates a network of firms pooling their resources together and drawing upon each other's capabilities and embedded knowledge and (ii) economies of scope in the sense that it creates a cross-functional linkage of firms, assigning tasks according to firm specialization and integrating the outcome into other areas at minimal or zero marginal cost. It is on this basis that Danzon, et.al. (2005) empirically document a role for alliances in enhancing research productivity. Using data on drugs being developed and clinically tested at various stages, they find that while the effect of individual firm experience on drug development and testing varies in stages, drugs developed in an alliance between pharmaceutical and biotechnology firms are more likely to advance through clinical tests and completed. This finding is shared by Arora, et.al. (2000) and Nicholson, et.al. (2005). Lerner, et.al. (2003) provide evidence of the significance of scale economies in alliances, reporting that sufficiently funded biotechnology alliances have a faster time to develop new products and obtain product approval.

3. Data and Variable Description

I use a panel of 586 firms that became publicly listed for the first time over the period 1990-2000. This sample is a merger of four different datasets. I assembled information on (i) initial public offerings, (ii) R&D alliances, (iii) stock exchange delisment, and (iv) financial data.

The sample of IPOs was obtained from the SDC Platinum Global New Issues database, which collects information on public offerings made worldwide. To make the analysis manageable and achieve focus, I restricted my data to firms that went public in the United States from 1990 to 2000. In particular, these firms had an IPO offer price of at least $1 and issued ordinary shares at the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and NASDAQ. The offer price criterion is meant to exclude firms which potentially have insecure trading behavior. The sample IPO period is meant to characterize newly listed firms; with reference to their IPO date, these firms are relatively young in that a firm is at least 1 year old (it had its IPO in 2000) and no more than 10 years old (it had its IPO in 1990).

I relied on NAICS codes (North American Industrial Classification System) that constitute the high tech industries prescribed by the US National Science Foundation

Science and Engineering Indicators (2006). For ease of classification, I used 2-digit NAICS codes to group the firms in my sample. These are NAICS codes 32 (e.g., pharmaceutical manufacturing), 33 (e.g., industrial machinery), 51 (e.g., software), 54 (e.g., computer systems), and 81 (e.g., computer and office machine maintenance).

I merged the sample of high tech IPOs with the SDC Platinum Joint Venture/Alliances database, which provides information on firms that entered into R&D alliance agreements domiciled or established in the Unites States. These are non-equity, contractual agreements among firms to collaborate on research and development activities. To ensure the integrity of this definition, I individually read the business profile of each participating firm and the specified alliance project. I particularly looked for R&D alliances that unambiguously describe the R&D activity. This may have involved the development of new technology, customization of a product, or redesign of a process. The matched sample therefore creates two IPO profiles: newly listed high tech firms that engage in R&D alliances and those that do not.

I used the Center for Research in Security Prices (CRSP) database to identify delisted firms. Firms are delisted or removed from the exchange for non-compliance of continued listing standards. To remain listed, firms must regularly demonstrate that they are in compliance with these standards, which are designed to protect the integrity of the exchange and maintain public trust (Macey, et.al., 2005). These standards run the gamut from legal requirements and corporate governance to trading volume. More pertinent for my analysis is when a firm gets delisted due to poor financial performance, as when a company files for liquidation or bankruptcy proceedings. The CRSP database provides codes that specify the reason for delistment. In my sample, I collected delistment codes that pertain to firm liquidations, bankruptcies, insolvencies, and precarious diminution of capital or equity, among others. I used the Compustat-WRDS financial and accounting database to obtain information on firm profits, R&D expenditures, cash flow, and outstanding shares, among others. These are used to construct the covariates essential for the empirical framework described in the succeeding section.

The sample selection process resulted in 928 firms, for a total of 6,971 observations. To obtain a sharper analysis of the effect of R&D alliances on the survival and profitability of newly listed high tech firms, I excluded firms that were incorporated or founded before 1990. Examining the potential benefit of collaborative R&D on well-established, old high tech firms is important in its own right, but may be confounded by the fact that these firms have had greater experience in the nuances of their chosen market. However, as detailed in the next section, their presence does not alter the hypothesized effect of collaboration. This exclusion resulted in a final sample of 586 firms or 3,723 firm-observations, which I use in my estimations.

Table 1 reports the industry and exchange distribution of firms. About 60% operate in NAICS industry code 33, which includes machinery, computer, and electronics. NASDAQ is the predominant choice for high tech initial public offerings, with about 93% of total listings. These averages may potentially mask annual distribution patterns, but the results persist systematically over the years (Figure 1A and Figure 1B). Table 2 provides a breakdown of the listing status and alliance profile of the sampled firms. Less than half of the total number of firms engages in R&D alliances. While R&D alliance participating and non-R&D alliance participating firms exhibit similar listing rates, firms that collaborate report lower delisting rates. Of those delisted, 65% are firms with no alliances. To test if this difference is statistically significant, I use a two-sample test of proportions that compares the delisting rate of participating firms $p_1 = 11\%$ with that of non-participating firms $p_2 = 20\%$. The *p*-value of 0.0013 rejects the null hypothesis $H_0 : p_1 = p_2$, in favor of the observed alternative $H_1 : p_1 < p_2$, implying that the latter type of firms are more likely get delisted due to poor performance. On average, compared with collaborating firms, those with no alliances are twice more likely to get delisted (Figure 2A), regardless of industry (Figure 2B) or exchange affiliation (Figure 2C). Figure 3 shows the number of R&D alliances formed over the period 1990-2005. There was a steady increase in the early part of the 1990s, culminating in a sharp peak by the close of the decade, followed by a slow-down. Firms participated twice in an alliance, and 95% of alliances are between two firms, on average. The latter result appears to support Deroin and Gannon's (2006) model in which R&D efforts decrease with collaboration size. Potential problems in alliances, such as free-riding and dissonance, become magnified when there are several firms working together.

To examine the impact of R&D alliance on firm survival and profitability, I define the variable *R&D alliance* =1 to indicate that a firm engages in a contractual, non-equity cooperative R&D agreement with other firms, and 0 otherwise. Firm survival is gauged by recording the listing duration of firms, which is measured from the time a firm had its IPO to the time it was delisted. This provides an empirical framework for assessing a firm's proneness to failure and eventual delistment. Since IPOs are recorded until 2000, I selected 2005 as the last window year to reasonably observe listing durations that available data permit.

I use *Tobin's q* as a market-based measure of profitability. This is calculated as follows (Kaplan and Zingales, 1997)

$$Tobin's\ q = \frac{Market\ Value\ of\ Assets}{Book\ Value\ of\ Assets} \quad (1)$$

where market value of assets = book value of assets + market value of common stock – (book value of common stock + balance sheet deferred taxes); book value of assets = Compustat item 6; market value of common stock = share price at the end of the fiscal year (Compustat item 199) × common shares outstanding (Compustat item 25); book value of common stock = Compustat item 60; and balance sheet deferred taxes = Compustat item 74.

To check for robustness, I also use return on assets or *ROA*, as an accounting-based measure of firm profits. This is defined as

$$ROA = \frac{EBITDA}{Book\ Value\ of\ Assets} \quad (2)$$

where the book value of assets is defined as in equation (1) and EBITDA = earnings before interest, taxes, depreciation, and amortization; this is also commonly referred to as as operating profits for the firm.

These two measures offer a nuanced perspective on profits. While ROA provides information on current profitability, Tobin's *q* additionally generates insight on expected profitability and incentives to invest in the future.

I use the following as control covariates of firm performance: *(log) Sales*, to account for the idea that large firms presumably have greater access to resources and opportunities which sustain profitability and survival (Klepper, 1996); *Debt/Assets*, following the empirical finding that highly leveraged firms are likely to experience stunted growth (Lang, et.al., 1996); *Cash flow/Assets*, in that internally generated funds relieve firms of financial constraints, raising the opportunity to embark on profitable ventures (Carpenter, *et.al.,* 1998); and *(log) R&D expenditures*, given that firms which devote resources to research and development activities are more likely to explore new ideas and find ways to implement and commercialize their innovation.

I measure *Debt/Assets* and *Cash flow/Assets* as follows:

$$Debt / Assets = \frac{Book\ Value\ of\ Total\ Debt}{Book\ Value\ of\ Assets}$$

$$Cash\ flow / Assets = \frac{Cash\ flow\ before\ interest}{Book\ Value\ of\ Assets} \tag{3}$$

The effects of debt and cash flow are scaled by the book value of assets defined previously. The book value of total debt = market value of equity + book value of debt + preferred stock – deferred taxed; market value of equity = share price at the end of the fiscal year (Compustat item 199) $\times$ common shares outstanding (Compustat item 25); book value of debt = sum of Compustat items 9 and 34; preferred stock = sum of

Compustat items 56, 10, and 130; deferred taxes = Compustat item 74; and cash flow before interest expense = sum of Compustat items 18 and 14.

Table 3A provides some summary statistics for the variables used in the estimation. To gain perspective on these numbers, I report in Table 3B separate summary statistics for firms with an R&D alliance and for those with no alliances. On average, firms engaged in an R&D alliance remain listed for 7 years compared with 6 years for those that do not have an alliance. These listing averages are taken at face value as they are unable to capture censored listing durations; there are firms in my sample whose exact delistment times are unknown. These censored observations will tend to overestimate listing times. A duration technique is introduced in Section 4 that can handle this situation.

Although both firm types displayed negative ROAs, collaborating firms reported higher profit valuations (as measured by *Tobin's q*) and operating profit (as measured by EBITDA). These firms also reported higher sales and R&D expenditures and lower debt. Figure 4 compares the operating profits of both firm types. Over the years 1990-2005, collaborating firms generated five times more profits, on average, than their stand-alone counterparts. Table 3B also provides p-values for the two-sample t test and Wilcoxon-Mann-Whitney test, to assess whether the observed differences between the R&D collaborating and non-R&D collaborating firms are statistically significant. The t test compares differences in terms of means, while the Wilcoxon-Mann-Whitney test compares differences in terms of medians. Except for ROA and cash flow, the p-values for the rest of the variables are well below the 1% level of significance, reinforcing the impression that participation in an R&D alliance enhances firm survival and profitability.

