

**LONG TERM VALUE CREATION OF TOP US R&D SPENDERS:
THE EFFECTS OF R&D ALLIANCES**

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ABSTRACT

This study empirically tests the long-term security price performance of research and development (R&D) alliance announcements, across industries, among the top US R&D spenders. Using a sample of 73 of the top US R&D spenders, listed on a major US exchange, 792 R&D alliance announcements were identified over the period from 1994 to 1998. There are four main issues addressed in this paper: (1) do R&D partnership announcements create value in the long-run; (2) to what extent does the type of partner chosen influence the potential value created in the long-run; (3) is level of experience in partnering a factor affecting long term results; and (4) do industry considerations result in different findings regarding long term performance of R&D alliances. The chosen method of estimating long run abnormal returns was the calendar-time portfolio approach. Given that the main difficulty with long term studies is its reliance on a model of asset pricing, both unadjusted and adjusted results are reported and compared in order to determine the robustness of the findings. Additionally, the mean calendar-time abnormal returns are also reported. In general, findings indicate evidence against the efficient market hypothesis, which states that; in the long run post-announcement performance of firms should equal zero in efficient markets since the market participants reflect all new information into prices immediately. More importantly, there is evidence that the choice of partner may influence the direction and extent of abnormal performance suggesting that market participants consider choice of partner to signal information regarding the motives for allying on certain projects. These motives may include technological development, the innovative process itself, namely shortening product lifecycles and gaining competitive information, and increased market access. Furthermore, firms with less experience in forming alliances tend to perform poorer than more experienced firms. Although inconclusive due to small sample sizes, different industries also seem to generate distinct reactions to alliance announcements. Once again market participants may attach more value to certain industries due to motives typically driving these industries or possibly to levels of concentration of each industry, as suggested by Schumpeter.

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1. INTRODUCTION

Over the last decade, firms have increasingly moved away from adversarial relationships toward more cooperative ways of doing business. Firms are more commonly opting for what is often referred to as a win-win relationship in which a mutual benefit can be derived by pooling resources together. Forming alliances is also becoming a more popular option because it is less costly and easier to manage than options such as mergers and acquisitions. A 1995 issue of the Wall Street Journal indicated that 55% of the fastest growing US firms were involved in an average of three alliances, while an additional 8% had intentions of forming alliances in the following 12 months. (Wall Street Journal, April 20, 1995, p.A1) According to Whipple and Frankel (2000), there are three main generally accepted reasons driving firms to engage in alliance activity. These include: transaction costs, enhancement of a firms' competitive position or market power, and a search for acquiring knowledge (Park, Mezias, and Song, 2004; Henderson and Cockburn, 1994; Sampson, 2003; Hagedoorn, 1993). They also comment on the choice of partners noting that prior alliance experience influences a firm's choice when considering new partnerships, a finding also validated by De Man (2002), Hagedoorn (2002), Powell, Koput, and Smith-Doerr (1996). The key in alliance relationships is the speed at which they are able to respond to changes (Hagedoorn and Duysters, 2002; Neill, Pfeiffer, and Young-Ybarra, 2001). This in turn leads to shorter product life cycles and increased market risk. Several articles also comment on the fact that partnerships, ranging from contractual agreements to joint ventures, help in reducing the problems of asymmetric information apparent in merger and acquisition transactions (Reuer, 2005; Reuer and Koza, 2000).

Investment in knowledge and innovation are the key to economic growth and research. Like many other activities in the contemporary world, it now occurs in the context of a global environment. Hall (2002) emphasizes the importance of investment in Research & Development (R&D), however addresses the fact that these activities are difficult to finance given their particular characteristics over alternative investments, specifically that R&D investment requires at least 50% of money raised, to be allocated to salaries and wages in order to recruit experts in the area. Investment in R&D is also

associated with high uncertainty of the resulting output. Consequently, the fact that R&D investment has knowledge as its primary output, which is an intangible asset easily transferable between firms, it discourages firms to take part in these types of activities, leading to an R&D gap in the economy. Nonetheless, the speed at which technology is changing is intensifying pressure on companies to be more innovative. These innovative pressures can be very costly and require the cooperation of competitors, in order to respond to the ever-changing demand of different economic agents. The magnified frequency of alliance deals in business life, are discussed in several contributions (Gomes-Casseres, 1996; Hagedoorn, 1996; Duysters, 2001). The Competitive Intelligence magazine has indicated that companies have reported that 35% of their stock market value depends on alliances (De Man, 2002). This statement, however, has yet to be explored empirically. Due to the more recent nature of alliances and the less stringent ways of accounting for this type of activity, data is more difficult to attain when compared to mergers and acquisitions. Thus, several of the articles on this topic are of an exploratory nature, focusing more on trends, managerial decisions, and alliance success factors (Hagedoorn, 1993; Hagedoorn, 2002; Duysters and Hagedoorn, 2002; Duysters, 2001; Siegel, 2000; Hall, 2002; Gulati, 1998; Whipple and Frankel, 2000; De Man, 2002; Murray, 1995). Numerous articles in the past have also studied the impact of R&D alliances and R&D spending on production (Baum, Calabrese, and Silverman, 2000; Belderbos, Carree and Lokshin, 2004; Datta, 2003; Henderson and Cockburn, 1994; Hagedoorn and Schakenraad, 1994). Few however, have explored the impact these alliances have on the value of a firm as measured by its stock value (Neill, Pfeffer, and Young-Ybarra, 2001; Chan, Kensinger, Keown, and Martin, 1997; Das, Sen and Senguta, 1998; Anand and Khanna, 2000; Park, Mezias, and Song, 2004). Moreover, of the few articles focusing on changes in the value of the firm following the announcement of collaborative agreements, none have examined the long-term stock market reaction.

The signaling power of the disclosure of research and development expenditures is a very controversial area in the current financial literature. The analysis of R&D expenditures on firm value has generated conflicting results. McConnell and Muscarella (1985) find an insignificant market response to R&D expenditures while Cockburn and

Griliches (1988) article find a significant market response to R&D expenditures. Doukas and Switzer (1992) also examine the question of the market's valuation of R&D expenditure, however they take into account a firm's market concentration. They find that R&D spending announcements do in fact signal information to the market. When looking more specifically at the impact of R&D alliance announcements on the stock market, the research is less extensive and the findings are controversial. Moreover, research to date focuses only on short-run performance. Some papers find positive abnormal returns surrounding the announcement of an R&D alliance (Chan, Kesinger, Keown, and Martin, 1997; Neill, Pfeffer, Young-Ybarra, 2001) while others find an overall insignificant abnormal result surrounding the alliance announcement (Das, Sen, and Sengupta, 1998). The latter article does, however, indicate positive performance for one of the subsets of its sample, namely for those firms forming technological alliances as opposed to marketing alliances.

There are several limitations in the previous literature in this area. They are often industry or company specific (Baum, Calabrese, and Silverman, 2000; Datta, 2003; Futrell, Slugay, and Stephens, 2001; Sampson, 2003), the latter being very interesting because of the in-depth analysis that can be done on a case study basis. Nonetheless, the results are not generalizable as is the case with more extensive research. Some studies frequently focus on the late 80s and early 90s, which may affect the results that have been reported (Chan et al 1997; Das et al, 1998; Neill et al, 2001; Sampson, 2003). This period directly follows legislation that had been passed in the US in the late 80s that facilitated and encouraged the formation of R&D alliances. In addition, several of the articles dealing with collaborative agreements tend to focus primarily on joint ventures (Reuer, 2001; Reuer and Koza. 2000; Madhavan and Prescott, 1995). Among the different types of collaborative agreements possible, joint ventures are the least flexible and the closest form to mergers. Therefore results from studies focused solely on these types of agreements, may not represent the market's perception of alternative and more flexible forms of partnering. In fact in recent years, trends indicate that the proportion of joint ventures out of all strategic forms of alliances is decreasing, while the overall number of strategic alliances is increasing (Hagedoorn, 2002).

Using an event study methodology, this paper will look at the long-term impact of R&D alliance announcements across industries on the stock price of the firm during the period from 1994 to 1998. Unlike event studies on mergers and acquisitions, there is no notion of bidder and target in a strategic alliance. Consequently both firms are in a position to gain or lose value. However several factors may influence the market value creation or destruction of partnering firms resulting from R&D alliance partnerships. These may include the choice of partner, the relative size of each firm engaged in the collaboration, the terms of the agreement, and each firm's prior experience in alliances, to name a few. Given that no distinction is made between partnering firms, this paper will examine the impact on all publicly traded firms involved in the specific sample chosen. The reason for restricting the sample in this study to alliances involving R&D as opposed to marketing or distribution alliances, is that these types of partnerships involve very specific expertise and highly sensitive transfer of information, since they often entail either new product or technology development. Hence, the degree of uncertainty is greater, therefore the value generated is also expected to be greater. In addition, numerous articles in the past have documented the fact that alliances involving R&D are perceived as more value-enhancing than other types of collaborations, due to the high costs of knowledge transfer and uncertainty of the associated output (Chan et al, 1997; Das et al, 1998; and Hall, 2002).

One of the distinguishing aspects of this paper is the *choice of sample* used in the analysis. Given that there are a large number of alliance announcements each year and that the intention of this paper is to avoid restricting the analysis to one industry as was done in previous event studies, a sample of the top 100 US R&D spenders was selected as a starting point. The sample will be described in more depth later in the paper. It is, however, important to understand that these firms were chosen because their significant level of spending on R&D serves as a first indicator on the degree of importance this variable has on their performance and growth. Consequently it is likely that these same firms would be very open to finding alternative ways to increase innovative R&D in a more cost-effective way.

Another distinct feature of my research is its focus on *long-term performance* of the stock market as related to announcements of collaborative agreements of varying types. With the number of research and development alliances and the number of companies involved on the rise, it is imperative to analyze the long-term performance associated with this activity. If these announcements are not reaping any positive returns, then the question becomes whether managers are engaging in these transactions for hubris reasons rather than to increase shareholder value. There are several reasons why long-run performance of R&D alliances is of interest as was also expressed by Ritter (1991). Among them, it may be of interest for investors seeking opportunities when developing their trading strategies, in order to reap superior returns. Another rationale for long-term event studies is the volume of announcements, which may suggest that event firms try to time the market in search of opportunities. Finally, there is much controversy surrounding the study of long-term performance since it calls into question the *efficient market hypothesis*. This hypothesis states that post-announcement performance of the firms involved should be equal to zero in an efficient market, since market participants react quickly to the firms' actions. Deigan and Hergert (1987) discuss the fact that R&D investment in particular, involves long-term objectives and is more difficult to manage, with high potential risks. Therefore the total potential of alliances may not be fully reflected in the initial announcement, also referred to as the issue of asymmetric information, thereby explaining any other advantage that may possibly occur over the long-term.

The debate lies especially in the choice of an effective method for measuring long-run abnormal returns (Barber and Lyon, 1997; Fama, 1998; Barber, Lyon, and Tsai, 1999; Mitchell and Stafford, 2000; Boehme and Sorescu, 2002). This study uses a monthly calendar-time portfolio approach to measure long-term abnormal performance as advocated by Fama (1998). A discussion of the choice of methodology is presented in the literature review. The shortcomings of alternative methods are explained, thereby arriving at the conclusion of the chosen calendar-time method. Furthermore, the sample is split according to a number of different factors in order to determine how these companies perform given certain characteristics. Some of these factors include partner

choice, industry classification, alliance experience (i.e. as measured by the frequency of their involvement), and the relative size of partners.

Although firms are required to disclose any information that is of material value to the market, accounting rules to track performance or synergies of these partnerships are not as clear. Moreover, the value of these partnerships is difficult to assess since the assets being shared by the partnering firms are often of an intangible nature, such as knowledge or know-how. Hence in terms of disclosure, the firms may file a material change report if it is believed that a liaison will significantly change the value of the public firm. In addition, the announcement of the partnership will be reported in major newswires, yet the extent of coverage each alliance receives varies considerably. Furthermore, the level of detail reported in these announcements is far less than is required for a merger or acquisition. In this context, *the question of whether public firms involved in R&D alliances of different types creates value in the long run*, becomes a very interesting avenue of research. Unlike the case of mergers and acquisitions, the investor has less information at the initial announcement, hence allowing for a reevaluation as the partnership progresses. The lower requirements of information disclosure of these types of partnerships and the fact that firms keep information about inventive activity very private, for fear of imitation by rivals, makes the main question of this research very important to address, though, often difficult to measure. This paper expects to find that firms involved in R&D alliances experience abnormal returns not only immediately following the announcement but that these abnormal returns continue in the months following the announcement. This is due to the fact that an R&D alliance enables firms to form avenues to increase their current knowledge base in a less costly and more efficient manner. In doing so, they are in a better position to compete and produce profitable results. In addition, in accordance with the Schumpeterian hypothesis I would expect this announcement effect to vary according to the level of concentration of the industry. I therefore measure the long-run response to an R&D alliance announcement by industry as classified by Fama and French (1997). The Schumpeterian hypothesis states that a monopoly structure economy allows for more rapid technological advancement, thereby justifying the higher prices associated with this type of market structure. Highly

concentrated industries are therefore associated with greater positive economic impacts when investing in research and development (Datta, 2003; Doukas and Switzer, 1992). Consistent with this hypothesis, it would be expected that firms in more highly concentrated industries would more likely choose to invest in R&D through sources other than alliances while low concentration industries may resort to partnerships due to the lower payback associated with in-house spending for these firms.

As will be addressed in the literature review, there are several mitigating factors that may indicate that an alliance will not be the optimal option in some cases, such as the choice of partner. I, therefore, further hypothesize that there may be a differential response to alliance announcements when firms collaborate with non-public organizations (i.e. private firms, universities, and/or government organizations), versus public firms not among the top R&D spenders, versus fellow members of the top R&D spenders list. Finally, I hypothesize that the long-run stock market response to an R&D collaborative agreement may depend on the level of experience with alliances that the firms involved possess. The four main hypotheses of this research are summarized in table 1. The variables that I will control for in my analysis include the leverage ratio and the R&D to Sales ratios.

Table 1: Main Hypotheses of Research on Long Run R&D Alliance Performance

H1:	Do research and development alliance announcements made by the top US R&D spenders, create value in the long run?
H2:	Does the possibility of long-run value creation of the top US R&D spenders depend on the type of partner chosen?
H3:	Does level of experience determine the long run performance of the top US R&D spenders involved in research and development partnerships?
H4:	Does industry of the top R&D spenders play a role in determining the long run value creation or value destruction of a research and development alliance?

The remainder of this paper is organized as follows: section two presents some definitions that are useful in understanding the phenomenon being studied. Also highlighted in this section are past and current trends in R&D spending and the alliance landscape. It examines both growth data as well as patterns of these partnerships by industry. The third section provides an overview of the previous literature in this area of research, describing the motives and reactions to R&D collaboration announcements. This section also addresses the various methodologies applied in these papers, which focus solely on short-term results, and how my paper will extend these findings on a long-term basis. Next the sample and methodology are described more in-depth in section four and the results are presented and discussed in section five. The final section provides some concluding remarks and suggestions for future avenues of research extending this paper's findings.

2. DEFINITIONS AND TRENDS

2.1 Research & Development Alliances Defined

Before defining alliances in greater depth it is important to understand what is meant by research and development (R&D). The Oxford Dictionary of Economics defines R&D as the use of resources to create new knowledge and develop new or improved products or more economic methods of production (2002, pp. 401). Discovering new knowledge is considered the research portion while the development aspect is focused on bringing these ideas to fruition and includes defining ways of making the products, testing them and bringing them to market. The development component tends to be the more expensive of the two. The National Science Foundation (NSF) extends this definition by making a distinction between basic and applied research. Basic research encompassing the acquisition of knowledge or understanding of a particular area without any specific commercial objectives attached to the knowledge acquired. Applied research, in contrast, studies a particular subject with the objective of meeting a need and is attached to commercial goals (2002, Chapter 4; pp. 10).

Alliances, as stated by De Man in *Competitive Intelligence Magazine*, 'are forms of cooperation between one or more independent companies, in which they share risks

and revenues with the aim to jointly achieve a stronger competitive position' (2002, pp. 14). An alliance is a cooperative form that is less intense than a merger or acquisition but more intense than a market transaction. There is a very distinct difference between strategic alliances and mergers and acquisitions that needs to be understood before continuing. The former is a cooperative effort between two or more separate entities that share mutual inputs but maintain their own corporate identities. The latter, conversely, can be described as a situation where two separate companies become one either through a merger of two approximately equal companies or through an acquisition where one company obtains majority ownership of a second company. Chan et al clearly make the distinction when they state that:

“Strategic alliances represent inter-corporate, cooperative agreements that lie within the intermediate range and along a continuum, with market transactions limited to the purpose of exchanging goods or services on the spot at one end of the spectrum and indefinite-lived relationships such as joint ventures or mergers at the other end of the spectrum” (1997, pp. 201).

There are several ways in which firms can join together and form R&D alliances. These include equity-based joint ventures, and the increasingly popular contractual alliances such as joint R&D pacts and joint development agreements. Joint ventures, once considered the most popular form of collaboration is defined by the Oxford Dictionary of Economics as a business where the provision of risk capital is shared between two or more firms and it is often adopted for projects where the risks or the scope is too large for one firm to attempt on its own (2002, pp. 257). The important thing to note about these types of partnerships is that each of the parent companies involved owns and controls part of the venture thereby increasing the interdependence of the participating companies. As mentioned in the article by Hagedoorn (2002), it is the semi-independent nature of joint ventures that enables them to be used in a wider setting, allowing firms to either enter new markets or reposition themselves in existing markets (2002, pp. 478). Contractual partnerships, in contrast, are more project-specific and therefore have limited time-horizons and require interdependence of the firms involved for the duration of the project. These collaborations are agreements to share specific

resources, often through project-based groups from each company, and share costs of capital investment required for the project clearly specified in the agreement. The main difference between the two is that joint ventures tend to have higher organizational costs as well as a higher failure rate. The latter may be due to the race for each company to gain more control thereby weakening the potential benefits of this type of organization. In addition to higher costs, joint ventures also tend to be more interdependent and have longer time-horizons. The decision to enter into one form over the other often depends on the motive for entering into an alliance however many factors play a role in this decision making process. In short, if the main motive for collaborating is to economize on costs of R&D projects then maybe the less costly contractual agreement will be chosen. Conversely, if the main motive for partnering were more strategic in nature such as the decision to enter a new market, then possibly a joint venture would be a more viable option. However the motives often intertwine and change over time, hence the management literature often studies the many other variables that need to be considered in the decision of choosing one form of partnership over another. This is also an area of research that is very controversial, yet, not the main focus of this paper. I am more concerned with how the different types of alliances may influence shareholder value in the long run than in the motives of companies to enter these partnerships.

Alliances can be very advantageous to a country's economy because it helps share the costs and risks of research programs, it also facilitates technology transfer, and it helps the economy to grow through innovation. However, alliances are not necessarily always advantageous. Several factors need to be considered before entering into an R&D partnership in order to increase the likelihood of success. Some important variables to consider when analyzing a competitor's Alliances according to Competitive Intelligence Magazine are as follows (2002, pp. 17-18):

- Number of alliances (in the past and currently)
- Strength of ties (i.e. licensing agreement less powerful than a joint venture or the number of alliances with one particular company)
- Existence of groups (multilateral alliances)
- Mix of alliances

- Location in the industry (having access to multiple alliance groups)
- Management capabilities (i.e. existence of an alliance department, alliance specialist or alliance VP, the existence of partner programs, and causes behind breakup of major alliances) the stronger the alliance skills the more profitable it will be.
- Relative size of partners and portion of alliance

There are different types of partners a company can chose to ally with as well. More specifically an alliance can be between two or more public companies, between a public and a private company or between a company and a university or government institution. This is a variable that is addressed in this paper in order to determine whether one type of partnership signals more value-increasing information than another. The alliance with a government institution or university occurs in situations where the resultant serves the greater good of the economy both socially and financially, whereas, alliances between companies (whether private or public) are often driven by a much wider range of motives. Hagedoorn (1993) summarizes the body of research related to the rationale of strategic partnering and finds a wide range of motives that can be grouped into three categories (see Appendix I for details). The first includes the set of motives related to some characteristics of technological development (i.e. increased complexity of new technologies, reduction of uncertainty in R&D, cost-sharing). The second relates to motives due to the innovative process, namely shortening the product life cycle, and/or gaining information on competitors' technology or knowledge. The final group of motives is related to market access and opportunities (i.e. globalization, new products and markets, etc).

2.2 R&D Spending and Alliance Landscape

The December 2002 issue of the Korean Herald demonstrates an excellent example of the increasing importance placed on R&D investment and the potential benefits that can be drawn from concentrating on this asset. The article discusses the results of the aggressive R&D investment activities done by LG Group Electronics. At the core of this

company is their belief in the necessity of R&D as the key driver of future growth in the global marketplace. The vice chairman of LG Electronics, John Koo, believes that “R&D is the only shortcut to strengthening the group’s position in the global marketplace” (p. 1, 2002). The keyword in this statement is that it is seen as a ‘*shortcut*’ to increasing competitiveness. Companies are constantly searching for the easiest and cheapest way to grow, all the while, increasing profit margins. However, R&D can be very costly and the fruits of this investment are often only realized on a much longer-term scale. In the fast-growing technology economy in which we currently live, with high degrees of integration at all levels, including globally, it is often difficult to justify the value of a long-term investment project in a non-physical asset, to investors. Hence, increasingly the option to ally with another company(ies) is very attractive because it could result in lower costs to acquire a much larger bank of knowledge in a shorter time. However, as is the case with all decision making there are pros and cons to establishing these types of relationships, the most important of which is ownership.

Hagedoorn’s (2002) paper on inter-firm R&D partnerships looks at the patterns of collaborative activity related to R&D during the approximately forty-year period between 1960 and 1998, as indicated in Figure 1.

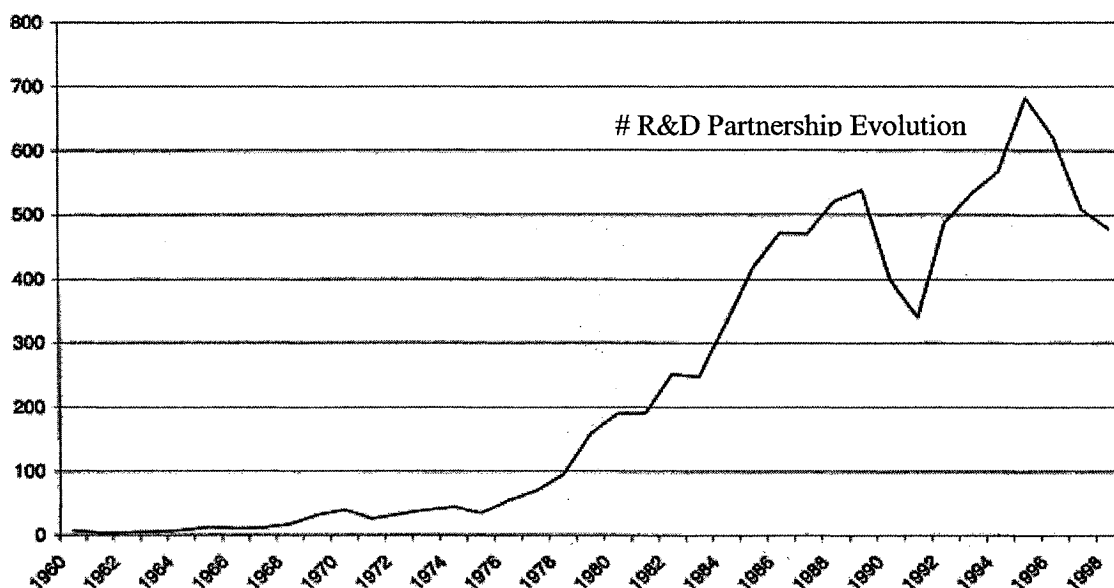


Figure 1: # of Newly Established R&D Partnerships per year (1960-1998), source: MERIT-CATI Database via Hagedoorn (2002)

As is evident, a sharp increase in collaborative activity began in the 1980s and stabilized in the 1990s but remained significantly higher than the first two decades observed. Note that the data source is the MERIT-CATI Database, which collects data on inter-firm alliances involving research & development either exclusively or in part. It does not consider publicly funded R&D partnerships; therefore public funding has no effect on the growth in R&D partnerships observed in the graph. Whereas the 60s saw very few strategic alliance announcements (i.e. approximately 10 per year), the 70s began to see gradual increases, peaking at 160 partnerships by the end of the decade. However it is only since the 80s that growth has accelerated significantly with over 500 reported R&D partnerships per year. The beginning of the 90s indicates a drop to about 400 but it peaks again in 1995 with approximately 700 announcements. Although it slightly decreases from this level following this point, it remains at an average of approximately 500 new partnerships yearly, significantly higher than in the years prior to the 80s. The abrupt jump in R&D partnerships is suggested to be related to changing economic conditions during this period, namely, shortened product lifecycles, a high level of global integration changing the competitive landscape, increased R&D costs, and increased complexity of scientific and technological development, to name a few.

In section 2.1 of this paper, the difference between the two types of R&D partnerships, namely, joint ventures versus contractual agreements, is defined. Figure 2 indicates the decreasing proportion of joint ventures out of total R&D partnerships over the same forty-year period. The proportion of joint ventures went from 100% in the 1960s to 70% in the 1970s, as low as 40% in the 1980s and reaching an all-time low in the 1990s of 10%. From this data, it is clear that not only have firms increasingly opted for contractual agreements over joint ventures, but more importantly that the increase in the number of R&D partnerships in the 80s and 90s is due, in large part, to the increase in contractual agreements between firms. (Hagedoorn 2002, pp. 481). The same trends are evident in the sample used in this paper as will be discussed further in the section on the sample description.

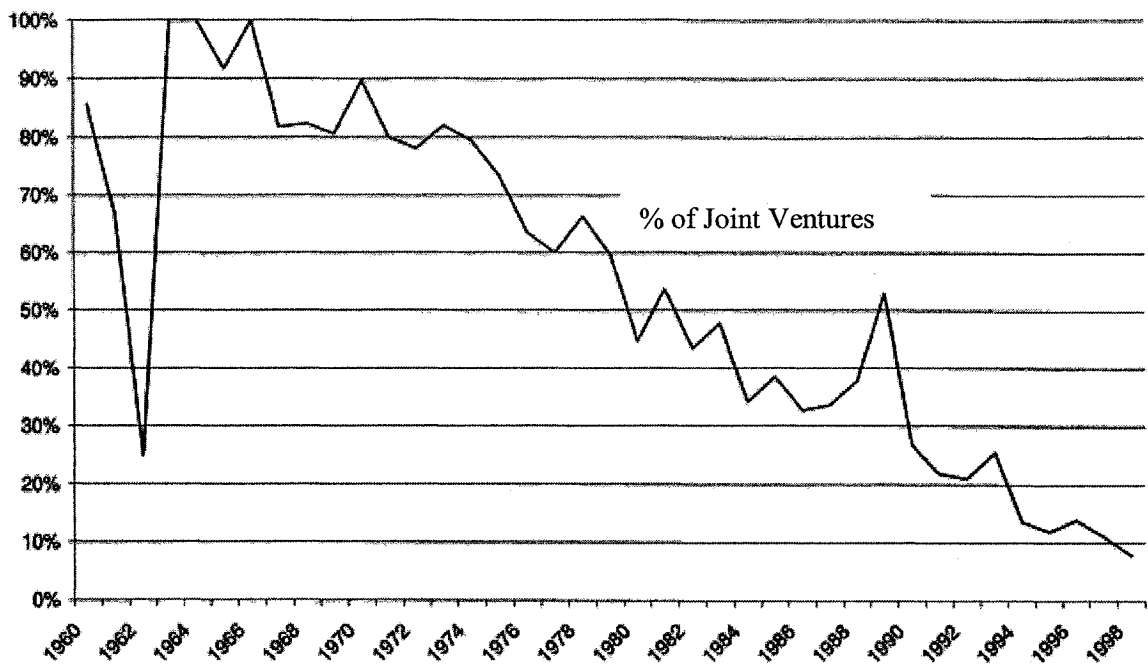


Figure 2: Share (% of Joint Ventures in all Newly-Established R&D Partnerships (1960-1998). Source: MERIT-CATI Database via Hagedoorn (2002)

Focusing more closely on the period investigated in this paper, trends discussed in the Science and Engineering Indicators of 2002, indicate that the period between 1994 and 2000 was characterized as the greatest increase in R&D spending in real dollars for any six-year period in US history. US R&D during that period grew from an estimated \$169.2 billion to approximately \$265 billion in 2000. The proportion of Federal support, however, has decreased from 46% of total US R&D in 1980 to 26% of total in 2000 (refer to figure 3).

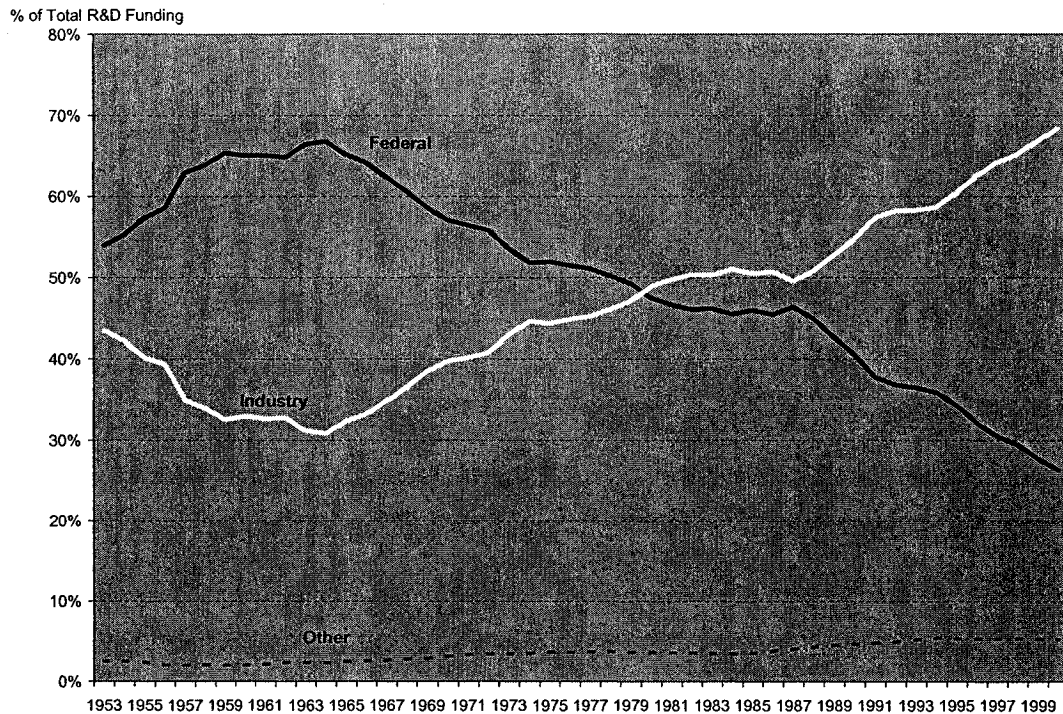


Figure 3: Shares of national R&D expenditures, by source of funds: 1953-2000
Source: Science & Engineering Indicators - 2002

The industries receiving federal support in order of importance are as follows: Department of Defense, Health and Human Services, National Aeronautics and Space Administration, Department of Energy, and National Science Foundation. Given that there is a shift in the role of the federal government versus the private sector in R&D spending, this leads to a change in the allocation of R&D funds to various activities. Historically, Federal funds have been used on basic research activities whereas the industry focused more on product development activities. A good example of the shift in industries involved in R&D partnerships, since the number of collaborations with the private sector has increased relative to those made with government, is the increased focus on the services industry versus the manufacturing industry. The largest share of the nation's R&D came from industry with approximately 75%, followed by Universities and Colleges (11%), and the Federal Government (7%). While Federal R&D spending accounted for only a 1% real growth rate per year, industry R&D grew at an annual rate of 7%. These changes identified by the NSF and also discussed in Hagedoorn's paper on the R&D partnership trends of the last forty years, indicate that there has been an increase in the share of R&D partnerships in high-tech industries due to the growth of partnerships

among US corporations. The increase in collaboration by high tech industries may explain the dominance of contractual agreements versus joint ventures, since contractual agreements by nature are more flexible and short-term, hence, better serving the needs of the rapidly changing environment faced by high tech industries. According to records of filings required by the National Cooperative Research and Production Act (NCRPA), more than 800 research joint ventures were identified in the US during the period from 1985 to 2000, with the peak reached in 1995 after 10 straight years of growth. Of these research joint ventures (RJVs), half were made up of companies in the electronic and electrical equipment, communications, and transportation equipment industries. Universities participated in 15% of all joint ventures and a federal presence existed in 11% of total RJVs.

When studying trends in the R&D alliance landscape one realizes their growing importance in our economy. It therefore becomes very important to understand the drivers behind this increased partnering activity among firms. As mentioned in the previous section, Hagedoorn's (1993) article does just that. It studies the motives for strategic alliances and the influence of sector/industry on the reason for partnering and type of partnership chosen. Reasons range from cost economizing to long-term strategy and a mix of the two. Findings show that research joint ventures, joint R&D contracts, and direct investment are more related to long-term positioning, while, technology exchange, customer-supplier relationships, and one-directional technology flows are more often related to cost economizing.