4. Estimation Strategy and Results

The economic thrust of this paper addresses two fundamental questions. First, it examines whether participation in an R&D alliance mitigates the risk or hazard of firm failure due to poor post-IPO performance. Second, it examines whether R&D participating firms experience higher profit valuations than those that do not engage in such alliances. The overarching aim is to analyze the extent to which inter-firm collaborations in R&D benefit the participating firm. I use duration models to address the first question, and panel data models for the second question.

Analysis of Listing Duration

My sample data consist of firms that became publicly-listed for the first time over the period 1990-2000. Once listed, these firms either continue to become going concern entities and operate profitably or become delisted from the stock exchange due to poor financial performance. Given data on the year in which the firm had its IPO at the exchange and the date in which it was delisted, I have a record of how long the firm remained listed. My estimation strategy relies on these duration distributions to examine whether participation in an R&D alliance can help attenuate the risk of poor firm performance and eventual delistment.

The outcome variable of interest is a nonnegative random variable *T*, which denotes the time from the firm's IPO to its delistment. Its distribution can be characterized by the survival function and hazard function. The survival function

$$S(t) = Prob(T > t) \tag{4}$$

gives the probability that a firm remains listed or survives longer than a particular listing duration t. The survival function is a nonincreasing function of time. It is equal to 1, at time $t = 0$, which means that all firms are listed and surviving at the beginning of their IPO, and decreases towards 0 as $t \to \infty$. Of particular interest is the hazard function

$$h(t) = \lim_{\Delta t \to 0} \frac{Prob(t \le T < t + \Delta t \mid T \ge t)}{\Delta t} \tag{5}$$

which defines the instantaneous rate of firm delistment or failure at time t, given that the firm has survived up to that time. This conditional failure rate gauges the newly listed firm's proneness to delistment, and the intent is to determine whether interfirm collaborations in R&D can be causally linked to the attenuation of this hazard.

The survival and hazard function are complementary representations of listing duration. For a given probability density $f(t)$, the hazard function can be derived from the survival function, and vice-versa in that $h(t) = \frac{f(t)}{S(t)}$.

A useful, indicative way to assess the impact of R&D alliances would be to compare the survival distribution of firms that engage in an alliance with those that do not. I estimate the survival functions for these two types of firms using the Kaplan-Meier estimator, which is given as (Lawless, 2003)

$$\hat{S}(t) = \prod_{j:t_j<t} \frac{n_j - d_j}{n_j} \tag{6}$$

where n_j counts the number of listed firms at risk of delistment at time t_j and d_j denotes the corresponding number of firms that have been delisted. The J duration data are arranged in ascending order such that $t_j < t$. An estimate of the conditional probability of delistment is given by $\frac{d_j}{n_j}$ and $\frac{n_j - d_j}{n_j} = 1 - \frac{d_j}{n_j}$ correspondingly provides the estimated conditional probability of surviving. Successive multiplication of the survival probabilities provides an estimate of the overall survival function. Viewed in this way, the Kaplan-Meier estimator $\hat{S}(t)$ intuitively gives the estimated proportion of firms listed and surviving at time *t*.

The Kaplan-Meier estimator is a consistent estimator of firm survival, accommodating the situation that not all firms in my sample have experienced delistment. While there are firms for which I can record their actual delistment time, there are also other firms which are still observed as listed up to 2005, the last year of my observation window. For these firms, their duration time is censored or unknown. Estimates of survival rates are seriously biased if censored observations are not appropriately accounted for. The estimator accordingly calculates the contribution of censored observations to risk of delistment up until the last time firms are observed to be listed.

Figure 5 plots the survival distributions of R&D participating and non-R&D participating firms. It shows that the survival curves monotonically decrease over time. Both types of firms exhibit similar survival rates for the first three years after IPO in that there are relatively few delistments. By the fifth year, however, a systematic pattern emerges: the survival curve of participating firms lies distinctly above those that do not engage in R&D collaborations. While half of non-R&D participating firms have survived at least 13 years, at that median survival time, 70% of R&D participating firms are still listed and surviving. By the 15th year, the survival rate for participating firms is twice that of their non-participating counterparts. R&D collaboration appears to mitigate the hazard of firm failure.

I use three tests to evaluate whether the observed separation of these two curves is statistically significant: the log-rank test, the Wilcoxon test, and the Peto-Prentice test. These are chi-square tests of the null hypothesis that the two survival curves are the same, against the alternative that the survival curve for collaborating firms is monotonically above that of non-collaborating firms. These tests differ in the way they detect differences in survival rates. While the log-rank test places emphasis on detecting significant differences at the end or tail of the survival curves, where the number of firms at risk has decreased over time, the Wilcoxon test is more sensitive to detecting early survival differences, in which more firms are at risk of failure. The Peto-Prentice test, on the other hand, evaluates the overall survival experience of firms. It is less sensitive to censoring patterns that can potentially distort detection of differing survival curves. The *p*-values for these three tests are practically zero, reinforcing the graphical impression that collaborating firms experience higher survival rates. The log-rank test is $\chi^2_{(1)} = 17.47$ with *p*-value = 0.000; Wilcoxon test: $\chi^2_{(1)} = 13.39$, *p*-value = 0.0003; and Peto-Prentice test: $\chi^2_{(1)} = 17.33$ *p*-value = 0.000.

I use regression analysis to better gauge the link between R&D alliance participation and the listing duration of firms. Because my primary interest is in exploring the notion that collaboration mitigates firm failure, I use the hazard function as a framework for the analysis. I estimate the following hazard specification

$$h(t, x_{it}) = h_0(t) exp(\beta_1 \ R\,\&\,D\ alliance_{it} + \sum_{k=1}^{K} \lambda_k x_{it}^k) \tag{7}$$

where $h(t, x_{it})$ is the hazard of poor performance and eventual delistment faced by firm *i* at time *t*. The indicator variable $R\,\&\,D\ alliance = 1$, denotes firms collaborating in R&D; 0, otherwise. The time subscript indicates that participation in an alliance varies over time for a given firm. The potential impact of collaboration on the hazard is determined by β_1. The vector of control covariates x_{it} represents firm-specific characteristics (profitability, debt, cash flow, and firm size) as well as industry and IPO year indicators that are likely to affect listing duration.

The specification in equation (7) is the Cox proportional hazards model. The hazard a firm faces is characterized by a baseline hazard $h_0(t)$, and is influenced by participation in an R&D alliance and the specified set of control variables. Because the hazard function is defined only over the interval $[0, \infty)$, the exponential form for the regressors assures that this condition is satisfied. There is no intercept in the set of regressors as it is subsumed under $h_0(t)$. The baseline hazard represents the intrinsic risk that firms experience over time; the hazard simplifies to $h_0(t)$ when the effect of the regressors is suppressed such that $exp(0) = 1$. The proportional hazards designation reflects the underlying assumption that the hazard of poor firm performance and delistment can be proportionally shifted up or down through participation in an R&D alliance.

The parameter estimates are obtained via maximum likelihood. Estimation is based on forming a partial likelihood function of the conditional probabilities of failure, which takes into account both actual and censored failure times. It is a partial likelihood in the sense that the baseline hazard $h_0(t)$ is left parametrically unspecified and not estimated. Despite this, the partial maximum likelihood estimator exhibits the same asymptotic properties obtained under standard maximum likelihood procedures. This correspondingly means that standard statistical tests and inference are carried out in the same manner.

The Cox model is a class of proportional hazards estimation that is semi-parametrically specified; while the baseline hazard is not characterized by any parametric distribution, the regressors in $exp(.)$ form a linear combination to explain the conditional failure rate. I use the Cox model to avoid making arbitrary parameterizations of the baseline hazard. This is important because the intrinsic risk firms face can exhibit various representations and combinations of duration dependency, or possibly none at all. For instance, the likelihood of getting delisted may increase (exhibiting positive duration dependency) or decrease (exhibiting negative duration dependency) the longer a firm remains listed. This situation may be up to a certain duration, monotonic in time, or a combination of both.

The implication is that an inappropriate specification can severely bias the hazard estimates and invalidate statistical inference. The Cox model carries the advantage that it is distribution-free and the results are valid, provided that the hazard proportionality assumption is correct. More pointedly, since my primary concern is in verifying whether R&D alliance participation shifts the hazard function of firms, estimation of the baseline hazard is not particularly essential in the analysis.

The Kaplan-Meier survival curves drawn in Figure 5 and the Nelson-Aalen cumulative hazard curves in Figure 6 provide a first-pass indication that the proportionality of hazards is a reasonable assumption. The survival rates for R&D collaborating firms appear to be proportionally shifted up relative to non-R&D collaborating firms. Because the cumulative hazard is $H(t) = -log\ S(t)$, the hazard estimates for firms in an alliance are correspondingly shifted down; the curves do not intersect and appear to move proportionally from each other over time. The cumulative hazard adds ups the hazard estimates up to time t. It is empirically implemented using the Nelson-Aalen estimator given as (Lawless, 2003)

$$\hat{H}(t) = \sum_{j:t_j<t} \frac{d_j}{n_j} \tag{8}$$

which follows the previous notations of the Kaplan-Meier calculation in equation (6). As the negative log-complement of the survival function, $H(t)=0$ and $S(t)=1$ at time $t=0$, and $H(t)=1$ and $S(t)=0$ at time $t=\infty$.