The main findings of the paper indicate three main reasons as playing a significant role in the motives for allying: technology complementarity, reduction of innovation time-span, and market access and influence of market structure. The author goes further to analyze motives for strategic alliances across industries. The results indicate that in more mature industries and those in low to mid-tech sectors, market access and market structure are the main concerns driving firms to partner. Technological complementarity and reduction of innovative span remain more important in the high tech sector and in industries where partners have a wide range of activities and technological savvy. One exception to note is the telecommunications industry, which is considered a high-tech

industry yet it scores high on the motive of market access in this study, notwithstanding the fact that it is not classified as a mature industry. The reason is likely the issue of global competitiveness in telecommunications hence alliances make it possible to gain access to otherwise inaccessible global markets. The same argument applies to the high percentage of 'access to markets' motives for the computer and microelectronics industries from this paper.

The explosion of alliance announcements in the 90s along with increased R&D spending despite an economic slowdown demonstrates the strong need in finance and related fields to examine the impact of R&D alliances on firm performance. This would enable both firms entering into these types of partnerships and investors to make better decisions as to what the success factors of such business practices may be. Several articles and news reports are indicating that strategic alliances are becoming more important for growth than mergers and acquisitions. As far as studying the impact by industry, no study to date has looked at this variable in relation to R&D alliance and shareholder value. Investigating R&D collaborations is important because it demonstrates how alliance networks change the competitive environment. The main limitation in addressing these research questions is the lack of available data given that alliances are still considered to be in their early stages, a problem also identified by the NSF, which is working on improving their indicators in this area.

2.3 Description of Industrial Research Institute (IRI)

One of the criteria of the sample selected for this study is that it be listed on the Industrial Research Institute's (IRI) leader-board. The leader-board published by IRI includes the top 100 US technology investors. These 100 selected companies are members of the institute, which comprises approximately 270 members in total. The IRI is an association whose member companies "share a common interest in promoting and accelerating innovation through effective management of R&D, engineering, and technology" (Website-Overview section: www.iriinc.org, constitution). Their mission statement is "to enhance the effectiveness of technological innovation in industry." This organization offers companies a forum for discussing and exchanging ideas in a

collaborative fashion. This is done not only between member companies, but also through interaction with science and technology policy makers in government and academic research establishments, and with R&D leaders abroad. Hence, there is a high probability that these companies engage in R&D alliance activities given the easy access to prospective partners. In addition to this high likelihood of participating in collaborative activities the member companies of the IRI come from a wide range of industries. Thus, unlike previous studies on this topic, this paper addresses the question of value-creation through R&D partnerships across different industries.

When matching the top 100 member firms with the list of R&D alliance announcements retrieved from SDC, only 73 of the 100 firms were identified as having participated in an R&D partnership during the time-period under study. Some partnerships were between member firms, others partnered with firms outside of the IRI association, and still others allied with government organizations or universities. The choice of partner is an important factor in determining the success of such projects and this study goes one step further by analyzing how choosing an IRI member firm versus a non-member firm or the choice between a listed versus a non-listed firm or government/academic institution can influence the response to such an event.

As a result the sample of 73 firms involved in 792 announcements is further decomposed into three sub-samples that will be described in more depth in the sample selection section (i.e. section 4.1.2). The first sub-sample involves partnering between firms listed on the top 100 leaderboard (*denoted* M_M). The second entails two or more firms partnering together with one listed on the top R&D spending list and the other(s) not IRI members and not listed on a major US stock exchange (*denoted* M_N_NL). This encompasses private firms, universities, and government labs or organizations. The final sub-sample is the group of collaborative agreements made between one of the Top IRI member firms along with a non-IRI member firm that is listed on a major US exchange (*denoted* M_N_L). Hence it includes public companies of all sizes partnering with some of the top R&D spenders in the country.

3. LITERATURE REVIEW

3.1 Research & Development Alliances

As was mentioned previously, much of the literature on research and development expenditures has focused on its' impact on firm productivity. One such example is the article on the 1984 divestiture of AT&T (Datta, 2003), which resulted in the end of the monopoly structure of the telecommunications industry in the US. The divestiture of AT&T in particular split the industry into local and long distance operations. More specifically this article attempts to examine the impact on R&D spending following the divestiture of AT&T. Like many other articles in this field, Datta tests the Schumpeterian hypothesis since the main result of the AT&T divestiture was a change in the market structure. According to this hypothesis a market characterized by a monopoly structure results in more rapid technological advancement thereby suggesting that the divestiture of AT&T would result in less spending in R&D. Another argument with respect to divestiture and research is that increasing competition has two conflicting effects on R&D.

“It lowers profit margins for firms as entry puts a downward pressure on product prices, thereby creating incentives for firms to carry out R&D in order to lower cost. But competition also causes market shares to fall, which reduces scale economies necessary for firms to reap the benefits of R&D. Thus, the cost savings of R&D may be eliminated by the revenue losses due to declining market shares and prices” (pp.646-647).

What is observed with AT&T is that even though operating revenue was reduced after divestiture, R&D spending remained the same or increased.

Datta (2003) uses a simultaneous-equations model to examine the relationship between productivity, R&D, market share, and firm size. The theoretical model indicates that total factor productivity (TFP) can be broken down into scale effects, market competition effects, and technical change. The author uses a three-stage least squares method to calculate the following regression model jointly, in order to account for any simultaneity between R&D and productivity growth.

$$TFP_t = a_{10} + a_{11}Divest_t + a_{12}MS_t + a_{13}Q + a_{14}R\&D_t + a_{15}KS_t + e_{1t}$$

$$R\&D_t = a_{20} + a_{21}Divest_t + a_{22}MS_t + a_{23}TFP_t + e_{2t}$$

Where;

Divest = a dummy variable that takes the value 1 following divestiture in 1984;

MS = is the market share of AT&T which is used as a proxy for competition;

Q = measures scale elasticity (i.e. output growth);

R&D = measures R&D intensity using the ratio of R&D to total operating revenues or sales;

KS = Proxy for capital intensity is the ratio of total telephone plant (gross to total operating revenues); and

TFP = total factor productivity from 1947-1994.

The findings indicate that there is a decline in productivity following divestiture that persists in the years following divestiture. Market share is negative meaning that a decline in market share (i.e. competition) led to improvements in productivity. Q is positive and significant and R&D is also significantly positive, while TFP and KS are negative meaning that a decrease in the size of the capital stock leads to productivity gains. The R&D equation shows that divest is positive which means that R&D increases following divestiture and Market Share is negative both of which are significant while Total Factor Productivity (TFP) is positive but insignificant. To account for slope differences before and after divestiture, Datta separates the regression; to study the pure divest effect on TFP. The link between R&D and productivity in the pre-divest period is negative and insignificant but it is positive and significant in the post divestiture period. Also adding the profit variable to the regression indicates that AT&T profit had a positive relationship with R&D expenditure in the post-divest period and no significant relationship in the pre-divest period. The main drawback of this paper is that it is a case study analysis that cannot necessarily be generalized to other cases of divestiture. However, it does present evidence that counters the Schumpeterian Hypothesis, in that R&D increases following divestiture of AT&T and the end of the monopoly structure. Recall that the main motives of strategic alliances across industries were studied by Hagedoorn (1993). He revealed that in general, high-technology industries are driven by technological complementarity and reduction of innovative life span. However, the exception to this is the telecommunications industry which is more concerned with the

motive of market access due to the fact that this industry competes on a much more global scale. Hagedoorn's findings may be a reason for the lack of support of the Schumpeterian hypothesis in the case of the AT&T divestiture. This gives further evidence that it is difficult to generalize results of a case specific study especially one that focuses on an industry with a very particular competitive structure.

The article by Doukas and Switzer (1992) takes the R&D spending plans of US firms and examines the market's valuation of these expenditure decisions. In particular, they examine the impact of these decisions on valuation by distinguishing between firms in industries characterized by high concentration versus those in low concentration industries, therefore testing once again the Schumpeterian hypothesis. The authors also look at the impact of the size of the R&D expenditures on stock valuation. Basically, the authors are looking at the signaling power of R&D programs by using an event study methodology and looking at stock market reaction to R&D announcements, taking into consideration the firm's market concentration characteristics.

In their study, the authors created two samples. One included 66 announcements on a firm's R&D expenditure plans for the next 12 months. The second included 21 announcements of long-term R&D expenditures. Their findings do not reveal any significant abnormal returns when making no distinction between the types of announcements or the level of market concentration. Therefore, their next step was to calculate abnormal returns for the two samples separately. They find that only the 21 project-specific and multiyear R&D announcements are on average associated with significant abnormal returns. Finally taking into account the market concentration effects, the authors further divided their sample of 66 annual R&D announcement firms into a high (i.e. 36 firms) versus a low (i.e. 30 firms) concentration group. They find positive and significant abnormal returns for firms in high concentration industries and insignificant AR's for firms in low concentration industries, again in line with the Schumpeterian Hypothesis. They did the same sample split for the entire sample of 87 firms and again found similar results.

Doukas and Switzer (1992) conclude their study with a cross-sectional analysis using OLS estimates of the coefficients. The independent variables include the market

concentration of the firm and the increase in announced spending over previous year's spending. The market concentration variable is measured using CR₄ which is the four-firm concentration ratio often used to measure a firm's market structure. More specifically, CR₄ is the percentage of market share owned by the largest n firms in an industry, where n is the number of firms, usually 4. If the resulting market share of the top four firms is close to zero this indicates a very competitive industry since the top four firms make up a very small share of the market. Doukas and Switzer (1992) find this variable to be positive and significant. Therefore the higher the market concentration, the greater the extent of the market response as measured by abnormal returns. The second independent variable, current year versus previous year spending, is measured as the firm's R&D intensity (i.e. proxied by the firms R&D-to-sales ratio) multiplied by its % increase of announced spending over that of the previous year. Results indicate that the size of the announced spending does influence the extent of the market response. These differential market responses support the Schumpeterian hypothesis on market concentration, in that the announcement of a firm's increase in R&D investment is perceived as good news in a highly concentrated market.

The previous articles (Datta, 2003; Doukas and Switzer, 1992) focus more generally on the impact of R&D expenditures on productivity and the signaling power of R&D increases on firm value. Both make the important analysis of the level of market concentration, however, neither looks at the impact of firms collaborating on R&D projects. The article by Sampson (2003) begins to examine more closely the impact of R&D alliances on firm performance by focusing on two key factors, first the technological diversity between partners and second the organizational structure of the alliances. The author's main hypotheses are that R&D alliances with moderate diversity contribute most to firm innovation and that alliances organized by joint ventures contribute more to firm innovation than alliances organized by bilateral contracts. The reason is that knowledge is easier to transfer within a firm than between firms. Therefore equity joint ventures are a better alternative than bilateral contracts because equity joint ventures have a board of directors with members from all firms and there is more

monitoring and control making firms more confident to share information. Bilateral contracts on the other hand require full contractual specifications.

The main sources used are the Securities Data Company (SDC) database on joint ventures and alliances and the Micro patent database. Sampson (2003) looks at all the alliances of firms in the telecommunications equipment industry starting between 1991-1993 and retrieves a sample of 464 alliances involving 487 firms and 34 nations. For each of these firms the author constructed a patent portfolio for the firm and all of its subsidiaries using the data in the micro patent database. She used the Directory of Corporate Affiliations to identify all subsidiaries of the firms.

The dependent variable in Sampson's (2003) model is firm innovative performance which uses citation-weighted patent data in a 4-year post alliance period as its proxy. The independent variables include diversity of technological capabilities, which is proxied by the construction of each partner's technological portfolio using the distribution of its patents across patent classifications over the years, and alliance organization, which is measured using a dummy variable equal to 1 when the alliance is an equity joint venture and 0 otherwise. There are several control variables that Sampson considers. They include the innovativeness of a firm measured by its pre-alliance firm patenting, the alliance scope, that is whether it is narrow, intermediate, or broad, uses 3 dummy variables. A dummy variable was also created to capture the effect of multilateral alliances. A count of alliance commencement, prior alliance experience, other current alliances, and international alliances were also all considered in the analysis.

The first regression finds that technological diversity is positive and TD^2 is negative and significant suggesting a non-monotonic relationship. Therefore meaning that technological diversity initially increases firm innovative performance but at a certain level reaches a maximum and then begins to reduce firm innovative performance. When the dummy for alliance organization is added to the regression, again a non-monotonic relationship is found between technological diversity and firm patenting, however, firm innovative performance reaches its maximum sooner in the case of bilateral contracts than in the equity joint venture option. Hence, this suggests that equity joint venture

alliances are more capable of benefiting from greater levels of diversity than are bilateral contracts.

Another key article that has influenced my research is the paper by Anand and Khanna (2000) entitled 'Do Firms Learn to Create Value? The Case of Alliances'. This article is one of the most comprehensive in the existing literature on the advantages for firms entering alliances and uses an event study analysis to examine the market reactions to alliance announcements. The main objective of this article is to determine whether firms learn to create value through alliances and how important these learning effects can be. Like other studies in this field the authors make a distinction between joint ventures and licensing stating in their first hypothesis that joint ventures should result in stronger learning effects than licensing agreements. Their second hypothesis extends the first by looking more specifically at the different forms of joint ventures and states that R&D joint ventures have stronger learning effects than other types of joint ventures, such as production or marketing.

As was the case in several other papers on strategic alliances, the main source of information on alliance announcements used by Anand and Khanna (2000) was the Securities Data Company (SDC). The accuracy of the data was checked with Lexis Nexis on elements such as contract type, SIC Code and announcement date and return data was collected from the Center for Research in Securities Prices (CRSP) and Compustat. Alliance announcements in the manufacturing sector were collected during the period from 1990 and 1993 focusing on those alliances where contractual form is specified, at least one participant is US based and at least one participant is a public firm. This resulted in a total of 870 joint ventures and 1106 licenses. Using daily returns of all public firms, the market model was estimated using a 240-day estimation window prior to the announcement date. This was then used to estimate daily returns for each firm over a period of 14 days surrounding the event day (-10 to +3). They also measure the number of joint ventures and licensing agreements entered into by the firm prior to and including the event. Event study results indicate significant abnormal returns for both joint venture and licensing contract announcements. When considering levels of experience, Anand and Khanna find that in the case of joint ventures, the value created is significantly higher

for firms with at least four prior joint ventures. In addition, they find that R&D joint ventures result in the largest experience-related returns, followed by production joint ventures and marketing joint ventures. On the other hand, prior experience has no clear impact on the value creation through licensing contracts.

Performance enhancement through alliance networks was also studied by Baum, Calabrese, and Silverman (2000) in their paper on the performance of startups in the Canadian Biotechnology industry that participated in strategic alliance activity. They test three main hypotheses that increased performance of startups results using the size of its alliance network, the efficiency of its network, and the choice of partner (i.e. avoiding competitors that can result in intrafirm rivalry). They further analyze the last hypothesis by looking at the scope advantage relative to potential rivals and the innovative capabilities of potential rivals with which it establishes alliances. Using the Canadian biotechnology annual directory of companies, Baum et al retrieved data on Canadian biotechnology firms that began operating between January 1991 and December 1996 and found at least one startup in 13 of the 16 sectors tracked by this source, resulting in 511 observations. The different measures of performance that they consider include year over year revenue and R&D spending growth to measure performance; number of non-R&D versus R&D employees to measure employment growth; and growth in patenting to measure the development of intellectual property. They use a log-linear growth model to estimate the above-mentioned variables on performance. There are three main independent variables in this study. The first addressed the hypothesis on firm size, it is the number of alliances each biotechnology firm was involved in at the time of its founding with various categories of partners (i.e. non-rival, potentials, vertical partners such as pharmaceutical or chemical firms, universities or government organizations). The second measures the efficiency of the network by calculating the Hirschman-Herfindahl index. This index is calculated as one minus the sum of the squared proportions of a biotechnology firm's alliances divided by that firm's total number of alliances. This measures the efficiency of the alliances (i.e. second hypothesis) by computing the startups level of diversity. Finally the hypothesis on relative scope is proxied by measuring the number of sectors the biotechnology firm collaborates in divided by the average number

of sectors its partners participate in. Baum et al (2000) also control for such things as start-up's initial endowment, measured by the number of patents it has been granted when it was founded; human versus non-human sectors controlled with a dummy variable; a set of dummy variables accounting for ownership differences (such as private, public, university, gov't etc) and several others to account for environmental factors. Results show that pharmaceutical companies, universities, government labs, research institutes and marketing alliances at founding have positive relationships with one or more of the performance measurements suggesting support for the hypothesis that number of alliances at founding favorably influence start-up performance. Government labs however, did indicate a negative relationship with one of the performance variables, namely revenue growth. Given it's positive relationship with R&D employment and patenting may indicate that there is more uncertainty in projects involving government labs. The efficiency of the network was found to be positive and significant for three of the five performance measurements, namely revenue rates of return, R&D spending growth and patenting. Non-R&D and R&D employment had no significant results when considering efficiency of alliance networks. Finally, the same three out of five performance indicators were found to be negative and significant when considering the partnering of Biotech start-ups with rival biotech firms. This last result is consistent with their last hypothesis that alliances with rivals result in weaker performance for start-ups. This paper sheds light on what factors may influence the success of start-ups involved in alliances at the time of founding. Although my research does not focus on start-up biotechnology firm performance, this paper provides insight on factors that may be important in influencing abnormal returns of firms involved in collaborative agreements in general, such as frequency of partnering and the choice of partner, two factors that are also addressed in my research.

Turning more toward market response research, a short-term event study analysis was conducted by Neill, Pfeffer, Young-Ybarra (2001) on a sample of 89 companies that engaged in ITR&D strategic alliances over the period between 1987-1994. The alliances in this paper were either joint development or joint research agreements in the information technology industry. Their study attempts to determine whether these types

of announcements create value in the market. Moreover they examine whether the relative size of the partners is a factor in determining their respective gains following an alliance announcement. The latter tests enable them to determine whether alliance activity results in wealth transfers between partnering firms. Neill et al (2001) use an event-study methodology to measure the abnormal returns surrounding the announcement date using an estimation period of 200 days ending 12 days prior to the announcement date. One of the key factors distinguishing their study from the rest is that they use a homogeneous sample made up of firms in the information technology industry that engage specifically in R&D alliances and not in other types of alliances such as marketing or production agreements. The main hypothesis tested in this research paper includes the expectation that IT R&D alliances will create value for firms thereby resulting in positive abnormal returns when announced. Previous research demonstrates mixed results with regards to this hypothesis, however, Neill et al (2001) believe that alliances are a good and flexible alternative to increasing knowledge without increasing too much uncertainty or risk. This is especially important in a fast-paced industry such as the one being studied. The second hypothesis reviewed in this article is whether there were any asymmetries in the market reaction to an ITR&D alliance as seen by the difference in abnormal returns between larger and smaller partners. Some past articles state that larger firms are more capable of reaping the benefits of additional resources and capabilities than are smaller firms. Still others argue that small start-up firms are in a better position to generate value because they have the know-how that larger firms are dependant on thereby giving them more bargaining power in the alliance relationship.

Neill, Pfeffer, Young-Ybarra (2001) used a sample of 89 publicly traded companies listed in CRSP that took part in information technology alliances during the period from 1987-1994. They use both a market model and a two-factor model in order to control for systematic size risk. They find positive abnormal returns surrounding the announcement period, indicating that ITR&D announcements are perceived as value enhancing by the market. They reran the model for a sub-sample of 73 announcements for which both firms were listed on CRSP. This sample was further separated between the group of larger firms and the group of smaller firms in the alliance. The results again

indicate a positive abnormal return surrounding the event for both the group of smaller firms and the group of larger firms using both the market model and the two-factor size adjusted model. Hence, according to Neill et al, both partners appear to gain from participating in the alliance and there is no indication of wealth transfers from larger to smaller partners. This result is consistent with that found in the article by Chan, Kensinger, Keown, and Martin (1997) which suggests that although there are asymmetric gains due to size, there is no evidence of wealth transfers between partnering firms.

Chan et al (1997) considers different types of announcements such as R&D, marketing and distribution announcements, unlike the more specific ITR&D announcements studied by Neill et al (2001), however it also focuses solely on non-equity alliances. This is also a short-run event study on the market response (as measured by share price) following the announcement of 345 strategic non-equity alliances. The time period studied was from 1983 to 1992, which was indicated in Hagedoorn (2002) as a period when alliance activity was at it's peak and when the share of alliances made up of joint ventures was beginning to decrease thereby making way for different types of partnerships (i.e. including non-equity based agreements). Their sample of 345 announcements made by 460 firms, of which at least one partner was publicly traded on a major American Exchange, was obtained from searches on the Lexis/Nexis database and the Dow Jones News Retrieval Service database. Their sample resulted in 43% involved in marketing alliances, 14% in R&D alliances, 11% in licensing agreements, and 7% in technology transfer agreements. The sample was highly concentrated in high-technology industries, with 86% classified as high-tech firms and the most firms found in the computer, IT and software industries. The authors also test the permanency of these announcements by examining the number of press releases made following the initial announcement. They find few follow-up press releases in the eight years following the initial announcement. The press release information was also used to determine the fact that alliances tend to have an average lifespan of 5-years and that few of these partnerships evolve into more permanent forms of relationships such as a joint venture or a merger.

Using a short-term event study analysis, Chan et al (1997) find significantly positive abnormal returns surrounding the event announcement. Moreover, they find that when comparing returns to each partner separated according to relative size, they find that smaller firms generate larger abnormal returns than larger firms, however their dollar value gains are approximately equal. The sample is also separated between high-tech and low-tech firms, and result in positive and significant results for high-tech firms and insignificant abnormal returns for low-tech firms. Confirming their hypothesis that high-tech firms have higher growth opportunities and thereby require more flexible ways of responding to technological change. A cross-sectional regression analysis was conducted to determine the influence of different factors. These factors include, firm size, proxied by the log of the market value; growth opportunities, measured by the market-to-book value of assets; high versus low technology industries, according to Business Week classification; and the potential for transferring knowledge as estimated by horizontal versus non-horizontal alliances, where they define horizontal as those involving partners in industries with the same three-digit SIC code. Their regression analysis indicates that the larger the firm size the lower the abnormal returns. Positive abnormal returns resulted for both horizontal and non-horizontal alliances, however the main difference between horizontal and non-horizontal alliances is that the former tends to gain more value when the partnership involves the sharing of technical knowledge versus marketing-type alliances. Finally the authors also find that partnering firms outperform their industry in terms of operating performance over the five-year period surrounding the year of the partnership. This finding, that these firms not only generate positive abnormal returns immediately after the announcement but also experience above average operating performance in the years that follow, is one of the motivations of my own research to study long-term performance.

Unlike the two previous articles, Das, Sen, Sengupta (1998) find overall insignificant abnormal returns for their overall sample immediately following the announcement of a strategic alliance. Nonetheless, when decomposing their sample further certain cross-sections of their data are in line with some of the findings by Chan et al (1997) and Neill et al (2001). Das et al's (1998) study focuses on all strategic alliances

announced over the period 1987-1991, from the Wall Street Journal and the Financial Times, excluding joint ventures and multi-party alliances. After removing firms that were not publicly traded on a major US exchange their final sample included 119 events across 18 industries, with 41% characterized as marketing partnerships and 59% characterized as technological alliances. They find that technological alliances are on average somewhat smaller and less profitable than those engaged in marketing alliances. The short-term event study methodology that they employ is that which is extensively used in the current financial literature. Findings indicate that there is weak evidence of positive abnormal returns for the overall sample, since results were positive but insignificant with the exception of the 0,+1 event window. Technological alliances, however, yielded positive and statistically significant results, while marketing alliances had negative yet insignificant results. Thus, the market ascribes more value to technological over marketing alliances. The result of a greater impact on technological alliances is consistent with the finding that alliances involving the transfer of technical knowledge versus marketing alliances tend to create more value (Chan et al, 1997). This justifies the reasoning for concentrating on R&D alliances in my own study. Since they are perceived as value enhancing in the short-term, the long-term impacts are of considerable interest.

Das, Sen, and Sengupta's (1998) next objective was to determine the relationship between profitability and abnormal returns. They measure profitability as the ratio of net income to the book value of a firm. A statistically significant negative relationship between profitability and abnormal returns was found for the total alliance sample. Moreover, this relationship is more pronounced for marketing alliances than for technological alliances, therefore marketing alliances are regarded as more detrimental to the value of the firm than technological alliances. The authors also determine that small partners reap greater benefits from the alliance in the overall sample, however, these differential benefits based on relative size are most apparent in the case of technological alliances. Once again the fact that R&D-type alliances tend to behave in a distinct fashion makes this area especially interesting to investigate further. Moreover, much like Chan et al (1997) and Neill et al (2001), this article demonstrates that relative size of

partners is a factor that may explain the extent of abnormal returns to different partners, this is a point that will be addressed later in the research.

There are indications in the literature that industry may play a role in the performance of companies involved in alliances. As was mentioned previously, several of the studies on strategic alliances are often industry specific, thereby possibly explaining some of the differential results. For example in one article, which analyses the market response to a strategic alliance between e-commerce firms (Park, Mezas, Song, 2004), results indicate positive abnormal returns surrounding the event, with marketing alliances producing greater value than R&D alliances. Note that the authors define e-commerce firms as companies selling products or services exclusively through the Internet. When compared to Anand and Khanna's (2000) study on the alliances in the manufacturing industry, they conclude that the largest experience-related returns are associated to R&D alliances, followed by production collaborations, and finally by marketing partnerships. Industry however, is not the only variable that differs in these two studies. Anand et al (2000) examines only the response of joint ventures whereas Park et al (2004) consider alliances of all types made by e-commerce firms. In addition, Anand et al (2000) includes the level of experience in each of the types of alliances while Park et al (2004) make no such distinction. Nonetheless, other articles that were not industry specific (Chan, Kensinger, and Keown, 1997; Das, Sen, and Senguta, 1998), also find R&D alliances to indicate more significantly positive results than marketing alliances. In the case of non-equity-based partnerships (Chan et al, 1997) this was especially apparent in horizontal alliances (i.e. two companies from similar industries). In the case of all alliances excluding joint ventures and multiple partners (Das et al, 1998) technological alliances yielded positive and significant results while marketing alliances generated negative and insignificant results.

Park et al (2004) explain the different market reactions of R&D versus marketing alliances by the nature of the e-commerce industry. Namely that R&D may have a less significant role in this industry since hardware and software packages are very easily accessible to e-commerce firms. Whereas marketing alliances in an industry where there is a great reach potential and larger installed customer base is more important since it is

needed to “announce existence, obtain brand awareness, and educate customers” (Park et al, 2004, p. 12). Marketing alliances are not only important for the acquisition of new customers but also for the retention of existing customers, in that they can provide sharing of loyalty programs and brand names, joint advertisements and sharing of distribution channels.

Despite their findings on the greater importance of marketing alliances versus R&D alliances in the e-commerce industry, there are also several similarities with this study and that which will be described in my paper. In particular they find that partnerships in general are value enhancing, however that type of partner chosen does influence the extent of these positive results. In fact Park et al (2004) compare results of e-commerce firms partnering with other online firms versus their partnerships with offline firms. The results reveal that partnerships with offline firms were more value enhancing than those with their online counterparts. They suggest the uncertainty in the e-commerce industry to be the key factor for these results, suggesting that investors may appreciate the involvement of a more experienced offline partner. It may also be due to the fact that offline partners may provide additional distribution channels not available to the e-commerce firms. Therefore the importance of choice of partner may vary by industry and is a variable that is addressed by this research in the fourth hypothesis described in the introduction (i.e. Table 1).

3.2 Long-Term Performance

One major contribution that my paper makes to the current literature is its focus on long-term performance in the context of strategic alliances. As mentioned in several studies, long-term performance questions the ability of the market to fully interpret information, regarding various punctual and regular firm events, rapidly when they are announced (Barber and Lyon, 1997; Barber, Lyon, and Tsai, 1999; Mitchell and Stafford, 2000; Boehme, and Sorescu, 2002; Andre, Kooli, and L’Her, 2004). Events considered over the long-term include dividend or earnings announcements (Bernard and Thomas, 1989; Boheme et al, 2002), initial public offerings (IPOs) (Ritter, 1991), seasoned equity offerings (SEOs) (Speiss and Affleck, 1995), share repurchase (Ikenberry, Lakonishok,

and Vermaelon, 1995), and mergers and acquisitions (Agrawal, Jaffe, and Mandelker, 1992; Andre et al, 2004) to name a few. Previous event studies in the area of strategic alliances have focused on short-term event impacts (Chan et al, 1997; Anand and Khanna, 2000; Neill et al, 2001; Reuer, 2001; Park et al, 2004). M&A studies are the most comparable to strategic alliances, however their very distinct feature, particularly the flexibility of alliances versus M&As may result in different conclusions. A number of articles have found long run returns of M&As to be null or negative in the years following the announcement, thereby calling into question why firms continue to engage in this type of activity. It is possible that the recent decline in M&As in favor of strategic alliances may indicate that the latter responds more adequately to the current global competitive nature of firms today, hence possibly more value enhancing over the long-term as well.

Furthermore, when studying the short-term performance of collaborative agreements of all types, it is difficult to isolate the event in question for several reasons. First, the informal fashion in which announcements are made and the varying degree of exposure each event receives, makes determining a specific and accurate event date an arduous task. Second, there are several instances when strategic alliance announcements are found to cluster through time. Figure 4 presents the distribution of R&D alliance announcements, demonstrating the fact that some months have a higher degree of activity than others. The white bold line demonstrates the overall sample distribution of announcements, whereas the bars indicate the frequency of announcements for each of the sub-samples and the bold black lines specify the three-month moving average of each sub-sample. Note that when studying the sub-samples, the M_M sample (i.e. two top R&D spenders partnering together) in particular includes some months of inactivity.

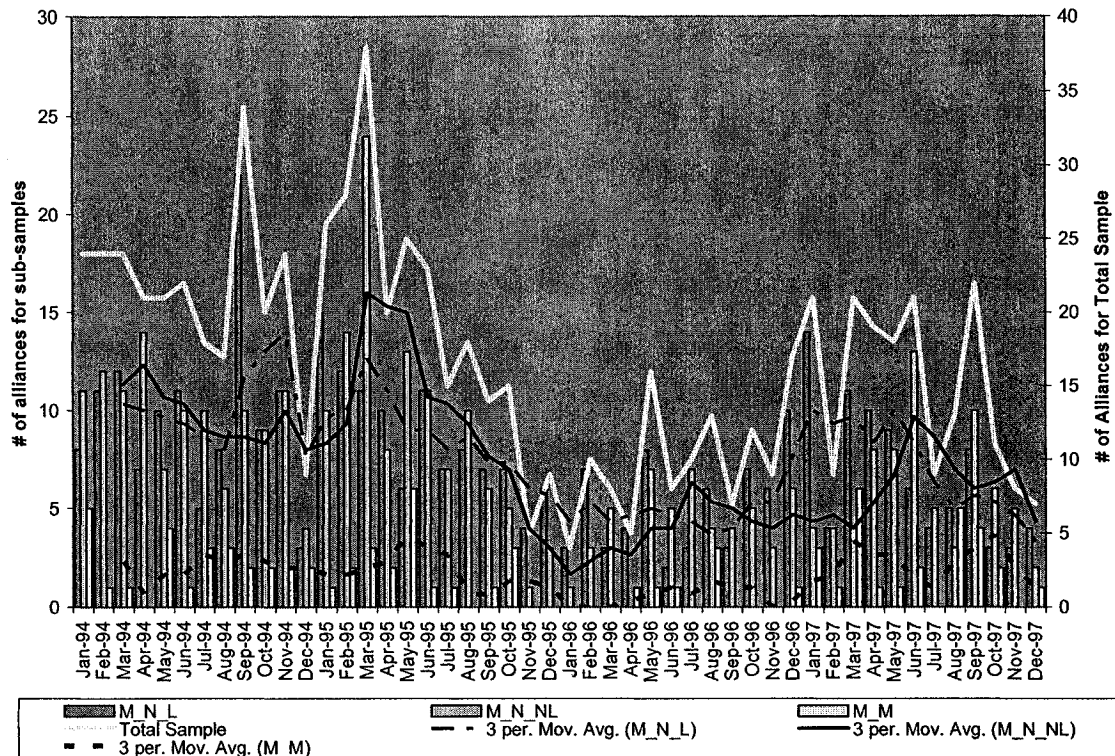
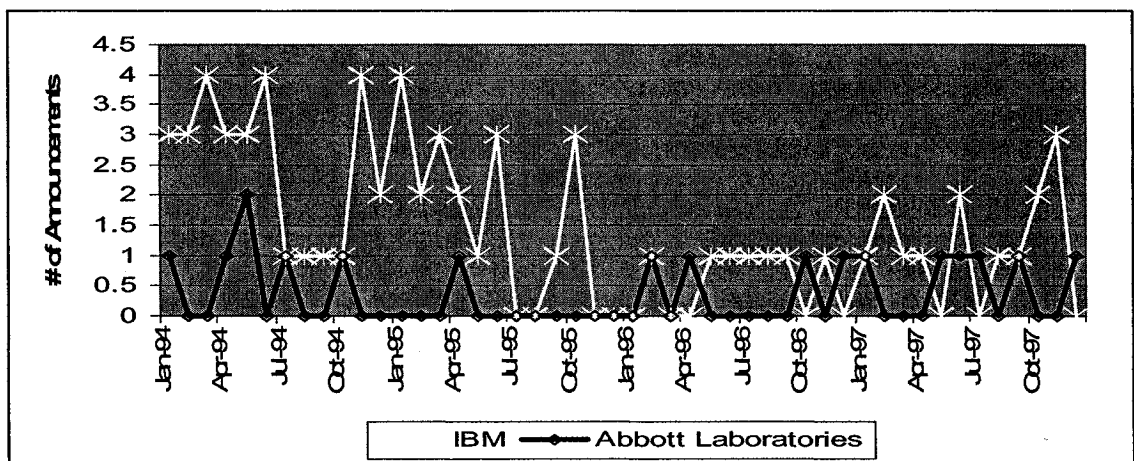


Figure 4: Distribution of monthly announcements made by total sample and three main sub-samples

When considering more specifically the case of IBM and Abbott Laboratories as examples, see figure 5, there are periods when the event of partnering is very pronounced and periods for which there is little or no activity. Hence, this justifies further the

Figure 5: Distribution of announcements for IBM and Abbott Laboratories



idea that the resulting abnormal performance found in the short run may be difficult to attribute to single events. Rather a long-term event study allows the analysis of how the

different groups of announcements may affect the stock value of involved firms over time. Long-term event study methodology however, is a very controversial area. Hence before describing the method used in this paper, a review of alternative methods is important.