As a benchmark for assessing the impact of R&D alliance participation, I estimate the Cox proportional hazards model with the alliance variable as the only regressor. Table 4 column 1 provides a point estimate of -0.594, with a default maximum likelihood standard error of 0.352. The negative sign indicates that the hazard of getting delisted due to poor performance decreases with alliance participation, and the result is statistically significant at the 10% level. To make economic sense of this, we need to calculate the marginal effect. To obtain the marginal effect of a regressor x in the Cox model

$$h(t,x) = h_0 \exp(x'\beta)$$

we transform it in logarithmic form as

$$log\ h(t,x) = log\ h_0(t) + x'\beta$$

so that the marginal effect of a variable x_j is

$$\frac{\partial log\ h(t,x)}{\partial x_j} = \beta_j$$

and $\beta_j \cdot 100$ is a semi-elasticity, which measures the percentage change in the hazard rate when x_j changes for one unit. This is reasonably accurate for small β_j. The interpretation becomes an elasticity if x_j appears logarithmically. For large β_j and x_j appearing as an indicator variable, as in the case of R&D alliance participation, it is more appropriate to calculate the proportionate change

$$[\exp(\beta_j)-1]\cdot 100 \tag{9}$$

since the change in expected duration associated with a variable x_j that takes only values 0 and 1 is

$$\frac{E[h(t,x\mid x_j=1)]-E[h(t,x\mid x_j=0)]}{E[h(t,x\mid x_j=0)]}=\frac{h_0\exp(\beta_j+x'\beta)-h_0\exp(x'\beta)}{h_0\exp(x'\beta)}$$

$$=\exp(\beta_j)-1$$

Using this interpretation, the point estimate has an estimated effect of $[\exp(-0.594)-1]\cdot 100=-44.788\%$, which suggests that R&D alliance participation can negate the hazard of delistment by about 45%.

Because I have repeated observations on individual firms, it is unlikely that the observations for each firm are independent. To account for possible serial dependence of the firm observations, I use robust standard errors computed using the Huber-White variance estimator, specifying the correlation of disturbances within firms as a cluster. In the estimations, I report both the default maximum likelihood standard errors (in parentheses) and robust standard errors (in brackets) to evaluate the sensitivity of parameter estimates. However, I use the robust standard errors for valid statistical inference.

In column 2 of the estimates, I add the control covariates likely to affect the listing duration of firms. The estimate for Tobin's *q* shows that profitable firms are more likely to remain listed and survive. On the other hand, highly-leveraged firms may be more susceptible to delistment. This effect is denoted by the variable *Debt/Assets*. It appears that large firms, as measured by *(log) Sales*, and those with a steady stream of internal funds, as denoted by *Cash flow/Assets*, are better able to attenuate problems associated with poor financial performance. Innovating firms, as measured by (*log) R&D expenditures*, can also lower this hazard.

While the R&D alliance variable remained negative, its statistical significance dissipates with the inclusion of control covariates. However, because firms participate in an alliance to jointly undertake R&D, it is more pertinent to consider that the differential effect of the alliance variable is not constant with the level of R&D spending. In contrast to the previous result, its effect likely depends on the amount of R&D expended by participating firms. While I do not have specific data on total R&D alliance spending and the amount contributed by each firm, the reported firm-level R&D spending may be a reasonable proxy to use.

On this basis, I recast the Cox model by including an interaction effect between the *R&D alliance* variable and (*log) R&D expenditures*. The model becomes

$$\begin{aligned} h(t, x_{it}) = h_0(t) exp(\beta_1\ R\&D\ alliance_{it} + \beta_2 (log) R\&D\ spending_{it} + \\ \beta_3\ R\&D\ alliance_{it} \times (log) R\&D\ spending_{it} + \sum_{k=1}^{K} \lambda_k x_{it}^k) \end{aligned} \quad (10)$$

The estimated effect of R&D alliance is then given by

$$\beta_1 + \beta_3 (log) R\&D\ spending_{it} \quad (11)$$

obtained by considering the change in expected duration when $R\&D\ alliance_{it} = 0$ and when $R\&D\ alliance_{it} = 1$, so that $E[h(t, x_{it} \mid R\&D\ Alliance_{it} = 1)] -$ $E[h(t, x_{it} \mid R\&D\ Alliance_{it} = 0)] = \beta_1 + \beta_3\ (log) R\&D\ Spending_{it}$.

The alliance effect varies based on particular values of (log) R&D spending. A meaningful way to pin this down is to report the average effect $E_x[\beta_1 + \beta_3 (log) R\&D\ spending_{it}]$, which is calculated by adding up the estimated individual effects for each firm-observation and taking the average. I then use equation (9) to obtain the appropriate interpretation.

The estimates are reported in column 3. The estimate for the alliance variable β_1 is positive, but not statistically significant using either the default or robust standard errors. The estimate for the interaction term β_3 is negative, but not significant using the default standard error. However, when inference is based on robust standard errors, it becomes significant at the 5% level. Using robust estimates, the *p*-value for testing the joint null hypothesis $\beta_1 = 0,\ \beta_3 = 0$ is 0.0875, which is significant at the 10% level. This provides support to the idea that alliance participation has an interactive effect with R&D spending. The average marginal effect $E_x[0.351 - 0.229 \cdot (\log) R\&D\ spending_{it}]$ yields an estimate of $[\exp(-0.180) - 1] \cdot 100 = -16.498 \approx -16\%$, which is more than a half lower than that suggested by the benchmark estimate with no control covariates. The control covariates are individually significant, which suggest that large, profitable firms with a steady cash flow are better able to attenuate delistment; this does not appear to be the case for highly-leveraged firms.

The final three regressions in the table incorporate IPO year dummies (column 4) to account for variations in the year in which the firm decides to go public. Jain and Kini (1994) and Benninga, et.al., (2005) provide evidence that firms may time their IPOs to take advantage of periods of high valuation and better investment returns. I include industry dummies in column 5 to allow for differences in the industry in which the firm operates, and both IPO and industry dummies in column 6. Controlling for these additional factors yielded mixed negative alliances estimates of 21% (column 4), 5% (column 5), and 7% (column 6). Estimates for the dummy variables are suppressed for brevity. The bottom row on the table reports joint hypotheses tests of their overall significance. The *p*-values indicate that these variables are not statistically significant for inclusion in the regressions.

An important assumption inherent in the Cox estimations is that the ratio of the hazard rates between R&D collaborating and non-R&D collaborating firms does not vary over time. This proportionality assumption relaxes the need to search for appropriate parameterizations of the baseline hazard and produces estimated parameters that are generally valid for all possible shapes of the hazard function. However, if this assumption is not met, the parameter values will be inconsistently estimated and the model is essentially misspecified. To more formally explore this possibility, I reestimated Kaplan-Meier survival curves for both R&D and non-R&D participating firms and plotted the generated hazards $-log[-log\ \hat{S}(t)]$ against log time *t*. If the hazard rates are proportional to each other and do not vary over time, then the hazard curves should be parallel. This provides a graphical assessment of the proportionality assumption because the Cox model $h(t,x) = h_0(t)exp(x'\beta)$ has the corresponding survival function

$$S(t,x) = S_0(t)^{exp(x'\beta)} \tag{12}$$

where $S_0(t)$ is the baseline survival function in which $exp(0) = 1$. Since the cumulative hazard is $H(t) = -log\ S(t)$, the logarithmic transformation of the survival function

$$-log[-log\ S(t,x)] = -log[-log\ S_0(t,)] - x'\beta \tag{13}$$

provides estimates for $x = 1$ (firm engages in an R&D alliance) and for $x = 0$ (firm does not engage in an R&D alliance). If the model is correctly specified, then the hazard curves plotted against log time should be vertical translations of each other as measured by β. Figure 7 illustrates that the two curves are reasonably parallel, which provides validity to the proportional hazards assumption. A residuals-based test also confirms this. If the effect β_j of the alliance variable x_j varies over time, then the Cox model becomes

$$h(t,x) = h_0(t)exp(x'\beta + \gamma g(t)) \tag{14}$$

implying that the alliance parameter

$$\beta_j(t) = \beta_j + \gamma g(t) \tag{15}$$

varies via γ over some function of time $g(t)$. If the proportionality assumption holds, then $\gamma = 0$, which I test as the null hypothesis. The test requires obtaining Schoenfeld residuals for x_j that are derived from the Cox partial likelihood function. The *p*-value for the alliance variable is 0.642, which is well above the 10% level of significance. The rest of the explanatory variables were also tested and reported similar *p*-values. In all, these results do not reject the null hypothesis, suggesting that the hazard rates remain reasonably proportional over time.

To investigate the robustness of the alliance effect, I also estimated a piecewise exponential model that partitions the baseline hazard into segmented or piecewise slopes. In this model, the time horizon is subdivided into J intervals, with breakpoints $0 = b_0 < b_1 < ... < b_J = \infty$. For each interval $[T_{j-1}, T_j)$, a separate baseline hazard is estimated, which is specified as constant within the interval, but differs across time intervals. We use an exponential distribution to obtain constant hazards for each interval, so that for $t \in [b_{j-1}, b_j)$

$$h_0(t) = k_j > 0 \tag{16}$$

With reasonable choice of breakpoints, the piecewise model can be flexible enough to approximate the overall shape of the baseline hazard. Maximum likelihood is used to estimate the parameters.

Table 5 summarizes estimates obtained from the piecewise model. As a further robustness check, I use two different interval specifications. Columns 1 and 2 of the estimates report results from using 12 time intervals $[0,4),\ [4,5),...,[13,14),\ [14,\infty)$, each having a length of one year. This approximates the hazard using closely-spaced boundaries. Columns 3 and 4 use 4 time intervals $[0,4),\ [4,8,),\ [8,12)$, and $[12,\infty)$, each having a length of 4 years. This approximates the hazard using wider intervals. Columns 1 and 3 of the estimates report a statistically significant average marginal effect of about -4% and -6%, respectively when the alliance variable and its interaction with R&D spending are estimated.

Columns 2 and 4 include the control covariates. In column 2, the effect of participating in an alliance is $[\exp(-0.1711)-1]\cdot 100 = -15.726 \approx -16\%$, which is about a percentage point difference from the analogous Cox specification (Table 4 column 3). In column 4, the effect elevates to about $[\exp(-0.2090)-1]\cdot 100 = -18.861\% \approx 19\%$. Overall, the piecewise estimates do not exhibit any substantial dissimilarity from that estimated by the Cox model. A test of the hypothesis that $\beta_1 = 0,\ \beta_3 = 0$ produced *p*-values 0.0176 (column 2) and 0.0174 (column 4), which indicate strong significance of the alliance effect. The bottom row reports *p*-values testing the significance of the two alternative interval specifications. The *p*-values are practically zero, suggesting that both specifications reasonably approximate the baseline hazard. Regressions which control for the effect of industry and IPO year were also estimated, but were not statistically significant for inclusion.

The similarity of the Cox and piecewise estimates suggests the robustness of the hazard attenuating effect of R&D alliance participation. This effect was obtained controlling for firm heterogeneity in profitability, leverage, cash flow, and firm size. There may be other factors associated with R&D alliance participation that explain differences in survival rates, but are not accounted for in the model. I explored the possible presence of unobserved heterogeneity by introducing a gamma distributed random variable in both the Cox and piecewise specifications. This variable enters multiplicatively in the hazard function and is gamma distributed as a parametric way to account for the unobserved factors. Estimations, however, did not reach convergence. As recognized in the literature, this may be due to overparameterization of the hazard function or that the estimates may be sensitive to parametric representations of unobserved heterogeneity (Heckman and Singer, 1984; Abbring; and Van Den Berg, 2006).

Despite this, unobserved heterogeneity may be innocuous in the analysis. Explicitly accounting for its effect is important to the extent that interest lies in characterizing the shape or possible duration dependency of the baseline hazard. The principal motivation for this paper, however, is to examine the hazard-attenuating effect of R&D collaboration, and not to extract the shape of the baseline hazard. As Wooldridge (2002, p.706) notes, unobserved heterogeneity does not alter how an explanatory variable affects mean duration. Also, my use of robust standard errors is helpful in suppressing erroneous inferences.

Of chief importance is the strict exogeneity of the alliance effect, because this establishes the causal link between post-IPO survival and R&D collaboration. The source of identification comes from participation in an alliance, which is time-varying. This means that firms may change their alliance status over time, deciding whether to join or getting selected to join an alliance at any time. The implication is that alliance participation may be endogenous. To mitigate this, I included firm specific attributes of survival such as profitability and size in the estimations. Importantly, there may be reverse causation in that collaboration may just as well be a consequence as it is cause a of survival. While collaborative R&D helps firms lower susceptibility to failure, those which have a remarkably pronounced survival may be more predisposed to forge an alliance to sustain, say, market dominance. This creates an upward bias in the alliance estimate.

To circumvent the confounding effect of this feedback, I lag by one year the alliance variable and its interaction. Lagging helps make clear the direction of causality and the interpretation is more intuitive: alliances formed last year help firms attenuate the hazard of failure, with the effect taking place a year later, and making clear that surviving firms cannot form alliances that happened in the past. I also create one-year lags for the control covariates as they also vary over time. In general, time-varying regressors under a duration framework are potentially endogeneous because their time path or evolution depends on their initial state (Lancaster, 1990). In particular, it no longer makes sense to define a firm's alliance status if it becomes delisted.

Table 6 presents the results from the lagged specification. Column 1 reports estimates using a Cox model. Columns 2 and 3 report piecewise estimates using the previously defined 12 time intervals and 4 time intervals, respectively. Overall, the results reinforce previous results: collaborative R&D helps firms mitigate poor performance and eventual delistment. The Cox estimate reports a 12% hazard attenuation, whereas the piecewise regressions report a 7% decrease, on average. The lagged estimates are comparably lower than those previously obtained, suggesting that reverse causation tends to amplify the impact of R&D alliance. When lagged control variables are used, leverage and firm size remained significant, with the former as hazard-increasing and the latter, hazard-decreasing. Tobin's *q* and cash flow remained negative, but were not significant using robust standard errors.

To gain additional insight on the alliance effect, I reestimated specifications in Table 6 using an expanded sample that includes older firms. These firms were founded or incorporated before 1990, which is the start of my IPO sample selection. The older firms are presumably well-established, seasoned firms. To control for the potential confounding bias this may bring, I add the variable *Age at IPO*, which is the age in years of the firm upon IPO since incorporation or date founded. About 10% have been in operation for 2 decades before going public. The results are reported in Table 7. The Cox estimate is in column 1 and the two versions of the piecewise regressions are in column 2 (12 time intervals) and column 3 (4 time intervals). The alliance effect is three times higher than the estimates in Table 3. This presumably suggests that collaborations in innovation are important for continued survival and long term growth.

Analysis of Profitability

I also investigate whether participation in an R&D alliance helps generate higher profits or leads to favorable profit valuations. I begin with the following framework

$$(log)\ Tobin's\ q_{it} = \beta_0 + \beta_1\ R\&D\ alliance_{it} + \beta_2 (log) R\&D\ spending_{it} + \\ \beta_3\ R\&D\ alliance_{it} \times (log) R\&D\ spending_{it} + \sum_{k=1}^{K} \lambda_k x_{it}^k + e_{it} \tag{17}$$

This retains the same variable definitions used before to estimate the effect of collaboration on firm survival. In this case, the outcome variable is (log) Tobin's *q*, which provides an economic-based measure of profitability. Because Tobin's *q* compares the market value of resources against their replacement value, it not only measures profitability, but also a firm's incentive to invest. More pointedly, Tobin's *q* also measures a firm's intangible resources or capabilities which are important for sustainable firm performance and competitive advantage (Villalonga, 2004).

The impact on profitability of R&D alliance participation is given by

$$\beta_1 + \beta_3 (log) R\&D\ spending_{it} \tag{18}$$

derived analogously by considering the change in expected profitability due to a discrete change in R&D alliance, $E[(log)\ Tobin's\ q_{it} \mid x_{it},\ R\&D\ Alliance_{it} = 1)] -$ $E[(log)\ Tobin's\ q_{it} \mid x_{it},\ R\&D\ Alliance_{it} = 0)] = \beta_1 + \beta_3 (log) R\&D\ spending_{it}$. I report the estimate by evaluating the average effect, calculated in similar fashion as before.

I include *Debt/Assets*, *Cash flow/Assets,* and *(log) Sales* among the set of control covariates λ_k that also influence profitability. We expect highly-leveraged firms to have lower profits, presumably because of the financial pressure of repayment. Large firms and those with adequate internal funds may be more profitable. The term e_{it} denotes the error shocks that can affect firm *i*'s profits at time *t*.

As a benchmark for assessing the effect of R&D collaboration, I estimate equation (17) using ordinary least squares (OLS) on pooled data, which means I disregard the cross-sectional and time variation inherent in the data. Table 8 presents the results from this baseline estimation. I use various specifications to gauge the sensitivity of estimates. Column 1 of the estimates reports the impact of collaboration by running a regression of (log) Tobin's q on the alliance variable alone. The estimate is statistically positive at the 1% level, suggesting that collaborating firms can expect about a quarter percent rise in their profits.

Following the same reasoning that the effect of R&D alliance likely depends on the amount of R&D expended, I reestimated equation (17) with the alliance variable and its interaction. The result is reported in column 2. The estimated impact did not substantially change with the inclusion of the interaction effect. The average marginal effect is $E_x[0.412 - 0.077(log)R\,\&\,D\ spending] = 0.233 \approx 24\%$. The p-value of 0.000 rejects the joint null hypothesis test $\beta_1 = 0,\ \beta_3 = 0$ at the 1% level. As before, the significance of the alliance effect is evaluated using Huber-White robust standard errors. The standard errors are clustered by firm to mitigate the possibility of serial correlation and heteroskedasticity. For all regressions, I report the default standard errors in parentheses and the robust standard errors in brackets, to compare the precision by which parameters are estimated.

I report in column 3 the result when the control covariates are included. Compared with previous estimates, adding the control variables somewhat decreased the effect of collaboration to about 21%, which is still statistically significant. In the succeeding columns, I add the effect of macroeconomic shocks using year dummies (column 4), industry variations using industry dummies (column 5), and both year and industry dummies (column 6). The bottom row shows that these indicator variables are jointly significant for inclusion. The individual estimates are not reported for brevity, as they do not particularly exhibit illuminating results. In these regressions, the alliance variable and its interaction are jointly significant. The alliance effect exhibits qualitatively comparable magnitudes, with collaboration increasing profit valuations by 17% (column 4), 19%

(column 5), and 15% (column 6). Compared with the specification in column 1 that parsimoniously estimates the alliance effect in the absence of control covariates, their subsequent inclusion tempered the impact of collaboration.

There are two issues that confront consistent estimation of the R&D alliance effect on profits: unobserved heterogeneity and reverse causality. The first underscores the fact that we cannot take into account all the other factors that are likely to affect firm profits. These omitted factors, or unobserved heterogeneity, do not pose a significant problem for estimation if the heterogeneity is uncorrelated with the alliance effect, as these factors are absorbed into the error term. Because these induce serial correlation in the errors, we use robust standard errors for valid inferences, as was done in the previous regressions. However, it remains unlikely that none of the omitted variables are vary systematically with R&D participation. For instance, some firms may enjoy tax concessions that facilitate involvement in an alliance. These concessions are also likely to affect profitability. Also, some firms may be geographically closer to each other, and such proximity may lower the barrier for cooperative agreements, and presumably eases the way in which customers are reached. The implication is that if these correlations are ignored, we create an omitted variables problem that leads to inconsistent estimation of the alliance effect. Also, a more appropriate specification is warranted to address selection bias that may arise if there are unobserved factors, other than those controlled for, that gets firms selected to join in an alliance.