Mitchell and Stafford (2000) address the question of which methodology to use when studying long-term abnormal performance subsequent to major corporate events. They examine the results using two main methods of evaluation, following the announcement of three different corporate events, namely, a merger announcement, a seasoned equity offering (SEO), and the announcement of share repurchases. These three events are studied using both the Buy and Hold Abnormal Return Approach (BHAR) as well as the Calendar Time Abnormal Return approach (CTAR). In their article, they document the often-overlooked problems with methodologies such as the BHAR and the closely-related Cumulative Abnormal Returns (CARs) approach, namely the problem of cross-sectional dependence among event firms. The following paragraphs describe these alternative methods and discuss the motivation for the selection made in this paper.

The most commonly used method for measuring abnormal returns over the long run, prior to more extensive research, was to sum the abnormal returns over time using the cumulative abnormal return (CAR) method.

$$CAR_{it} = \sum AR_{it} \text{ where, } AR_{it} = r_{it} - E(R_{it})$$

Or the difference between the actual rate of return for firm i over period t (r_{it}) and its expected return $E(R_{it})$. As stated by Barber and Lyon (1997), this approach is subject to a measurement bias, a new listing bias, and a skewness bias.

In sum, the BHAR is calculated as the difference of a sample firm's 3-year return and the 3-year return on a benchmark portfolio:

$$BHAR_i = (1 + R_{i,t}) - (1 + R_{\text{Benchmark},t})$$

And the mean BHAR is :

$$BHAR = w_i * BHAR_i,$$

And can be computed using equally-weighted or value-weighted averages.

To solve one of the statistical problems with the BHAR method, namely that BHARs are positively skewed, a bootstrapping procedure is performed to generate an

empirical distribution. It is in this attempt to simulate a distribution, that Fama (1998) identifies the bad model problem because the simulation assumes that the size and BE/ME benchmark portfolios completely describe expected returns. More critical than this first problem, the authors indicate that the bootstrapping technique also is at a disadvantage because of the assumption that the randomly selected firms have similar residual variances to the sample firms which is not necessarily the case and more importantly that they are independent therefore not capturing possible clustering since benchmarks use only size and BE/ME to construct portfolios. These problems may overstate the statistical significance.

The Mean BHAR method, although very widespread, is questioned on its assumptions of normality and independence of event firm abnormal returns. Several corrections have been proposed such as the construction of benchmark portfolios to solve for some of the biases and a bootstrapping procedure that simulates a null distribution of the estimator, thereby relaxing the normality assumption. Barber and Lyon (1997) and other advocates of the BHAR methodology argue that careful construction of the benchmark portfolios is imperative in avoiding some of the known biases. However, Mitchell and Stafford (2000) find that using different methods to calculate the benchmark portfolios does not change the conclusions drawn from mean BHAR estimates. In fact in their three samples they find that average BHARs following the announcement of major corporate events is far from zero regardless of how the benchmark was constructed. Their main concern, however, is that BHARs assume that event-firm abnormal returns are independent. As is well-documented in the literature, corporate actions tend to cluster through time and by industry thereby creating positive cross-correlations of abnormal returns. Moreover as the sample size increases so does this problem of dependency, however, the normality assumption for the mean BHAR is reasonable for large samples. Mitchell and Stafford's (2000) results indicate no abnormal returns when taking into consideration the positive cross-correlations of individual firm BHARs. These modified results were similar to their results using the CTAR approach.

Calendar-time portfolios, on the other hand, are constructed by including all firms participating in the event within a specific number of prior periods (n) and rebalancing

the portfolios monthly to drop any of the firms that have reached the end of their n-period and add all companies that executed a transaction within the n prior periods. The excess returns of the portfolio are then regressed on the three Fama and French (1993) factors as follows:

$$R_{p,t} - R_{f,t} = a_p + b_p(R_{m,t} - R_{f,t}) + s_pSMB_t + h_pHML_t + e_{p,t}$$

The variance of the calendar-time event portfolios account for any cross-sectional correlations of individual firms therefore representing one of the main improvements over the assumption of independence in the BHAR methodology. The intercept (a_p) in the calendar-time portfolio regression method represents the abnormal returns of the event portfolio. This presents the joint test problem, where if the model does not provide a complete description of the expected returns, then the intercept does not only measure mispricing but also includes model misspecification. In order to correct for this, Mitchell and Stafford use an adjusted intercept which separates the intercept in two, with the first representing abnormal returns given the sample composition (i.e. size and BE/ME) and the second representing abnormal performance attributed to other sources.

There are three main potential problems with the calendar-time portfolio regression method, namely, it assumes factor loadings are constant over time, since the portfolio composition is constantly changing the problem of heteroscedasticity may arise, and finally that weighing each month equally leads to a low power to detect abnormal returns since abnormal performance is averaged over low and heavy activity periods. The authors require a minimum of 10 firms per portfolio to mitigate the heteroscedasticity problem and they find no evidence that abnormal performance is systematically related to periods of high versus low intensity. Nonetheless the measurement of calendar-time abnormal returns (CTARs) is an improvement over even the calendar portfolio regression method, in that it controls for heteroscedasticity and it gives more weight to periods of heavy event activity than periods of low event activity. The CTAR is calculated as the difference between the monthly return on the portfolio of the event firms and the expected return on the event portfolio:

$$CTAR = R_{p,t} - E(R_{p,t}),$$

Where the latter is proxied by 25 size and BE/ME portfolios (Fama, 1998; Mitchell and Stafford, 2000). Note that as was attempted in Boehme and Sorescu (2002), I employ a modification to the method of matching the event firm portfolios, which will be discussed later in the methodology section. The CTAR and the portfolio regressions yield similar results indicating the robustness of the latter method, however the CTARs were smaller in magnitude. Overall the article demonstrates that choice of methodology is very important when analyzing long-term abnormal performance. Studies where previously wide-spread methods such as BHARs or CARs were used should be reconsidered since both portfolio regression analysis and CTARs indicate the lack of reliability of the BHAR results due to its assumption of independence of events.

Mitchell and Stafford (2000) show that with the calendar-time methodology, “monthly returns are less susceptible to the bad model problem”, second “cross-correlations of event-firm abnormal returns are automatically accounted for in the portfolio variance” and finally, “the distribution of the estimator is better approximated by the normal distribution” (pp 288). Barber, Lyon, and Tsai (1997), on the other hand argue that the CTAR approach does not capture the investor experience, as does the BHAR method. Although previous literature of long-term performance favors the use of the Buy-and-Hold abnormal return (BHAR) methodology, this paper measures post-event abnormal performances using the calendar-time methodology developed by Fama (1998) and strongly advocated by Mitchell and Stafford (2000), Boehme and Sorescu (2002) and Andre, Kooli, and L’Her (2004). Therefore the well-documented calendar-time portfolio regression method in conjunction with the mean CTAR method, will be used in order to ensure the robustness of the results and are discussed in the context of strategic alliances in the methodology section.

4. SAMPLE AND METHODOLOGY

4.1 Sample

4.1.1 Data and Sample Selection

As mentioned in section 2.3, this research focuses on the top 100 R&D spenders in the US as stipulated in the Jan/Feb 2003 edition of the Industrial Research Institute’s

(IRI) 4th Annual R&D Leaderboard (see appendix II for the complete list of Companies). The rationale for using the leaders in R&D spending, as the starting point, is explained later in this section.

I constructed my R&D alliance dataset by matching the top 100 R&D spenders to all R&D alliance announcements flagged for each of these companies from 1994 to 1997. My main data source for the alliance announcements was the Securities Data Company (SDC) Database on Joint Ventures and Alliances. Several articles studying joint ventures and other types of alliance activities have relied solely on information from the business press and in some cases from only one news source, such as the well-reputed Wall Street Journal (Murray, 1995; Das et al, 1998; Chan et al, 1997). Although a good starting point, the problems as identified by Murray (1995) are the possible misinterpretations, incompleteness of information and the fact that these sources may be biased toward large and domestic firms.

In more recent studies, authors tend to rely more often on the SDC database (Anand and Khanna, 2000; Sampson, 2003). SDC data goes as far back as 1975 but the information is more accurate and consistent as of 1990. It collects data worldwide and is updated daily using SEC filings and International counterparts to SEC, trade publications, wires and news sources from all over the world. I then reduced this initial sample by selecting only those completed/signed R&D alliance announcements that involved one or more of the companies that were included in the top 100 R&D investors list. Only 73% of the top 100 list had R&D alliance announcements during the period under study. Each of these announcements either involved R&D activities exclusively or in conjunction with marketing, production, and or supply activities.

Although SDC is the most reliable source and the most extensively used database for research on joint ventures and alliances, the study by Anand and Khanna (2000) points out the lack of accuracy in the announcement date reported by SDC. Consequently it needs to be cross-checked with another source, in this case Lexis Nexis was used. Each announcement was verified in Lexis Nexis in order to validate whether an announcement in fact took place and identify the exact date of the announcement. The search combined words such as, 'strategic', 'alliance', 'partnership', 'Research & Development',

‘collaboration’, and ‘joint venture’, with the company names identified from the initial match between SDC and IRI member firms. This led to the elimination of 220 announcements out of the original 1,012 identified as being in both SDC and matched to the IRI list of firms. The eliminations were due to three main reasons; first, the failure to find the announcement in Lexis Nexis, second, the double counting of the announcements in the retrieval of data from SDC, and third, the determination of the announcement as not fitting the criteria to be considered an R&D alliance¹. One example of the latter is that in some cases the announcement identified in SDC was the resulting product from an R&D alliance that had been ongoing and not the initial announcement of the partnership, hence warranting the removal of these data points². Hence the final sample of firms had to incorporate the following criteria in order to be included in the study:

- 1- Announcement must involve at least one member from among the top 100 R&D spenders, as stipulated in the 4th annual IRI leaderboard;
- 2- The IRI member involved must be publicly traded on a major US exchange, over the period studied from Jan-94 to Dec-1997;
- 3- The announcement tagged in SDC must be associated to a news release found in the Lexis Nexis Database;
- 4- The alliance must include as one of its goals collaboration on research and/or development activities.

These criteria led to a sample of 792 R&D alliance announcements involving at least one of the firms included in the top 100 IRI leaderboard, involving a total of 73 firms, across 9 main industries. Only 11% of all announcements involve joint ventures, 12% of total involve more than two firms, and 67% of all announcements are between partners from different industries as proxied by their 4 digit SIC code (i.e. considered non-rival firms). The fact that there is a disproportionately larger number of firms partnering with non-

¹ The following headline is an example of an announcement that is not considered an R&D alliance but rather it is an alliance to distribute a product jointly in the hopes of gaining more access to markets, hence removed from the sample: HEADLINE: Netscape and Oracle Sign Strategic Agreement to Integrate and Distribute Flagship Products; Oracle Selects Netscape Navigator as Preferred Internet Client for Oracle's Intel-based NC; Netscape Selects Oracle as Preferred Database for Commercial Applications

² This announcement is another example of an event excluded from the sample since it is the announcement of the launch of the product resulting from a previously established alliance. HEADLINE: Computer

rivals supports the findings from Hagedoorn and Duysters (2002), that companies will tend to opt for M&As when dealing with partners involved in the same core business (i.e. rivals) and will take the form of strategic alliances when dealing with non-core businesses. The distribution of announcements per year for the overall sample, are presented in Table 2 below.

Table 2: Distribution of announcements per year

Total R&D Alliance Announcements made by the top US R&D spenders included in my sample. Also included, is the proportion of announcements made between members in different industries (i.e. non-rivals), the proportion of announcements involving more than two firms (i.e. multiple), and the proportion of announcements involving the least flexible form of partnership, joint ventures.

	1994	1995	1996	1997	TOTAL
Total Monthly Announcements	258	236	119	179	792
Non Rivals(i.e. different industries)	163	170	78	119	530
Multiple	37	27	14	14	92
JV	22	26	17	20	85
% of Non Rivals(i.e. different industries)	63%	72%	66%	66%	67%
% of Multiple	14%	11%	12%	8%	12%
% of JV	9%	11%	14%	11%	11%

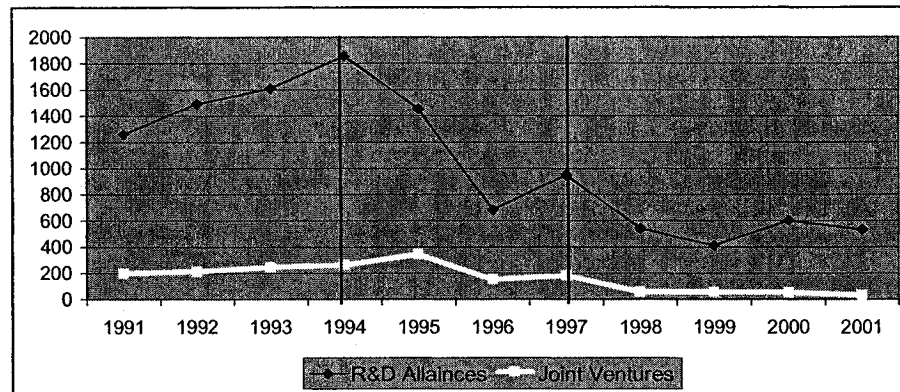
There are several reasons for having selected this time period: in particular, several of the latest short term event studies in this area have focused on the period between 1987 to 1993 (Anand et al, 2000; Chan et al, 1997; Neil et al, 2001), and I wanted to test whether some of those results were still apparent in the mid to late 90s. Nevertheless, I also chose not to select the last three years of the 90s where the markets surged upward, in order to avoid confounding my results from R&D announcements with the particularity of this period. When retrieving the data on R&D alliances in the joint venture database from SDC for all industries, I found that in the first five years of the 1990s there were an average of approximately 1,500 announcements per year. Yet the second half of the 1990s resulted in an average of approximately 500 announcements per year, as can be seen in figure 6.

Associates International, Inc. has announced Jasmine, an object-oriented database management system, and Jade, an application development environment. Both were co- developed with Fujitsu Ltd.

Figure 6: R&D Alliances vs Joint Venture Yearly Trends

Total # of R&D alliances and Joint Ventures retrieved from SDC over the ten year period, between 1991 and 2001. Period studied in my paper is highlighted.

Years	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001
# of alliances	1262	1494	1609	1,857	1,454	683	949	542	410	603	534
Growth Rate		18%	8%	15%	-22%	-53%	39%	-43%	-24%	47%	-11%
# of JV	199	213	245	263	344	151	183	57	57	54	31
% of JV	16%	14%	15%	14%	24%	22%	19%	11%	14%	9%	6%



The research team for SDC confirmed that their methodology in data collection for this particular database has not changed in the last ten years, hence this leaves us with two other possible explanations for the sharp decrease in alliance announcements. First, it is possible that an economic slowdown may have influenced companies not to invest in further R&D activities. Or it is possible that an economic slowdown may have resulted in increased R&D spending in-house and less outsourced type of activities including partnerships. In fact the following graph, figure 7, indicates that over the entire period total R&D spending of the top IRI firms is increasing during the periods where total market R&D alliance announcements are decreasing. Therefore confirming the inverse relationship suggested.

Second, firms may have learnt more about R&D alliances that may have indicated that not all alliances are recipes in creating firm value and are therefore more selective in making these types of decisions. Past research (De Man, 2002; Hagedoorn, 2002; Whipple, 2000) have shown that a research & development partnership requires several factors to exist in order for it to create value for the companies involved hence it is highly likely that companies have become more selective with increased experience in this area. These are all

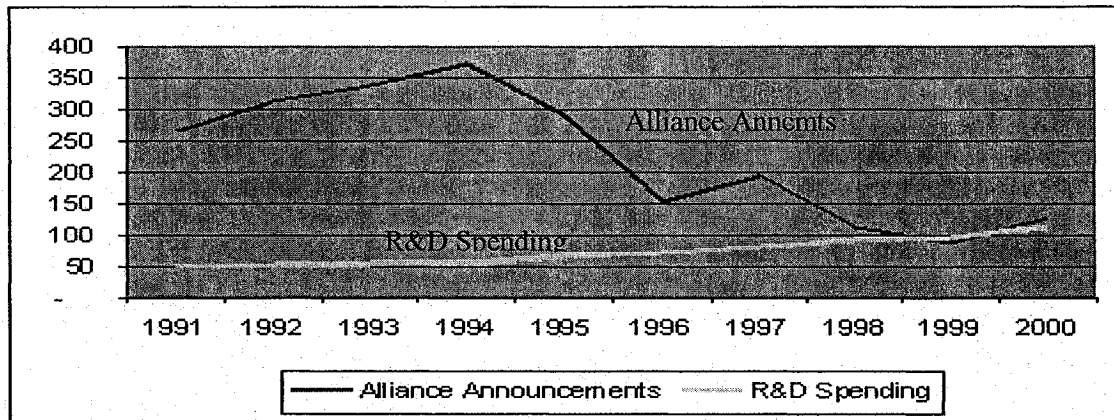


Figure 7: # of Alliance Announcements vs R&D Spending

difficult explanations to test but what is interesting, is to see the type of information these announcements send to the market in a period when both firms and investors are beginning to know more about the results of past alliance agreements both through experience and research.

The reason for using the IRI's leaderboard on the top US R&D spenders as a starting point is related to a statement made by Hagedoorn and Schakenraad (1994) that:

“the intensity of strategic partnering tends to rise with the increasing size of companies. In other words, firm size, reflects the degree to which firms actively seek and find external opportunities in strategic linkages” (Hagedoorn and Schakenraad, 1994: pp.303)

Hence, given that the companies on the IRI list tend to not only be among the top R&D spenders but are also some of the largest companies within their respective industries, this makes them more likely to have participated in strategic alliances. Firm size, as measured by market value, is presented in table 3. It demonstrates that market value of the top R&D spenders, as stipulated in the IRI leaderboard, is well above the average of all other companies listed on one of the major US exchanges over the same period. While 77% of the total market falls in the 1st quintile, defined as having market value less than or equal to 1000 (in '000000), the IRI event firms have only 3% of the firms in this category.

Table 3: Market Value Groupings of Event Firms vs Total Market

First column refers to the statistics of the IRI event firms while the second column identifies these statistics for the whole market, which is comprised of all active firms during the period under study. Number of companies and number of events these companies are involved in as a whole are presented in the first two rows and market value groupings in the last five rows. The groupings are ranges of market values determined in order to draw some conclusions regarding Event firm size characteristics versus the rest of the market. These comparisons are done in the last column where event firm characteristics are represented as a percentage of the total market.

		IRI Event Firms	Total Mkt	% of Total Mkt
# of Companies		76	3,224	0.02
# of Events		792	4,900	0.16
Market Value Groupings ¹				
1st Quintile	<=1000	3%	77%	0.04
2nd Quintile	>1000&<=5000	30%	15%	2.00
3rd Quintile	>5000&<=20000	31%	6%	5.17
4th Quintile	>20000&<=50000	22%	1%	22.00
5th Quintile	>50000	14%	1%	14.00

¹ Market Value in '000000

This confirms the statement made by Hagedoorn and Schakenraad (1994) that larger firms tend to more often be involved in alliance activity, since the ratio of strategic alliance events to number of firms is seven times higher for the IRI event firms (i.e. a ratio of 10.4 events per firm) than for the total market (i.e. a ratio of 1.5 events per firm). The next section will explain in greater detail the manner in which the original sample was decomposed into sub-samples for the purposes of this study.

Another reason for using the firms from the IRI leaderboard is that it is very heterogeneous, in that it lists companies from various industries unlike some of the short-run event studies in the past, which focus on one or two key industries (Neill et al, 2001; Baum et al, 2000; Park et al, 2004). Nonetheless, the list confirms the findings in the trends section of this paper that R&D alliance announcements are more apparent in the high-tech industries such as pharmaceutical and information technology industries than in the low and mid-technology industries. Using the definition of high-, mid-, and low- tech industries applied in the Hagedoorn (1993) publication, which was based on the OECD observer (1990) list, each of the IRI member event firms was grouped into one of the three categories. This resulted in over 50% in the high-technology industries (i.e. pharmaceuticals, information technology, and Aerospace and defense sectors) and the remainder mainly in the mid-technology sector (i.e. medical equipment, automotive,

consumer electronics, and chemicals). Similar findings are reported in Hagedoorn (1993) with the largest number of alliances in the High-tech industries, which are more motivated by technological complementarity and reduction of innovative time span whereas the low to mid-tech industries are motivated more often by gaining access to new markets and are generally found in more mature industries.

4.1.2 Sub-Samples and Industry Classification

The main sample of firms under study are the top 100 IRI firms from the IRI's 4th annual leaderboard that have made an R&D alliance announcement in the 4-year period from January 1994 to Jan 1998. However, in order to test whether there are differences based on the selection of partner, I further decompose the original sample into three sub-categories. The first includes all IRI member firms that have made an R&D alliance announcement with another IRI member firm (denoted M_M for member/member partnership)³. This is of interest because given that both firms are known for spending considerable amounts of money on R&D investment, they may have similar interests and yield different results than firms without this variable in common. In addition firms on the top 100 IRI firm list may have more experience in matters involving R&D thus enabling them to create more value from this type of announcement. The latter, however, may also indicate that their experience and frequency of being involved in these types of transactions may not provide any new information to the market thereby resulting in no abnormal performance. The second sub-sample includes all announcements made between IRI member firms partnering with non-member firms that are also not publicly traded on any exchange such as government or university institutions or private firms (denoted M_N_NL, for member/nonmember non-listed)⁴. Finally, the third sub-sample

³ An example of a headline of a Member/Member (M_M) partnership is as follows: HEADLINE: Compaq and Microsoft Developing Video Servers; Cost Effective Technology To Bring True Video-On-Demand May 17, 1994--Compaq Computer Corporation (NYSE: CPQ), the personal computer industry's leading technology innovator, today announced that it has joined forces with Microsoft to bring cost-effective continuous-media servers to market. The software technology will represent a breakthrough because it can be implemented on widely-available industry- standard hardware, yet offers a comparable level of video service performance at a fraction of the cost of solutions based on mainframes, minicomputers, or parallel supercomputers.

⁴ An example of a Member/Unlisted Non-Member partnership is as follows: HEADLINE: Sensus Announces Collaboration With Genentech To Develop Growth Hormone Antagonists, Feb. 24, 1995.

includes all IRI member firms partnering with non-member firms that are publicly traded on a US Stock Exchange (denoted M_N_L, for member/non-member listed)⁵.

The main goal is to determine which type of partner yields the most value (hypothesis 2 in table 1). Often partnering with other publicly traded firms may involve rival firms and this in turn may introduce additional obstacles in the organization of the alliance and hence may not produce positive value creating opportunities. These types of alliances are often driven by cost sharing motives. Partnering with government or university institutions, on the other hand, may result in less conflict since the goals are more oriented towards introducing improvements to serve the greater good.

Table 4 illustrates the announcement distribution of the sub-samples. The top panel shows that the sample including events between two member firms is the smallest, making up only 10% of all announcements. While the announcements of partnerships between member and nonmember IRI firms make up 44% in the case where the non-member is a public company and 46% in the instance where it is a non-public organization. Going past the top panel, each section describes in more detail the composition of each of the sub-samples. Comparing these results to those from table 2, which summarized the characteristics of the overall sample, a few key findings can be mentioned. First, the M_M sample has a higher proportion of it's announcements engaging in multiple partner alliances and in joint ventures than the overall sample, 28% and 15% respectively in the M_M sample versus 12% and 11 % in the overall sample. Second, both the M_M sample and the M_N_NL samples tend to be above the overall average in terms of the proportion of alliance events where the partnering firm is considered a non-rival firm (i.e. in different industry as it's partner based on 4-digit SIC code). Third, the final sub-sample composed of partnerships between M_N_L

Sensus Drug Development Corporation (Sensus) today announced an agreement with Genentech, Inc. (NYSE: GNE), through which the companies will collaborate in the research, development, and production of human growth hormone (hGH) receptor antagonists (GHAs) for use as potential therapeutic agents.

⁵ An example of a headline of a Member/Listed Non-Member partnership is as follows: HEADLINE: Proteon, Inc., (NASDAQ: PTON) a manufacturer of networking and internetworking products based in Westborough, Mass., and IBM's (NYSE: IBM) Networking Hardware Division today announced the signing of an agreement for the joint development of a new generation of internetworking products in the remote site category that will complement each company's products. The agreement encompasses joint development, manufacturing, technology licensing and support.

companies, demonstrates that it's composition is below the overall sample average on all three elements, namely that it has the smallest proportion of partnerships with non-rival firms, a larger proportion of it's sample opting for alliances in alternative forms to joint ventures, and the lowest proportion of multiple firm partnerships.

Table 4: Distribution of Announcements by Sub-Sample

Total R&D Alliance Announcements made by the top US R&D spenders by Sub-sample. The top panel presents the percentage of total R&D alliance announcements made by each sub-sample of partnering firms. For each sub-sample, also included, is the proportion of announcements made between members in different industries (i.e. non-rivals), the proportion of announcements involving more than two firms (i.e. multiple), and the proportion of announcements involving the least flexible form of partnership, joint ventures

	1994	1995	1996	1997	TOTAL
% of Total Announcements in each Sub-Sample					
% of M_M	10%	8%	6%	15%	10%
% of M_NM_L	45%	47%	42%	40%	44%
% of M_NM_NL	45%	44%	52%	45%	46%

Member/Member Sample	26	20	7	26	79
Non Rivals(i.e. different industries)	15	17	4	20	56
Multiple	8	6	0	8	22
JV	7	2	0	2	11
% of Non Rivals(i.e. different industries)	58%	85%	57%	77%	71%
% of Multiple	31%	30%	0%	31%	28%
% of JV	27%	10%	0%	8%	14%

Member/Non-Member & Not-Listed Sample	115	112	50	72	349
Non Rivals(i.e. different industries)	82	79	38	53	252
Multiple	11	13	6	5	35
JV	7	15	10	12	44
% of Non Rivals(i.e. different industries)	71%	71%	76%	74%	72%
% of Multiple	10%	12%	12%	7%	10%
% of JV	6%	13%	20%	17%	13%

Member/Non-Member & Listed Sample	117	104	62	81	364
Non Rivals(i.e. different industries)	66	74	36	46	222
Multiple	18	8	8	1	35
JV	8	9	7	6	30
% of Non Rivals(i.e. different industries)	56%	71%	58%	57%	61%
% of Multiple	15%	8%	13%	1%	10%
% of JV	7%	9%	11%	7%	8%

Each of the above sub-samples as well as the initial sample is further decomposed by industry. The main intention of dividing the sample by industry is to determine whether there are differences in abnormal performance in high concentration versus low

concentration industries in the hope of relating the Schumpeterian Hypothesis in the case of R&D alliance announcements. Industry Classification of member firms was determined using the classifications established by Fama and French (1997). IRI members and industry classification is presented in appendix II. They use four-digit SIC codes to assign firms to 48 industries. This was done initially by Fama and French (1997) in order to have a manageable number of distinct industries that cover all major US stock exchanges (NYSE, NASDAQ, and AMEX). The sample of IRI firms involved in R&D alliance events, cover 18 different industries using the Fama and French (1997) classification.

Table 5 summarizes the industries covered by the overall sample of IRI event firms and the number of companies in each one. Due to the lack of firms or the infrequency of announcements in certain industries only the 9 highlighted industries were analyzed for abnormal performance. The industries in this table are sorted according to the number of announcements made by the IRI companies in each industry. With the exception of the Aerospace and Energy industry companies, all other high-tech industries are among the most frequent R&D alliance participants. This is consistent with the fact that these industries are in need of very quick and flexible ways of developing new products or methods due to the high rate of obsolescence of technology. The last column in this table indicates the number of alliances per company, giving a better indication of the frequency or infrequency of these companies involvement in collaborative activities. This will be important in explaining the event study results and in relating frequency of announcements back to the Schumpeterian Hypothesis and will be discussed in the results section.

Table 5: List of Industries Covered

of IRI member event firms and # of announcements they are involved in are classified by industry and level of technology. This generates a measure of intensity of alliance activity per company in each industry in the last column. Results in 64% of companies from high-tech sectors, 35% from mid-tech sectors, and 6% from low-tech sectors.

	Industry ¹	H/M/L Tech ²	# of companies	# of Announcements	Announcements per company
1	Bussv	H	9	189	21
2	Comps	H	10	176	18
3	Drugs	H	14	144	10
4	Chips	H	7	108	15
5	Labeq	M	2	67	34
6	Hshld	M	5	54	11
7	Telec	H	2	49	25
8	Chems	M	3	27	9
9	Medeq	M	2	19	10
10	Autos	M	4	15	4
11	Eleeq	M	3	13	4
12	Aero	H	4	10	3
13	Boxes	L	1	8	8
14	Mach	M	3	3	1
15	Enrgy	H	1	2	2
16	Paper	L	1	1	1
17	BLDMT	L	1	1	1
18	Steel	L	1	1	1

¹ Industry Classification based on Fama & French (1997)

² High/Mid/Low Tech classification based on Hagedoorn (1993)

4.2 Research Methodology

4.2.1 Calendar-Time Portfolio Regressions

Calendar-time abnormal returns track performance of an event portfolio in calendar time relative to either an explicit asset pricing model or some other benchmark. The event portfolio is formed each period and includes all companies that have completed the event within n previous periods. This gives a rolling portfolio, which automatically accounts for the cross-correlations of individual event firms, in the portfolio variance at each point in calendar time. It is calculated using both the one-factor and three-factor Fama and French (1993) regression model as follows:

Equation 1

$$R_{p,t} - R_{f,t} = a_p + b_p(R_{m,t} - R_{f,t}) + e_{p,t}$$

Equation 2

$$R_{p,t} - R_{f,t} = a_p + b_p(R_{m,t} - R_{f,t}) + s_pSMB_t + h_pHML_t + e_{p,t}$$

where $R_{p,t}$ is the calendar time portfolio of R&D alliance event firms, and $R_{f,t}$ is the return of the one-month Treasury Bill. The independent variables are the excess return on the market ($R_{m,t} - R_{f,t}$), the difference between the returns of value weighted portfolios of small and big firm stocks (SMB_t), and the difference between the returns of value-weighted portfolios of high and low book-to-market stocks (HML_t). Hence a_p represents the mean monthly abnormal return of the calendar time portfolio. Given that the sample size in the portfolios formed each month differs, the variance of $e_{p,t}$ is changing thereby introducing the problem of heteroscedasticity. According to Mitchell and Stafford (2000), the problem of heteroscedasticity is reduced significantly by requiring a minimum of 10 firms in each event portfolio in order to account for the diversification effect of the portfolio residual variance. In the sample used in this paper, this approach is possible when studying the entire portfolio of announcements made by IRI members regardless of their choice of partner. However, when considering the subsamples, some of the event months include less than 10 firms hence relying solely on the OLS results may be inefficient. The correction for heteroscedasticity can be performed using a weighted least squares (WLS) estimation method (Barber, Lyon, and Tsai, 1999; Kothari and Warner, 2004). The weights are calculated as $1/n_t$, where n_t is equal to the number of firms in the portfolio in month t . Equations 1 and 2 are therefore recalculated for each of the equally- and value-weighted samples after weighting each variable. Before resorting to this however, I first tested for heteroscedasticity in my initial OLS regressions using the Breusch Pagan test and found no clear evidence suggesting a problem of heteroscedasticity. This result, however, is probably due to the small sample size, giving this test a weaker ability to detect the problem of changing variances. Nevertheless, based on the fact that the sample size varies from one portfolio to the next, the WLS is

still estimated in order to assess the robustness of my initial OLS results. Future research should consider examining a longer period.