To address this concern, I recast equation (17) into an unobserved effects model

$$(log)\ Tobin's\ q_{it} = \beta_0 + \beta_1\ R\&D\ alliance_{it} + \beta_2 (log) R\&D\ spending_{it} + \beta_3\ R\&D\ alliance_{it} \times (log) R\&D\ spending_{it} + \sum_{k=1}^{K} \lambda_k x_{it}^k + c_i + v_{it} \tag{19}$$

which makes explicit the effect of unobserved heterogeneity c_i, which is specific to the firm and random shocks v_{it}, which changes across time for each firm. Viewing the inherently panel nature of the sampled high tech IPOs in this way allows us to test for the presence of unobserved factors and to test whether these factors are uncorrelated with the alliance variable , as well as the rest of the regressors.

Under fixed effects estimation, we remove the potentially confounding effect of c_i by subtracting off time-demeaned transformations of the variables and applying the OLS estimator. We remove c_i because its correlation with the regressors leads to parameters being inconsistently estimated. Under random effects estimation, we view no correlation between c_i and the regressors. If this assumption is correct, a more efficient generalized least squares estimator is used rather than the previous pooled OLS estimator as it explicitly accounts for serial dependence in the errors.

I present the panel estimates in Table 9. To get a sense of the effect of omitting relevant variables in the model, I report the results of the random effects (column 1) and fixed effects (column 3) estimations of equation (19) that omit the control covariates. The results of the fully specified model with control covariates and year effects are reported in column 2 (random effects) and column 4 (fixed effects). Omitting the control covariates leads to a statistically significant alliance impact of 20% under random effects (column 1) and 16% under fixed effects (column 3). These estimates are not dissimilar to the OLS regressions with control covariates in Table 5.

Panel estimation appears to tone down the confounding effect of omitted variable bias. Adding the control covariates and year dummies yields a 13% alliance impact under random effects (column 2) and 10% under fixed effects (column 4). A fixed effects specification somewhat provides a more conservative estimate of the impact of R&D alliance. The respective *p*-values for the null hypothesis $\beta_1 = 0,\ \beta_3 = 0$ are well below the 5% level of significance; *p*-value = 0.002 for the random effects in column 2 and 0.029 for the fixed effects in column 4. This implies that R&D alliance generates statistically significant changes on firm profits. Looking at the controls, while cash flow has a negative impact on profits under random effects, it has a positive impact under fixed effects. In both models though, the effect of cash flow is not statistically significant, using either the default or robust standard errors. Leverage is statistically negative for both random and fixed effects. Firm size appears to negate the ability to generate profits, but this impact is only significant under random effects.

In all, the panel estimations in columns 2 and 4 yielded comparatively lower values for the alliance effect than those reported by pooled OLS, suggesting that unobserved heterogeneity induces an upward bias and should not be ignored. Also, on average, the OLS standard errors are lower by half than those derived under panel estimation, which induces a tendency to place significance on the regressors. Employing estimates from the random effects specification in column 2, I use the Breusch and Pagan test to verify the presence of unobserved heterogeneity, which is represented through its variance. A pooled OLS estimator may be sufficient to extract the effect of R&D alliance on profits if the variance of the unobserved effects is equal to zero. Under this null, the *p*-value is 0.000, which suggests that it is more appropriate to use the panel estimators.

I accordingly apply Hausman's test to ascertain whether there is significant correlation between the unobserved factors c_i and the regressors. Although both random effects and fixed effects estimates of alliance participation do not differ substantially from each other, it is important to discriminate between the two estimators because they statistically differ in the treatment of unobserved heterogeneity. A random effects specification assumes non-correlation between c_i and the regressors; if this assumption is valid, then it is appropriate to use random effects because it is consistent and efficient. The fixed effects estimator remains consistent but is no longer efficient. However, if the assumption of non-correlation is rejected under the null, then it is appropriate to use fixed effects as it is consistent, but not the random effects. The *p*-value that compares the random effects (column 2) and fixed effects (column 4) estimates is 0.000. The null hypothesis is rejected, suggesting use of the fixed effects specification is appropriate.

An equally substantive issue in my estimation is the possible feedback that happens between profitability and alliance participation. To reasonably invoke causality, we need to establish that alliance participation is an exogenous firm decision. This appears untenable in that profitable firms, say, may be the ones particularly attracted to form an alliance as a way to reinforce their market position. This presumably creates a positive bias in the alliance effect which loses causal interpretation. A firm effects specification may not be sufficient to address this concern. A way to test the significance of this feedback or reverse causation is to include a firm's alliance status (and its interaction) in the ensuing year in equation (19). This provides a test for endogenous shifts in alliance participation in that if its estimated lead effect is significant, then future alliance participation reacts to profitability generated in the past. I also do the same for the rest of the regressors and perform a joint test of significance. The *p*-value for the lead variables is practically zero, suggesting that the alliance effect, as well as the covariates, is not strictly exogenous. A way to mitigate this feedback is to reestimate a fixed effects specification of Table 9 column 4 using one-year lagged values of the regressors. As before, this helps make clear the direction of causality, offering the more plausible intuition that alliances formed in the past help generate future profits and discounting the possibility that profitable firms form alliances in the past. I report the results in Table 10 column 1. Containment of the endogeneity conspicuously lowered the marginal effect to $2.83\% \approx 3\%$. This reinforces the concern that feedback can magnify the beneficial effect of collaboration and should be reasonably accounted for.

To check for robustness, I use ROA as an alternative measure of profitability. The results are displayed in column 2. The alliance effect has a similar magnitude of $3.24\% \approx 3\%$. There is a nuanced difference in profit interpretation between the two measures. Through participation in an R&D alliance, a firm is able to raise the return on its historically acquired resources, as measured by ROA, and enhance its competitive advantage and future profitability, as measured by Tobin's *q*. As in duration models, a final robustness test is to verify whether these results hold with an expanded sample that includes older, well-established firms. To mitigate the potential profitability bias associated with these firms, I include the variable *Firm Age*, which measures the age in years of the firm since incorporation or date founded. Columns 3 and 4 replicate estimations in Columns 1 and 2 using the larger sample. Controlling for firm age, I find that alliance participation statistically leads to a 6% increase in Tobin's *q* and 2% increase in ROA. Even when controlling for firm age, the effect of R&D alliance on profits, as measured by Tobin's q, is distinctly larger, suggesting that R&D alliances become even more important over time for sustaining profitability, just as it is the case for survival.

5. Conclusion

The aim of this paper is to investigate the extent to which interfirm collaborations in R&D affect firm performance. Using a panel sample of 586 high tech firms newly listed over the period 1990-2000, I analyze whether R&D alliance participation helps (i) attenuate the hazard of poor firm performance and eventual delistment from the stock exchange and (ii) bolster profitability. The estimation strategy identifies the potential impact through changes in the firm's alliance status.

Under a duration framework, I find that R&D collaborating firms experience higher survival rates than their non-R&D collaborating counterparts. Alliance participation retards the hazard of substandard performance that can eventuate to delistment. This result accounts for possible reverse causation between survival and alliance membership, and is not particularly sensitive to model and sample specification. Under an unobserved effects lag specification, I find evidence suggesting that participation in an R&D alliance elevates profits and future income streams, as measured by ROA and Tobin's q, respectively. The profit-enhancing effect of R&D alliance is generally impervious to estimation technique and sample selection, controlling for firm heterogeneity and feedback between profitability ad alliance participation.

Taken together, this paper provides policy insights on sustainable firm performance. Finding that R&D alliances help firms elevate survival and profitability calls for opportunities to enhance cooperative agreements. It would be interesting to distinguish whether R&D alliances perform better and concomitantly confer more benefits to participating firms if they perform single or multiple projects. How are project tasks assigned? Are they based on firm expertise or on the need to develop desired capabilities?

Equally important to ask is what begets future cooperative agreements. These questions provide interesting topics for future research.

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Table 1: Industry and Exchange Distribution of Firms

NAICS Industry Code	% of Firms	Stock Exchange	% of Firms
32	17.24	AMEX	3.58
33	60.75	NASDAQ	92.83
51	5.29	NYSE	3.58
54	16.21		
81	0.51		
Total	100	Total	100

Table 2: Listing Status of Firms

Status	Firms in an R&D alliance		Firms not in an R&D alliance		Total
	No.	%	No.	%	
Listed	254	89	240	80	494
Delisted	32	11	60	20	92
Total	286	100	300	100	586

Table 3A: Overall Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Tobin's *q*	3,628	3.709	5.622	0.258	104.172
ROA	3,695	-0.123	0.531	-17.092	1.712
Sales (MM$)	3,718	217.928	1,306.512	0	39,124.620
R&D expenditures (MM$)	3,420	35.434	198.774	0	5,278.756
Debt/Assets	3,624	0.073	0.144	0	0.971
Cash flow/Assets	3,715	-0.184	0.624	-16.922	1.154
EBITDA (MM$)	3,695	16.661	233.333	-5,608.398	7,371.808
Listing Duration	3,723	6.683	3.047	2	15

Table 3B: Summary Statistics According to Alliance Status

Variable	Firms in an R&D Alliance		Firms not in an R&D Alliance		Two sample *t*-test	Wilcoxon-Mann-Whitney test
	Obs	Mean (std. dev.)	Obs	Mean (std. dev.)	*p*-value	*p*-value
Tobin's *q*	1,923	4.318 (6.931)	1,705	3.023 (3.495)	0.000	0.000
ROA	1,981	-0.119 (0.627)	1,714	-0.127 (0.393)	0.323	0.427
Sales (MM$)	1,991	319.033 (1,763.832)	1,727	101.367 (252.349)	0.000	0.000
R&D expenditures (MM$)	1,897	54.216 (264.960)	1,523	12.039 (17.735)	0.000	0.000
Debt/Assets	1,923	0.055 (0.116)	1,701	0.093 (0.169)	1.000	0.000
Cash flow/Assets	1,990	-0.188 (0.741)	1,725	-0.179 (0.453)	0.669	0.390
EBITDA (MM$)	1,981	27.719 (316.608)	1,714	3.881 (35.169)	0.001	0.8128
Listing Duration (years)	1,992	7.136 (2.843)	1,713	6.162 (3.189)	0.000	0.000