For each month from January 1994 to December 1997, I construct equally-weighted and value-weighted portfolios of all sample firms that participated in an R&D alliance in the last three months. The portfolios are then rebalanced monthly to drop all companies that reach the end of their 3-month period and add all companies that have just executed a transaction. The Fama and French three-factor model described in equations 1 and 2, was then used to calculate portfolio abnormal returns.

The above-mentioned portfolio construction was done for all announcements made by IRI member firms (i.e. a total of 73 firms participated in collaborative activities involving R&D) during the period under study regardless of partner, and is denoted the *ALL* sample. In order to analyze the impact of the type of partner, member firms allied with, three separate portfolios were built given the following criteria as discussed in section 4.1.2:

- 1- All announcements of IRI member firms allying with other IRI member firms *[M_M]*;
- 2- All announcements of IRI member firms partnering with non-member firms that are publicly traded on an American Exchange *[M_N_L]*;
- 3- All announcements of IRI member firms allying with non-member firms/organizations that are not publicly traded (i.e. government organizations or private companies) *[M_N_NL]*.

In order to investigate in greater depth, all four of these portfolios (i.e. the *ALL* announcement portfolio and the three more specific afore-mentioned portfolios) were split further to address the question of whether industry plays a part in the success of an alliance announcement. The latter breakdown enables us to test the Schumpeterian hypothesis on the role of the level of concentration of different industries. As mentioned in the previous section the industries considered (i.e. highlighted in table 5), do not make up an exhaustive list of industries involved in the *ALL* announcements sample, however they are the ones for which the most data points are available to draw some conclusions from. Also mentioned in the sample description section 4.1.2, only 9 of the 18 industries

covered by the top 100 IRI firms were analyzed due to lack of firms or infrequency of announcements, making the sample size too small to draw conclusions from. For the list of industries considered the same regression analysis was done as for the four aforementioned non-industry specific samples. Hence equations 1 and 2 were estimated for each industry, the market factor (R_m), however, varied according to industry for each of the regressions estimated. An appropriate market benchmark was estimated as the return on the portfolio of firms in each of the respective industries (Fama and French, 1997). The separate industry market returns were obtained from the Kenneth French data library website, which includes a compilation of US market returns and other benchmarks since the 1920's as well as details on the construction of the Fama and French (1993) factors (<http://mba.tuck.dartmouth.edu/pages/faculty/ken.french>). This website uses the CRSP database as it's source for company stock returns and market values.

With the aim of addressing the Schumpeterian hypothesis, concentration ratios were calculated for each of the 9 industries highlighted in table 5. The concentration ratios will be displayed in the industry results section. There are two main ways of calculating industry concentration ratios. The first CR_4 , (Doukas and Switzer, 1992) is calculated as the percentage of market share owned by the largest firms in the industry, typically the top four firms are used and it can be expressed as:

Equation 3:

$$CR_m = s_1 + s_2 + s_3 + s_4,$$

where s_i = the market share of the i th firm.

If CR_4 is close to 0, then the industry is considered to be extremely competitive, since the four largest firms have an insignificant market share. The generally accepted rule by economists is that if the CR_4 measure is less than 40%, then the industry is considered to be very competitive, with several firms competing but none dominating the market. If CR_4 is more than 90%, the industry is considered a monopoly.

The second measure of industry concentration is the Herfindahl-Hirschman Index (HHI) used in Baum, Calabrese, and Silverman (2000). This index provides a more complete picture of industry concentration since it uses the market shares of all the firms in the industry. In addition these market shares are squared in the calculation, hence

placing more weight on larger firms. For n number of firms the HHI is expressed as follows:

Equation 4:

$$HHI = s_1^2 + s_2^2 + \dots + s_n^2$$

A HHI equal to 10000 (i.e. the maximum possible value) characterizes a monopolistic industry, whereas a HHI of 0 indicates perfect competition. According to the US Department of Justice a HHI less than 1000 represents a relatively unconcentrated market, a HHI between 1000-1800 indicates a moderately concentrated industry, and a HHI greater than 1800 is considered to be highly concentrated.

Another main variable used to test the third hypothesis (H3) on frequency of firms uses the same methodology to evaluate abnormal performance. The level of experience of the IRI member firms was determined based on the number of times each firm announced an R&D alliance over the 4-year period studied. This was done only for the sample of all announcements (ALL) since splitting the sub-samples (i.e. based on partner choice) further to address experience level in each case would have resulted in small samples and this would not permit clear conclusions to result. The number of each firm's announcements is compared to the average of all IRI firms in the sample, each year from 1994 to 1997. If the number of alliances made by a particular firm exceeds the average, it is classified as frequent. By the same token, if the number of alliance announcements made by a firm falls below the average, then it is classified as an infrequent participant. These yearly results are averaged over the 4-year period and determined as frequent if a company is classified as frequent in more than two of the four years and infrequent if it is classified as infrequent in less than two of the four years. Companies classified as frequent in two years and infrequent in two years were excluded. This resulted in a sample of 63 firms of which 27% participated frequently in R&D alliances and 73% did not engage in this activity very regularly.

It may be argued that the fact that in all the samples addressed in this paper, with the exception of the sub-sample of partnering between IRI member firms (M_M), the regression outcome may be influenced by the fact that only one members' performance is evaluated. First, examining only one partner's change in returns is unavoidable in the

case of firms partnering with non-IRI member firms that are not publicly traded (M_N_NL). However, any implications that this consideration may have can be tested in the instance of firms partnering with publicly traded but non-IRI member firms (M_N_L). Using once again the same methodology this is tested. Second, comparing results of the M_M sample, which includes both partners, to samples where only one partner is studied can also help to determine whether studying only one partner versus both may influence results.

4.2.2 Adjusted Calendar-Time Portfolio Regressions

According to Fama and French (1993) expected returns should be explained by the market, size and book-to-market therefore $a_p = 0$ if there is no abnormal return. The main problem with this approach is that the Fama and French model introduces the joint test or bad model problem. That is, if expected returns are completely explained by these three factors then a_p reflects only mispricing. But if not then a_p reflects both mispricing and model misspecification.

An adjusted Fama and French model is proposed, as is suggested in Mitchell and Stafford (2000) and Boehme and Sorescu (2002), in order to account for the joint test problem. A portfolio of control firms is thus constructed based on what I consider the fundamental factors required to describe a normal expected return of my event portfolio. In the previous literature on long-term event studies, size and book-to market ratios are among the typical factors to consider when selecting control firms (Mitchell and Stafford, 2000; Boehme and Sorescu, 2002). Provided the nature of the topic addressed in this paper, other factors were deemed more relevant in selecting a group of control firms to match the event firm portfolios. Considered important when constructing an index portfolio, are selecting firms of similar characteristics as the event firms so as to eliminate any mispricing due to characteristics of the sample rather than to the event itself. Consequently I chose my sample of control firms by considering two main factors, namely, the level of leverage of my control firms and their level of R&D intensity. The leverage variable is important, since the response of an event such as an R&D alliance announcement may differ for firms which are highly leveraged versus those that have a

low debt-to-market value ratio. Additionally, according to Hall (2002) there is evidence that debt is a disfavored source of finance for R&D investment. Hence we would expect for the event firms to have a capital structure less dependent on debt as a source of financing than firms that are possibly of similar size and industry but are less active in R&D collaborative activity. Finally, given that there is strong focus on the level of R&D of the firms in the event portfolio, another variable considered important in estimating expected portfolio returns, is the R&D-to-Sales ratio. Control portfolios were therefore constructed using the Compustat Database of all actively traded firms on a major US stock exchange, according to the combination of the following criteria of all the event firms that have made an announcement in the last twelve months:

1. A Debt-to-Market Value Ratio as a proxy for leverage levels; and
2. An R&D to Sales Ratio as a proxy for R&D intensity.

Table 6 demonstrates the groupings used to match leverage levels and R&D intensity of event firms versus all active firms over the period from 1994-1998 for the ALL sample. It indicates that IRI firms on average have a higher R&D to Sales ratio than the market, with over 83% in the 2nd to 4th quintiles (i.e. the 5% to 20% range of R&D/Sales) and 11% in the 5th quintile (i.e. above 20% R&D/Sales group). This compares to the overall market distribution of over 80% in the first two quintiles (i.e. below 5% range). It is not surprising that the event firms are well over the market average R&D-to-Sales ratios since these firms are the leaders in terms of R&D spending.

Table 6 also validates the finding by Hall (2002) that high R&D spenders tend to rely less on debt for financing since IRI firms tend to have lower leverage ratios than the market, with 45% of event firms in the 0-0.05 leverage ratio range (i.e. group 1) versus 44% of the market as a whole in the above 0.20 debt-to-market value range (i.e. group 3). These findings are consistent with the negative correlation found in the USA that R&D intensity and leverage are negatively correlated across firms (Bhagat and Welch, 1995; Hall, 2002). The findings may also be due to the fact that the sample includes very large companies, hence higher market values leads to a lower ratio. Hall (2002) explains that the main reason for avoiding debt in companies highly involved in R&D investment, is that a debt-funded program requires a stable cash flow thereby imposing the need for

stable productivity from the R&D investment. This is clearly not always the case since R&D can often involve exchange of information that may not be applied immediately. The problem of asymmetric information only amplifies this problem and makes debt financing very difficult especially in the case of lack of collateral.

Table 6: Characteristics of Event Firms vs Market: Used to Generate Control Portfolio

First column refers to the statistics of the IRI event firms while the second column identifies these statistics for the whole market, which is comprised of all active firms during the period under study. Number of companies and number of events these companies are involved in as a whole are presented in the first two rows and R&D-to-Sales and Debt/Mkt Value groupings are presented thereafter. The groupings are ranges of R&D-to-Sales and Debt/Mkt Value determined in order to draw some conclusions regarding Event firm R&D intensity and leverage levels respectively versus the rest of the market. These comparisons are done in the last column where event firm characteristics are represented as a percentage of the total market. These classifications were also used in the random draws of non-event firms used to construct a control portfolio of firms with similar characteristics to event firms, as well as in the construction of pseudo-portfolios for the determination of an empirical distribution discussed later in the paper.

		IRI Event Firms	Total Mkt	% of Total Mkt
# of Companies		73	3,224	0.02
# of Events		792	4,900	0.16
R&D To Sales Ratio Groupings				
1	0%	6%	65%	0.09
2	0%-5%	22%	17%	1.29
3	5%-10%	27%	7%	3.86
4	10%-20%	34%	6%	5.67
5	>20%	11%	6%	1.83
Debt/Makt Value Groupings				
1	0 - 0.05	45%	37%	1.22
2	0.051 - 0.2	33%	19%	1.74
3	> 0.2	21%	44%	0.48

Derived from these distributions of R&D-to-Sales and Debt-to-Market Value, the algorithm for selecting the control portfolio is as follows: for each of the event firms making an announcement in the first year (i.e. 1994), 9 control firms were selected for each event firm based on the event firm's pre-event debt-to-market ratio and R&D-to-Sales ratio grouping. These matched firms were kept in the portfolio for the entire year. Note that "pre-event" is defined as the previous year $[m-1]$ where m is the year of the

R&D alliance announcement. The portfolio was rebalanced each year, hence new matches to all event firms making an announcement in the second year based on their previous year characteristics, were reselected and once again kept in the portfolio for the entire year. This process was done for the entire 4-year period for the sample of ALL announcements made by IRI member firms as well as for the three main sub-samples that were constructed based on type of partner selected, M_M, M_N_NL, and M_N_L. The characteristics of the sub-samples are found in tables 7 to 9 and are compared to both the total IRI event portfolio (i.e.ALL) and the total market. Note that control portfolios were also constructed for the samples separating the ALL portfolio based on level of experience (i.e. frequent versus infrequent R&D alliance announcers).

Some distinctions can be made when comparing the composition of the different portfolios of firms in the tables that follow. First, it is important to indicate that IRI member firms tend to less often partner together than with non-member firms, with only 39 firms involved in 79 events in the M_M sample. As opposed to the 63 firms to 349 announcements in the M_N_NL sample and the 63 firms to 364 events in the M_N_L sample. Hence the top R&D spenders are more actively seeking out partners that are not also among the IRI member list. Second, the M_M sample has a greater proportion than the ALL announcements sample in the highest quintiles of R&D-to-sales ratio. Despite these small differences between samples, the same main conclusions can be drawn from all three of the groupings based on partner type. Namely, that they have among the highest R&D to sales ratios, and the lowest Debt-to Market Value ratios compared to the overall market of actively traded firms on a major US exchange over the period under study. Further, the IRI member firms have a much higher ratio of events to firms than does the total market, thereby suggesting that these firms may be more experienced in alliance-type activity than the market in general.

Table 7: Characteristics of Event Firms of M_M Sample vs ALL Sample and vs Market: Used to Generate Control Portfolio for M_M event sample

Similar information to that in table 6, however refers more specifically to the sub-sample of IRI member firms partnering together (M_M). Note also that in addition to the comparisons made to the market, the second to last column also presents the M_M statistics as a percentage of the full sample of event firms.

		M_M Portfolio Event Firms	Total IRI Event Firms	Total Mkt	% of Total IRI Event Firms	% of Total Mkt
# of Companies		39	73	3,224	53.4%	1.2%
# of Events		79	792	4,900	10.0%	1.6%
R&D To Sales Ratio Groupings						
1	0%	4%	6%	65%	0.68	0.06
2	0%-5%	15%	22%	17%	0.68	0.87
3	5%-10%	39%	27%	7%	1.45	5.60
4	10%-20%	28%	34%	6%	0.83	4.73
5	>20%	14%	11%	6%	1.23	2.25
Debt/Mkt Value Groupings						
1	0 - 0.05	35%	45%	37%	0.78	0.95
2	0.051 - 0.2	38%	33%	19%	1.16	2.01
3	> 0.2	27%	21%	44%	1.27	0.61

Table 8: Characteristics of Event Firms of M_N_NL Sample vs ALL Sample and vs Market: Used to Generate Control Portfolio for M_N_NL event sample

Similar information to that in table 6, however refers more specifically to the sub-sample of IRI member firms partnering together (M_N_NL). Note also that in addition to the comparisons made to the market, the second to last column also presents the M_N_NL statistics as a percentage of the full sample of event firms.

		M_N_NL Portfolio Event Firms	Total IRI Event Firms	Total Mkt	% of Total IRI Event Firms	% of Total Mkt
# of Companies		63	73	3,224	86.3%	2.0%
# of Events		349	792	4,900	44.1%	7.1%
R&D To Sales Ratio Groupings						
1	0%	5%	6%	65%	0.89	0.08
2	0%-5%	20%	22%	17%	0.93	1.21
3	5%-10%	28%	27%	7%	1.03	3.98
4	10%-20%	36%	34%	6%	1.05	5.94
5	>20%	11%	11%	6%	0.97	1.78
Debt/Mkt Value Groupings						
1	0 - 0.05	38%	45%	37%	0.85	1.04
2	0.051 - 0.2	40%	33%	19%	1.21	2.10
3	> 0.2	22%	21%	44%	1.03	0.49

Table 9: Characteristics of Event Firms of M_N_L Sample vs ALL Sample and vs Market: Used to Generate Control Portfolio for M_N_L event sample

Similar information to that in table 6, however refers more specifically to the sub-sample of IRI member firms partnering together (M_N_L). Note also that in addition to the comparisons made to the market, the second to last column also presents the M_N_L statistics as a percentage of the full sample of event firms.

		M_N_L Portfolio Event Firms	Total IRI Event Firms	Total Mkt	% of Total IRI Event Firms	% of Total Mkt
# of Companies		63	73	3,224	86.3%	2.0%
# of Events		364	792	4,900	46.0%	7.4%
R&D To Sales Ratio Groupings						
1	0%	3%	6%	65%	0.54	0.05
2	0%-5%	17%	22%	17%	0.79	1.02
3	5%-10%	33%	27%	7%	1.22	4.72
4	10%-20%	37%	34%	6%	1.08	6.12
5	>20%	10%	11%	6%	0.88	1.61
Debt/Mkt Value Groupings						
1	0 - 0.05	42%	45%	37%	0.94	1.14
2	0.051 - 0.2	34%	33%	19%	1.03	1.79
3	> 0.2	24%	21%	44%	1.13	0.54

Once control firms were selected, value-weighted and equally-weighted control portfolios were created, and the hedge portfolio (i.e. long position on event firms and short position on control firms) was regressed once again on the one-factor and three-factor Fama-French variables:

Equation 5

$$R_{p,t} - R_{c,t} = a_p + b_p(R_{m,t} - R_{f,t}) + e_{p,t}$$

Equation 6

$$R_{p,t} - R_{c,t} = a_p + b_p(R_{m,t} - R_{f,t}) + s_pSMB_t + h_pHML_t + e_{p,t}$$

where $R_{p,t}$ is the calendar time portfolio of R&D alliance event firms, and $R_{c,t}$ is the calendar time portfolio return of the control firms. The independent variables are the same as in equations 1 and 2, namely, excess return on the market ($R_{m,t} - R_{f,t}$), the difference between the returns of value weighted portfolios of small and big firm stocks (SMB_t), and the difference between the returns of value-weighted portfolios of high and low book-to-market stocks (HML_t). This model generates an “adjusted” Fama-French intercept (a_p) which is a measure of abnormal performance that corrects specifically for

the leverage and R&D intensity biases inherent in my sample when using the original Fama and French (1993) model in equations 1 and 2.