Table 4: Cox Hazard Estimates

Dependent Variable : Hazard of Delistment Due to Poor Performance						
Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)
R&D Alliance	-0.594	-0.015	0.351	0.317	0.367	0.336
	(0.352)*	(0.401)	(0.442)	(0.518)	(0.458)	(0.522)
	[0.352]*	[0.391]	[0.392]	[0.500]	[0.392]	[0.469]
(log) R&D expenditures		-0.266	-0.216	-0.210	-0.169	-0.158
		(0.077)***	(0.085)**	(0.088)**	(0.090)*	(0.094)*
		[0.065]***	[0.073]***	[0.073]***	[0.074]**	[0.074]**
R&D Alliance × (log) R&D expenditures			-0.229	-0.240	-0.180	-0.175
			(0.156)	(0.184)	(0.166)	(0.194)
			[0.106]**	[0.137]*	[0.115]	[0.139]
Tobin's *q*		-0.303	-0.309	-0.317	-0.290	-0.312
		(0.059)***	(0.060)***	(0.064)***	(0.062)***	(0.067)***
		[0.055]***	[0.056]***	[0.063]***	[0.059]***	[0.064]***
Debt/Assets		1.979	1.967	2.069	2.114	2.169
		(0.595)***	(0.596)***	(0.617)***	(0.603)***	(0.629)***
		[0.544]***	[0.544]***	[0.570]***	[0.537]***	[0.573]***
Cash flow/Assets		-0.873	-0.894	-0.929	-0.853	-0.918
		(0.129)***	(0.132)***	(0.144)***	(0.135)***	(0.149)***
		[0.111]***	[0.113]***	[0.131]***	[0.118]***	[0.131]***
(log) Sales		-0.247	-0.242	-0.250	-0.290	-0.304
		(0.062)***	(0.063)***	(0.064)***	(0.071)***	(0.074)***
		[0.041]***	[0.041]***	[0.044]***	[0.051]***	[0.054]***
Observations	3,723	3,185	3,185	3,185	3,185	3,185
IPO Year Effects?	No	No	No	Yes	No	Yes
Industry Effects?	No	No	No	No	Yes	Yes
p-value for the significance of the effects				0.644	0.243	0.329

Default standard errors in parentheses; Robust standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5: Piecewise Exponential Hazard Estimates

Dependent Variable : Hazard of Delistment Due to Poor Performance				
Explanatory Variables	12 time intervals		4 time intervals	
	(1)	(2)	(3)	(4)
R&D Alliance	0.707	0.402	0.680	0.371
	(0.405)*	(0.435)	(0.405)*	(0.431)
	[0.327]**	[0.350]	[0.329]**	[0.344]
(log) R&D expenditures	-0.390	-0.211	-0.390	-0.215
	(0.082)***	(0.085)**	(0.082)***	(0.084)**
	[0.069]***	[0.073]***	[0.070]***	[0.070]***
R&D Alliance × (log) R&D expenditures	-0.321	-0.247	-0.322	-0.250
	(0.161)**	(0.156)	(0.162)**	(0.156)
	[0.097]***	[0.098]**	[0.098]***	[0.097]**
Tobin's *q*		-0.354		-0.362
		(0.059)***		(0.058)***
		[0.056]***		[0.056]***
Debt/Assets		2.163		2.056
		(0.592)***		(0.566)***
		[0.544]***		[0.477]***
Cash flow/Assets		-1.010		-1.028
		(0.129)***		(0.127)***
		[0.114]***		[0.113]***
(log) Sales		-0.230		-0.219
		(0.062)***		(0.060)***
		[0.042]***		[0.038]***
Observations	3,382	3,185	3,382	3,185
p-value for the significance of the time intervals	0.000	0.000	0.000	0.000

Default standard errors in parentheses; Robust standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6: Cox and Piecewise Exponential Hazard Estimates - Lagged Regressors

Dependent Variable : Hazard of Delistment Due to Poor Performance			
Explanatory Variables	Cox	Piecewise	
		12 time intervals	4 time intervals
	(1)	(2)	(3)
R&D Alliance	-1.003	-0.926	-0.887
	(0.898)	(0.907)	(0.892)
	[0.884]	[0.937]	[0.917]
(log) R&D expenditures	-0.269	-0.245	-0.250
	(0.086)***	(0.086)***	(0.086)***
	[0.075]***	[0.076]***	[0.076]***
R&D Alliance × (log) R&D expenditures	0.383	0.370	0.355
	(0.271)	(0.271)	(0.267)
	[0.220]*	[0.231]	[0.226]
Tobin's q	-0.044	-0.065	-0.064
	(0.041)	(0.045)	(0.044)
	[0.096]	[0.118]	[0.115]
Debt/Assets	1.883	2.005	1.982
	(0.742)**	(0.741)***	(0.724)***
	[0.762]**	[0.801]**	[0.743]***
Cash flow/Assets	-0.383	-0.434	-0.437
	(0.109)***	(0.115)***	(0.113)***
	[0.254]	[0.299]	[0.296]
(log) Sales	-0.201	-0.197	-0.190
	(0.064)***	(0.064)***	(0.063)***
	[0.049]***	[0.051]***	[0.049]***
Observations	2,696	2,696	2,696
p-value for the significance of the time intervals		0.000	0.002

Default standard errors in parentheses; Robust standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7: Cox and Piecewise Exponential Hazard Estimates – Lagged Regressors and Expanded Sample

Dependent Variable : Hazard of Delistment Due to Poor Performance			
Explanatory Variables	Cox	Piecewise	
		12 time intervals	4 time intervals
	(1)	(2)	(3)
R&D Alliance	-0.120	-0.094	-0.065
	(1.259)	(1.252)	(1.264)
	[0.723]	[0.717]	[0.706]
(log) R&D expenditures	-0.254	-0.239	-0.242
	(0.110)**	(0.109)**	(0.111)**
	[0.084]***	[0.083]***	[0.086]***
R&D Alliance × (log) R&D expenditures	-0.162	-0.171	-0.177
	(0.449)	(0.446)	(0.452)
	[0.169]	[0.171]	[0.159]
Tobin's *q*	-0.050	-0.056	-0.044
	(0.039)	(0.040)	(0.045)
	[0.034]	[0.037]	[0.045]
Debt/Assets	1.640	1.644	1.603
	(0.984)*	(0.982)*	(0.973)*
	[0.766]**	[0.761]**	[0.792]**
Cash flow/Assets	-0.667	-0.697	-0.601
	(0.155)***	(0.152)***	(0.144)***
	[0.149]***	[0.152]***	[0.149]***
(log) Sales	-0.140	-0.137	-0.129
	(0.087)	(0.086)	(0.086)
	[0.079]*	[0.077]*	[0.077]*
Age at IPO	-0.046	-0.046	-0.048
	(0.029)	(0.029)	(0.030)
	[0.023]**	[0.022]**	[0.023]**
Observations	3,927	3,927	3,927
p-value for the significance of the time intervals		0.000	0.056

Default standard errors in parentheses; Robust standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8: Pooled OLS Estimates

Dependent Variable : (log) Tobin's *q*						
Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)
R&D Alliance	0.234	0.412	0.287	0.235	0.264	0.206
	(0.036)***	(0.084)***	(0.080)***	(0.077)***	(0.081)***	(0.078)***
	[0.041]***	[0.096]***	[0.084]***	[0.082]***	[0.084]***	[0.080]**
(log) R&D expenditures		0.048	0.068	0.093	0.049	0.073
		(0.011)***	(0.011)***	(0.011)***	(0.012)***	(0.012)***
		[0.018]***	[0.016]***	[0.016]***	[0.016]***	[0.017]***
R&D Alliance × (log) R&D expenditures		-0.077	-0.035	-0.029	-0.031	-0.025
		(0.026)***	(0.025)	(0.024)	(0.025)	(0.024)
		[0.030]***	[0.026]	[0.026]	[0.026]	[0.025]
Debt/Assets			-1.541	-1.357	-1.620	-1.426
			(0.107)***	(0.102)***	(0.108)***	(0.104)***
			[0.130]***	[0.124]***	[0.135]***	[0.129]***
Cash flow/Assets			-0.074	-0.124	-0.081	-0.131
			(0.028)***	(0.027)***	(0.028)***	(0.027)***
			[0.077]	[0.062]**	[0.074]	[0.059]**
(log) Sales			-0.051	-0.052	-0.032	-0.033
			(0.009)***	(0.008)***	(0.010)***	(0.010)***
			[0.012]***	[0.012]***	[0.015]**	[0.014]**
Observations	3,628	3,304	3,185	3,185	3,185	3,185
Year Effects?	No	No	No	Yes	No	Yes
Industry Effects?	No	No	No	No	Yes	Yes
p-value for the significance of the effects				0.000	0.024	0.000

Default standard errors in parentheses; Robust standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 9: Fixed Effects and Random Effects Estimates

Dependent Variable : (log) Tobin's *q*				
Explanatory Variables	Random Effects		Fixed Effects	
	(1)	(2)	(3)	(4)
R&D Alliance	0.389	0.274	0.363	0.265
	(0.080)***	(0.074)***	(0.084)***	(0.076)***
	[0.100]***	[0.085]***	[0.114]***	[0.100]***
(log) R&D expenditures	-0.032	0.031	-0.211	-0.122
	(0.014)**	(0.015)**	(0.020)***	(0.021)***
	[0.015]**	[0.016]*	[0.027]***	[0.030]***
R&D Alliance × (log) R&D expenditures	-0.085	-0.062	-0.087	-0.073
	(0.026)***	(0.023)***	(0.027)***	(0.024)***
	[0.031]***	[0.027]**	[0.036]**	[0.032]**
Debt/Assets		-1.517		-1.515
		(0.109)***		(0.122)***
		[0.126]***		[0.157]***
Cash flow/Assets		-0.003		0.040
		(0.027)		(0.029)
		[0.049]		[0.037]
(log) Sales		-0.040		-0.0003
		(0.010)***		(0.015)
		[0.011]***		[0.019]
Observations	3,304	3,185	3,304	3,185
Year Effects?	No	Yes	No	Yes

Default standard errors in parentheses; Robust standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 10: Fixed Effects Estimates - Lagged Regressors

Explanatory Variables	Dependent Variable			
	(log) Tobin's q (1)	ROA (2)	(log) Tobin's q (3)	ROA (4)
R&D Alliance	0.125	0.159	0.144	0.001
	(0.083)	(0.180)	(0.065)**	(0.127)
	[0.099]	[0.200]	[0.074]*	[0.154]
(log) R&D expenditures	-0.185	-0.267	-0.206	-0.429
	(0.022)***	(0.063)***	(0.017)***	(0.045)***
	[0.037]***	[0.085]***	[0.024]***	[0.063]***
R&D Alliance × (log) R&D expenditures	-0.042	-0.055	-0.034	0.008
	(0.026)	(0.056)	(0.019)*	(0.035)
	[0.030]	[0.059]	[0.021]	[0.040]
Debt/Assets	-0.371	-0.199	-0.507	-0.742
	(0.136)***	(0.288)	(0.113)***	(0.233)***
	[0.134]***	[0.269]	[0.119]***	[0.359]**
Cash flow/Assets	-0.092	0.294	-0.141	-0.021
	(0.030)***	(0.150)*	(0.028)***	(0.098)
	[0.061]	[0.253]	[0.034]***	[0.176]
(log) Sales	-0.048	0.471	-0.035	0.434
	(0.015)***	(0.075)***	(0.013)***	(0.055)**
	[0.019]**	[0.142]***	[0.020]*	[0.088]***
Firm Age			0.027	-0.013
			(0.014)**	(0.022)
			[0.011]**	[0.015]
Observations	2,658	1,264	3,880	2,134
Year Effects?	Yes	Yes	Yes	Yes

Default standard errors in parentheses; Robust standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Figure 1A: IPOs by Industry, 1990-2000

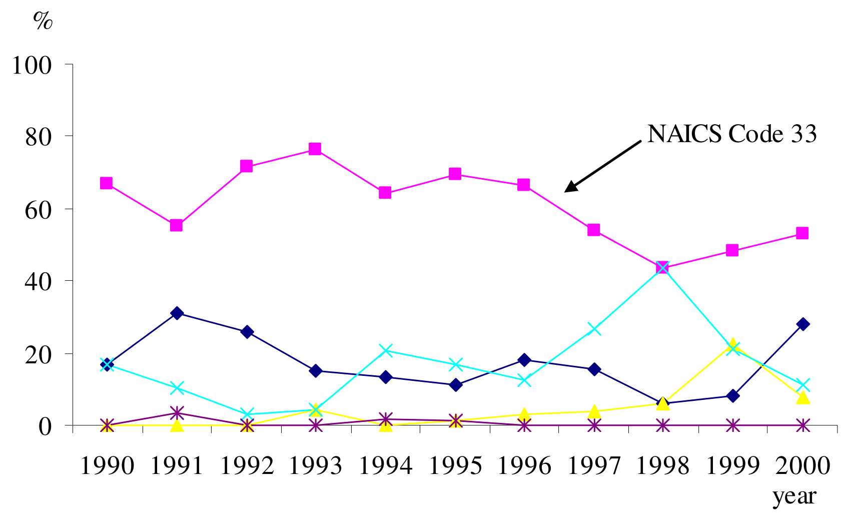

Figure 1B: IPOs by Exchange, 1990-2000

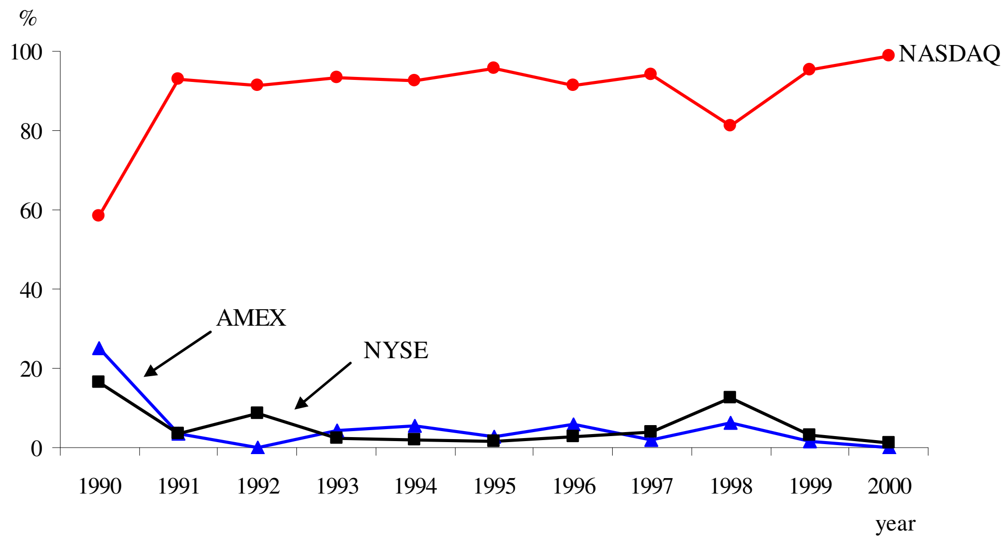

Figure 2A: Firm Failures, 1992-2005

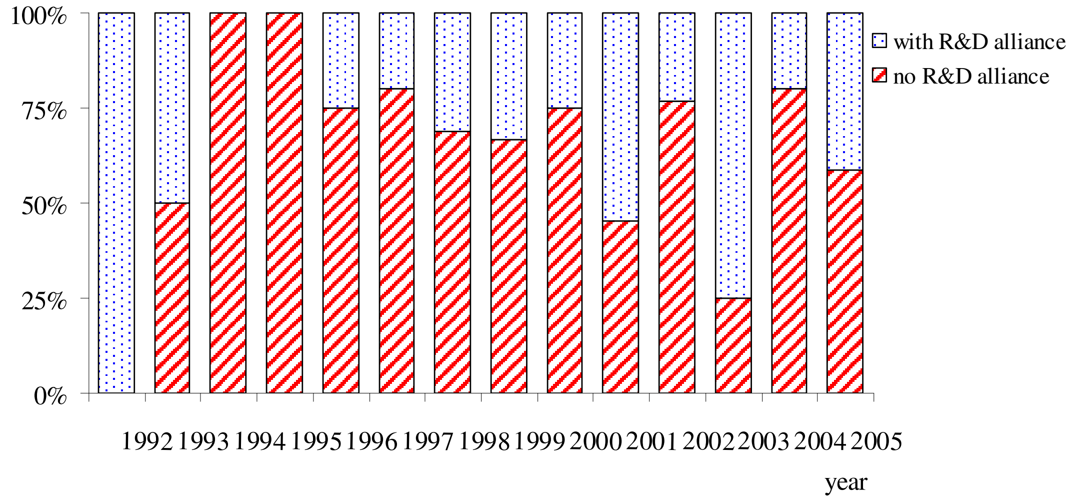

Figure 2B: Firm Failures by Industry

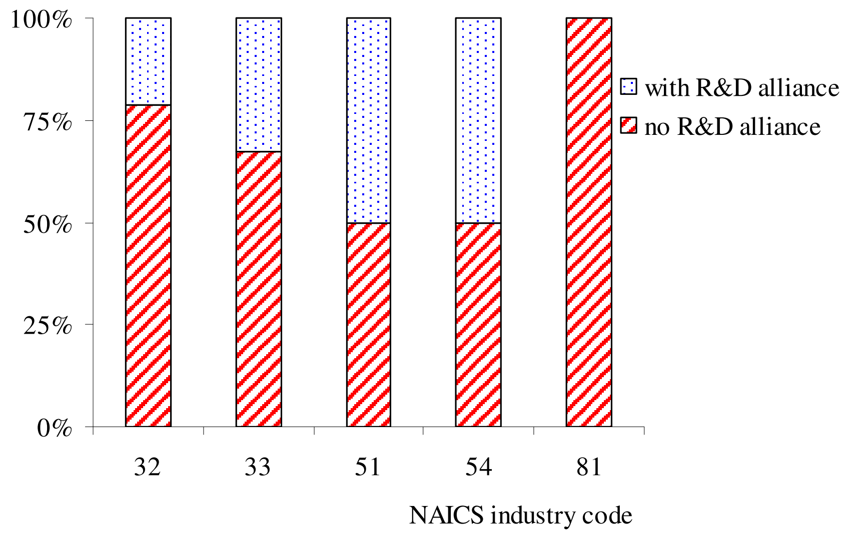

Figure 2C: Firm Failures By Exchange

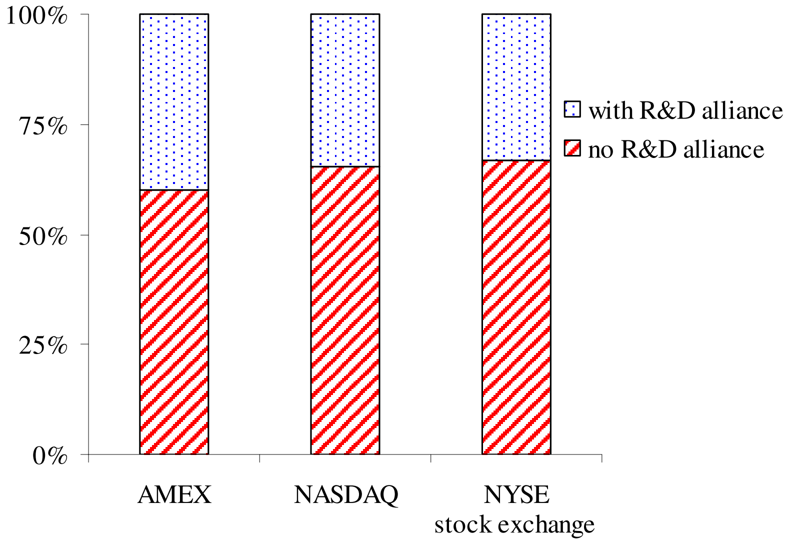

Figure 3: Number of R&D Alliances Formed, 1990-2005

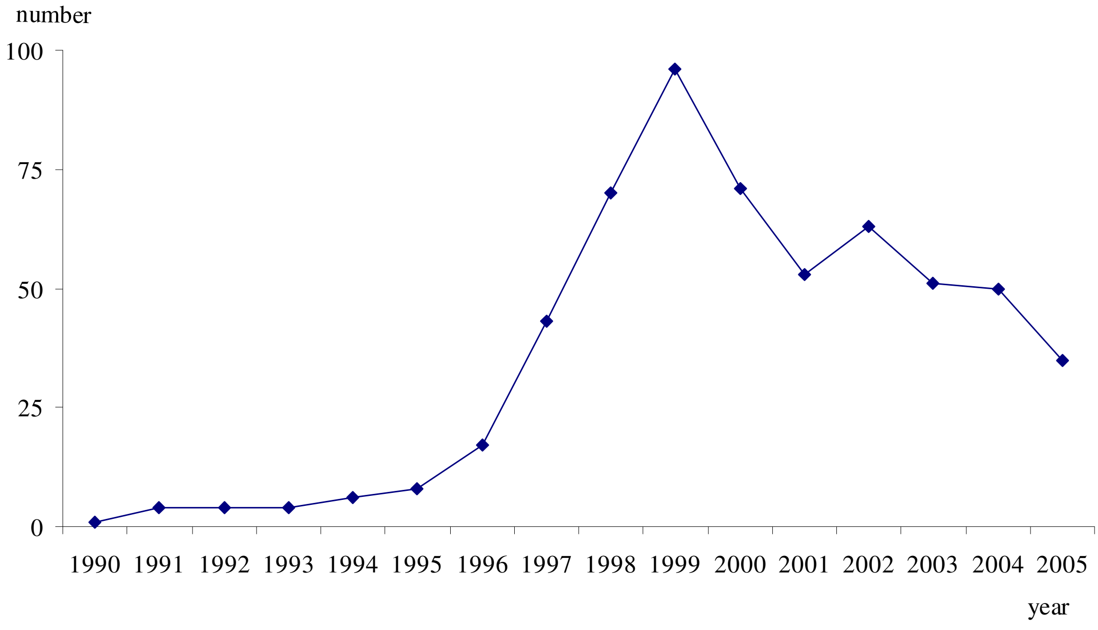

Figure 4: Operating Profits by R&D Alliance Status, 1990-2005

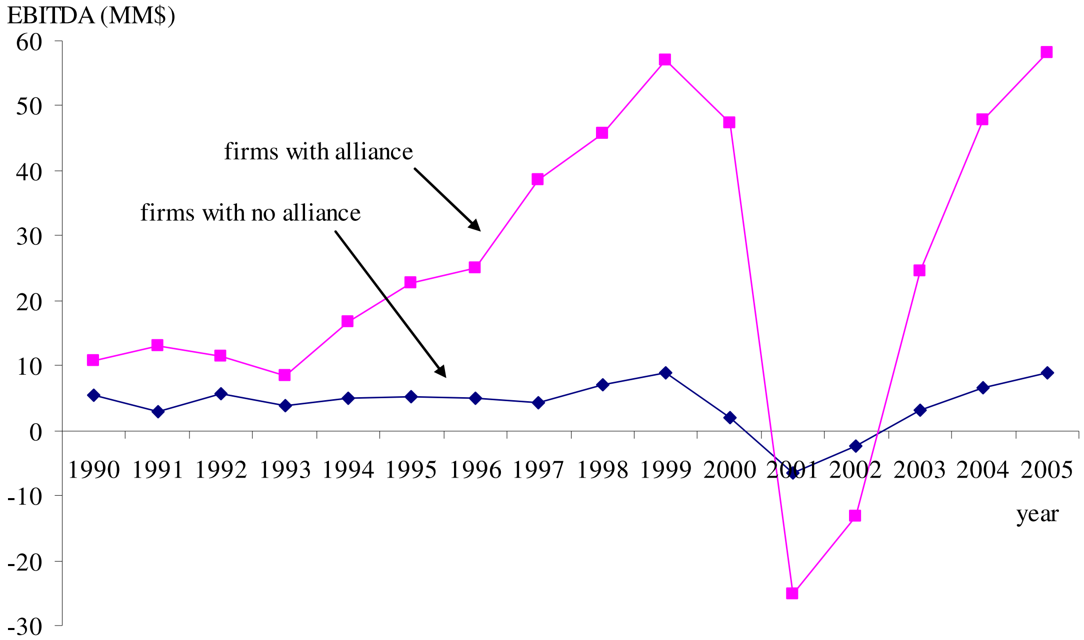

Figure 5: Kaplan-Meier Survival Estimates by R&D Alliance Status

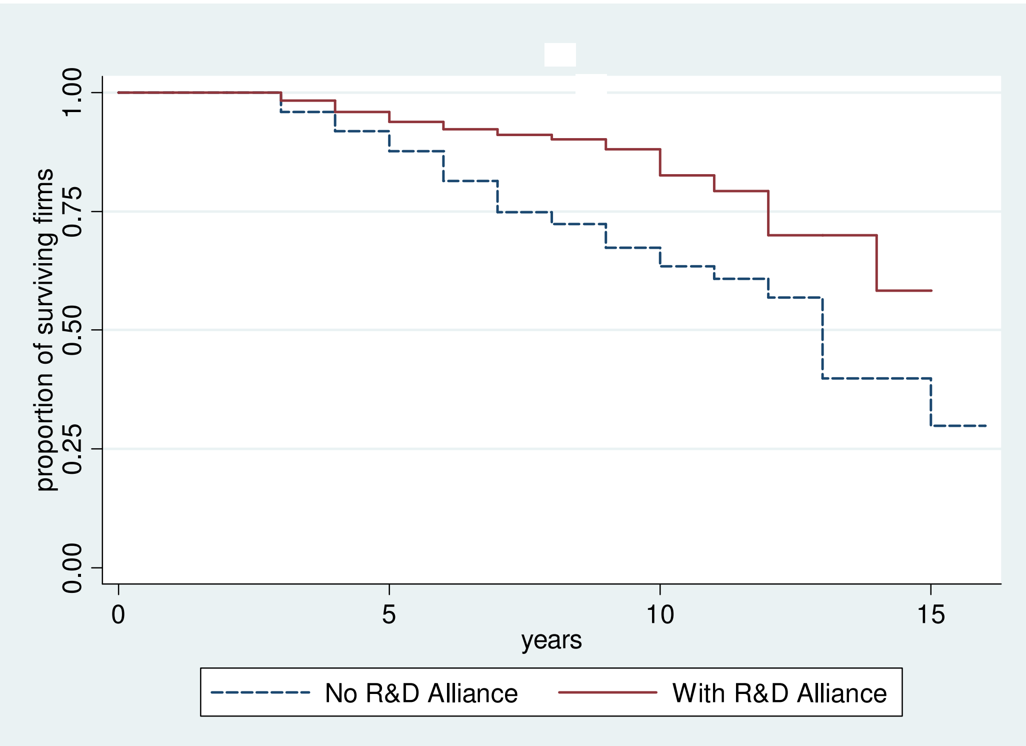

Figure 6: Nelson-Aalen Cumulative Hazard Estimates by R&D Alliance Status

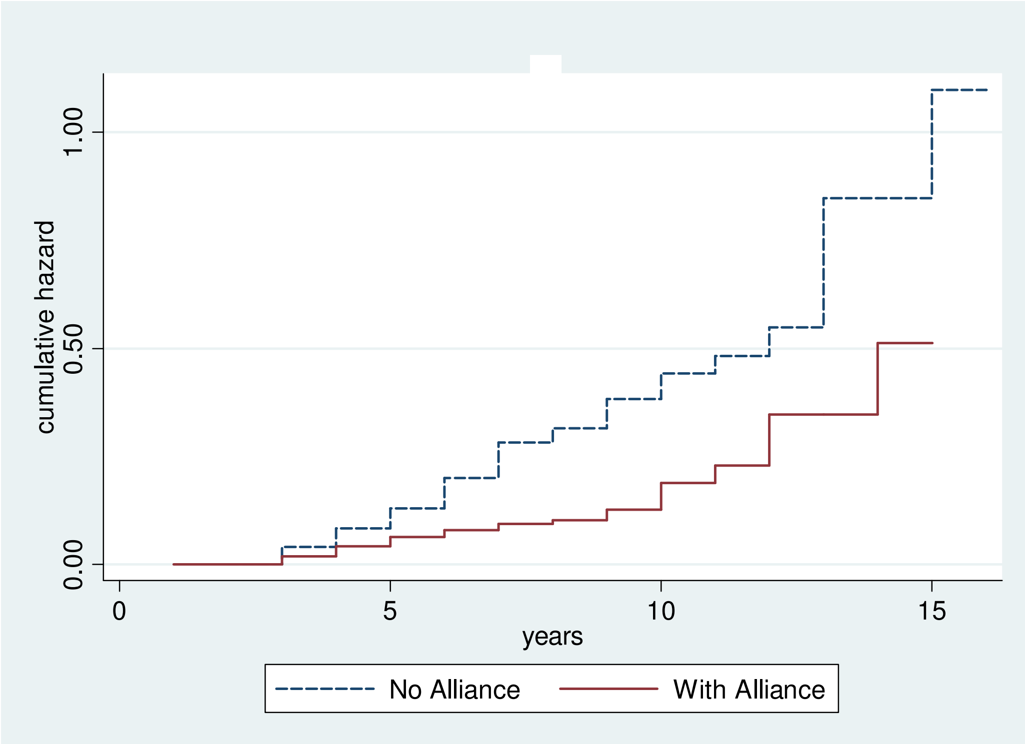

Figure 7: Complementary Log Plot of Survival Estimates by R&D Alliance Status