4.2.3 Simulation Method and Mean Monthly Calendar-Time Abnormal Returns

Another method considered to evaluate the statistical significance of long-run abnormal stock returns is the construction of non-event pseudo-portfolios to compute empirical p-values for the three main partnering sub-samples in this paper (i.e. M_M, M_N_NL, and M_N_L). It is a method also employed by Brock, Lankonishok, and LeBaron (1992), Ikenberry, Lankonishok, and Vermaelen (1995), Lee (1997), Lyon, Barber and Tsai (1999), and Mitchell and Stafford (2000). In this approach, an empirical distribution of long-run abnormal stock returns is generated. The pseudo-portfolio of firms was constructed by randomly matching with replacement, each of the event firms in calendar month t , to one public firm traded on a major US exchange based on leverage ratio and R&D to sales ratio groupings. After forming one matched non-event portfolio, the long run abnormal performance was calculated using the three-factor calendar time portfolio regression from equation 2. However, R_{pt} was equal to the calendar-time portfolio return of non-event firms. As was done for the original sample, abnormal performance of the non-event portfolios was measured by the alpha estimate of this regression. This yields one observation of the abnormal performance obtained from randomly forming a portfolio with similar leverage and R&D-to sales ratios as the original sample. This entire process was repeated for 1000 pseudoportfolios and thus 1000 abnormal return observations. These 1000 alphas are used to approximate the empirical distribution of long-run abnormal returns. One important consideration was the simultaneous matching of the 3 partnering portfolios, which ensures that overlap of firms in the control portfolios is similar to that of the event portfolios. For example, if Microsoft made two announcements in month 1 with different partner types (i.e. one being with another IRI member firm and another being with a public but non-IRI member firm), then Microsoft would have the same company matched to it in both portfolios. This facilitates the comparisons between portfolios as will be seen later in this section.

Unlike the conventional t-statistic, in which the null hypothesis is that the mean long-run abnormal return is zero, in this case the null hypothesis tested is that the mean long-run abnormal return of event portfolios equals the mean long-run abnormal return of the 1000 non-event pseudoportfolios. The null hypothesis is therefore rejected for values of alpha that fall in the rejection region of the empirical distribution of non-event alphas, as will be displayed in the figures in the results section. The simulation of control portfolios permits us to verify whether the conventional t-statistics calculated in the original OLS model are accurate estimates of abnormal returns and demonstrates the characteristics of the non-event portfolios of matched firms.

Although the calendar time portfolio method performs well when cross-sectional dependence is severe (namely, when return calculations are overlapping), it remains sensitive to the bad model problem however to a lesser extent than other methods (Barber, Lyon and Tsai, 1999; Mitchell and Stafford, 2000). The best way to deal with the problems associated with different methods of calculating abnormal returns is to adopt several approaches and look for any consistent findings. Hence the next method that was used was the calculation of mean calendar time abnormal returns (MCTARs) also adopted in several of the articles using calendar time approaches to long term studies (Barber, Lyon and Tsai, 1999; Mitchell and Stafford, 2000; Boehme and Sorescu, 2002; Andre, Kooli, and L'Her, 2004). MCTARs are calculated by taking the difference between event portfolio returns and expected portfolio returns and dividing by the total number of alphas calculated and is represented as follows:

Equation 7

$$MCTAR = \frac{\sum_{i=1}^n CTAR_i}{n} \quad \text{For } i = 1 \text{ to } n \text{ and } CTAR_i = R_p - E(R_p)$$

As was the case in the portfolio regression, R_p represents the return of the calendar time portfolios comprising R&D alliance event firms for all member IRI firms and for the sub-samples that depend on partner selected. In this case however, $E(R_p)$ is the expected return of a dynamically constructed control portfolio, that is, it is a portfolio that is matched during each calendar month according to the same factors determined for the static portfolio constructed in the adjusted Fama/French regression analysis. This dynamic matching methodology, also documented by Mitchell and Stafford (2000),

selects a new set of firms for each month of the post-event period. The same pseudoportfolios generated for the simulation of non-event firm alphas was used to generate the event firm distribution. That is, for each event firm in month one, a firm is randomly selected from the Compustat database according to pre-event period leverage and R&D intensity groupings and kept in the portfolio for three months. This portfolio is rebalanced each month to add new companies and remove companies reaching the end of their three month period. This process is reiterated to create 1000 matched portfolios that are used to estimate $E(R_p)$ and to create an empirical distribution. When constructing the portfolios another consideration was the fact that some of the IRI member firms have made announcements in more than one of the sub-samples of events in the same month. In such cases the same firm is matched to the event firm during that period in the separate portfolios. The CTAR represents the alpha estimate of the event portfolio minus the 1000 control portfolios regressed on the three factors from the Fama and French model. This is calculated using both equally-weighted and value-weighted methodologies. Hence generating a distribution of event firm alphas whose mean is equal to the mean calendar-time abnormal return. The null hypothesis here is that the MCTAR of each of the sub-samples (M_M , M_N_NL , & M_N_L) is equal to zero. Given the large sample size required to generate a distribution for the grand mean abnormal return (i.e. MCTAR), then the MCTAR is $\sim N(\mu, \sigma^2)$ and the z-value is calculated as:

$$\frac{\text{Mean}}{\sigma/\sqrt{n}}; \text{ where } \sigma = \text{Standard deviation and } n = \text{the 1000 portfolios.}$$

There is concern that this approach has low power to detect abnormal performance. However, Mitchell and Stafford (2000) find that CTAR's do have high power. In fact, they measured abnormal returns using BHAR measures adjusted for positive cross-correlations and using the CTAR's and found that both resulted in similar findings however the CTAR measure had a higher power.

Finally the question of size of abnormal returns is important to consider since it contributes in demonstrating the shape of the distribution of both the non-event empirical distribution and the event distribution as calculated with the CTARs. This allows the calculation of the percentage of the 1000 portfolios that reject the null hypothesis of no

mean monthly excess returns when the holding period is three months, at theoretical significance levels. At the 5% level of significance, abnormal returns are significantly negative if the calculated p-value is less than 2.5% or significantly positive if the calculated p-value is greater than 97.5%. Hence as stated by Barber et al (1999), a test is well-specified when 1000α tests reject the null hypothesis, it is considered conservative if fewer than 1000α null hypotheses are rejected and is anticonservative if more than 1000α null hypotheses are rejected. Based on this procedure, I test the specification of each test statistic at the 5% theoretical levels of significance for the distribution of pseudo-portfolio non-event intercepts and the event intercepts resulting from the 1000 CTAR calculations for each of the partnership type subsamples.

5. RESULTS

5.1 Calendar Time Portfolio Results

5.1.1 Ordinary Least Squares Results for Overall Sample and choice of Partner

Tables 10 and 11 display the value-weighted calendar time portfolio regression results for the four samples over the period from April 1994 through Jan 1998. Note that these tables present both the *unadjusted* and the *adjusted* Fama and French (1993) intercept results. Each regression was run on both the market model as well as the 3-factor Fama/French Model. In all cases, the 3-factor model resulted in better R^2 values and more significant p-values. Hence the focus of the discussion of the results will be on the 3-factor model regression estimates (i.e. table 11). Nonetheless, the market model estimates are also presented in table 10. The market (R_m) refers to the value-weighted return of all NYSE, AMEX, and NASDAQ stocks from CRSP.

The value-weighted 3-month alliance portfolio of member firms, for the sample considering all alliance announcements (ALL) made by member firms regardless of type of partner chosen, exhibits statistically significant positive average abnormal returns: 0.82% per month or 2.46% after 3 months ($0.82\% \times 3$ months), with a t-statistic of 2.06 (see Table 11). When decomposing the sample into the three categories based on type of partner member firms ally with it was found that no significant abnormal returns result from the alliance between two member firms (M_M). IRI firms partnering with non-

member and non-public firms (M_N_NL) on the other hand, experience significant positive abnormal returns of 1.13% per month or 3.38% after 3 months. This may suggest some benefits may be reaped from allying with private corporations or governmental agencies and universities. This seems quite intuitive since these types of partners would characterize less rivalry hence facilitating the flow of information all the while keeping costs down since they are shared between the partners. These results are further broken down by industry in the next section. Results from the sample of all R&D alliance announcements made between IRI members and public non-members (M_N_L), indicate positive abnormal return in the three months following the announcement of an alliance of approximately 0.93% or 2.79% over three months.

The conclusion from these initial regressions is that, on a value-weighted basis, firms tend to significantly over-perform in the three-months following the R&D alliance announcement, with the exception of the case in which two member firms choose to partner together. This suggests that there may in fact be benefits from engaging in this type of activity and that this in turn is perceived in a favorable light in the market over the long run. These initial results are consistent with short term event studies that suggest that R&D alliance announcements produce overall positive results in the stock market (Chan, Kensinger, Keown, and Martin, 1997; Neill, Pfeffer, and Young-Ybarra, 2001; Anand and Khanna, 2000; Das and Senguta, 1998). Moreover, the fact that type of partner chosen generates different results, specifically in the case of the M_M sample, suggests that partner chosen plays an important role in the long run stock market reaction of R&D alliance announcements, as was the case in short-term studies (Baum, Calabrese and Silverman, 2000; Park, Mezias and Song, 2004).

The same regressions are run using equally-weighted portfolios and the conclusions are comparable to those of the value-weighted portfolios hence adding to the robustness of the results. In particular, overall R&D alliance announcements, regardless of partner, generate positive abnormal returns in the three months following the event. Table 11 indicates a 0.73% abnormal return comparable to the 0.82% found in the value weighted regressions. Moreover, when examining the same three scenarios of choice of partners, results indicate that only the portfolio involving announcements made between

members displays no significant abnormal returns, equivalent to the conclusions of the value-weighted portfolios. Although the inferences from the equally-weighted regressions are the same as the value-weighted regressions, the magnitude of the abnormal returns differs between methodologies.

This same table can also be used to study the abnormal performance of the event portfolios when correcting for the possibility of mispricing in the original Fama and French (1993) model. The column titled 'Adjusted α ' gives the results of the excess event portfolio returns over the control portfolios regressed on the three Fama-French factors. Recall that the control portfolio was constructed by matching each event firm announcing an alliance in the last twelve months, to a group of firms based on similar groupings of leverage levels and R&D intensity. Note that a new set of matches is selected each year, however rebalancing occurs each month just as in the event portfolio. When correcting for potential mispricing in this way, results indicate that all portfolios previously resulting in positive abnormal returns are no longer indicating any abnormal performance. Value- and equally- weighted estimates both yield the same conclusions. This is consistent with the efficient market hypothesis, in that in the long run, all information available to the public should be reflected in prices relatively quickly, thereby not expecting abnormal performance in the long-run.

In the case of the sub-sample of two or more IRI member firms partnering together for R&D projects (M_M), the adjusted α indicates a negative and significant abnormal return in the value-weighted estimate and no abnormal performance in the equally-weighted regression. This rejects the efficient market hypothesis as well as the results in previous short-run studies indicating positive abnormal performance following the announcement of an R&D alliance. Given that these results suggest that when correcting for possible mispricing R&D alliance announcements result in value-destruction, contrary to previous belief, this sub-sample is investigated in greater depth in the next section.

Table 10: OLS Regression Results of 1-Factor Model Per Sample

Abnormal returns are estimated for the 3-month post-announcement horizons for the combined sample of alliance announcements from the period 1994-1998. Equal- and value- weighted (rebalanced monthly) calendar time portfolio returns are calculated each month from all firms involved in an R&D collaborative activity in the previous 3 months. The monthly excess returns to the calendar time portfolios, $R_{p,t} - R_{f,t}$, are regressed on the Fama and French 1 factor market model in order to calculate the unadjusted intercept:

$$R_{p,t} - R_{f,t} = a_p + b_p(R_{m,t} - R_{f,t})$$

$R_m - R_f$, the excess return on the market, is the value-weight return on all NYSE, AMEX, and NASDAQ stocks (from CRSP) minus the one-month Treasury bill rate (from Ibbotson Associates). See Fama and French (1993) for a complete description.

For the adjusted Fama and French regression, the dependent variable is the difference between event firm portfolios and the control firm portfolio, constructed based on similar R&D-to-Sales Ratio and Debt-to-Market Value levels. This difference is regressed on the Fama & French factors:

$$R_{p,t} - R_{c,t} = a_p + b_p(R_{m,t} - R_{f,t})$$

Here $R_{p,t}$ is subtracted by $R_{c,t}$ which is the calendar time portfolio return of the control firms.

	Equal Weight				Value Weight			
	a (t-statistic)	R ² [N]	Adjusted a (t-statistic)	Adjusted R ² [N]	a (t-statistic)	R ² [N]	Adjusted a (t-statistic)	Adjusted R ² [N]
ALL	0.10 (0.2)	64% [73]	-0.41 (-0.66)	10% [657]	0.40 (0.85)	63% [73]	-0.64 (-1.44)*	19% [657]
M_M	0.005 (0.01)	50% [39]	-0.950 (-0.92)	25% [351]	-0.11 (-0.15)	50% [39]	-2.37 (-2.37)***	40% [351]
M_N_NL	0.40 (0.73)	55% [63]	0.33 (0.43)	52% [567]	0.77 (1.5)*	58% [63]	0.24 [567]	1% [63]
M_N_L	0.57 (1.12)	57% [63]	0.68 (0.99)	44% [567]	0.52 (1.01)	58% [63]	-0.02 [567]	0% [63]

***, **, *, Significant at the 1, 5, 10, and 15 percent levels, respectively

NOTE: The t-statistics are in parentheses, and N, the number of companies in the sample are in square brackets.

Table 11: OLS Regression Results of 3-Factor Model Per Sample

Abnormal returns are estimated for the 3-month post-announcement horizons for the combined sample of alliance announcements from the period 1994-1998. Equal- and value- weighted (rebalanced monthly) calendar time portfolio returns are calculated each month from all firms involved in an R&D collaborative activity in the previous 3 months. The monthly excess returns to the calendar time portfolios, $R_{p,t} - R_{f,t}$, are regressed on the Fama and French 3 factor market model in order to calculate the unadjusted intercept:

$$R_{p,t} - R_{f,t} = a_p + b_p(R_{m,t} - R_{f,t}) + s_p(SMB_t) + h_p(HML_t)$$

$R_m - R_f$, the excess return on the market, is the value-weight return on all NYSE, AMEX, and NASDAQ stocks (from CRSP) minus the one-month Treasury bill rate (from Ibbotson Associates). SMB_t is the difference between the returns of value weighted portfolios of small and big firm stocks, and HML_t is the difference between the returns of value-weighted portfolios of high and low book-to-market stocks. See Fama and French (1993) for a complete description.

For the **adjusted** Fama and French regression, the dependent variable is the difference between event firm portfolios and the control firm portfolio, constructed based on similar R&D-to-Sales Ratio and Debt-to-Market Value levels. This difference is regressed on the Fama & French factors:

$$R_{p,t} - R_{c,t} = a_p + b_p(R_{m,t} - R_{f,t}) + s_p(SMB_t) + h_p(HML_t)$$

Here $R_{p,t}$ is subtracted by $R_{c,t}$ which is the calendar time portfolio return of the control firms.

	Equal Weight				Value Weight			
	a (t-statistic)	R ² [N]	Adjusted a (t-statistic)	Adjusted R ² [N]	a (t-statistic)	R ² [N]	Adjusted a (t-statistic)	Adjusted R ² [N]
ALL	0.73 (1.81)**	78% [73]	-0.27 (-0.56)	51% [657]	0.82 (2.06)***	77% [73]	-0.41 (-1.05)	44% [657]
M_M	0.577 (0.86)	58% [39]	-0.470 (-0.45)	36% [351]	0.16 (0.2)	55% [39]	-2.07 (-2.03)***	48% [351]
M_N_NL	0.86 (1.62)**	64% [63]	0.01 (0.02)	52% [567]	1.13 (2.54)****	73% [63]	0.28 (0.55)	24% [567]
M_N_L	1.23 (2.88)****	74% [63]	0.62 (1.12)	44% [567]	0.93 (2.00)***	71% [63]	0.11 (0.25)	13% [567]

****, ***, **, * Significant at the 1, 5, 10, and 15 percent levels, respectively

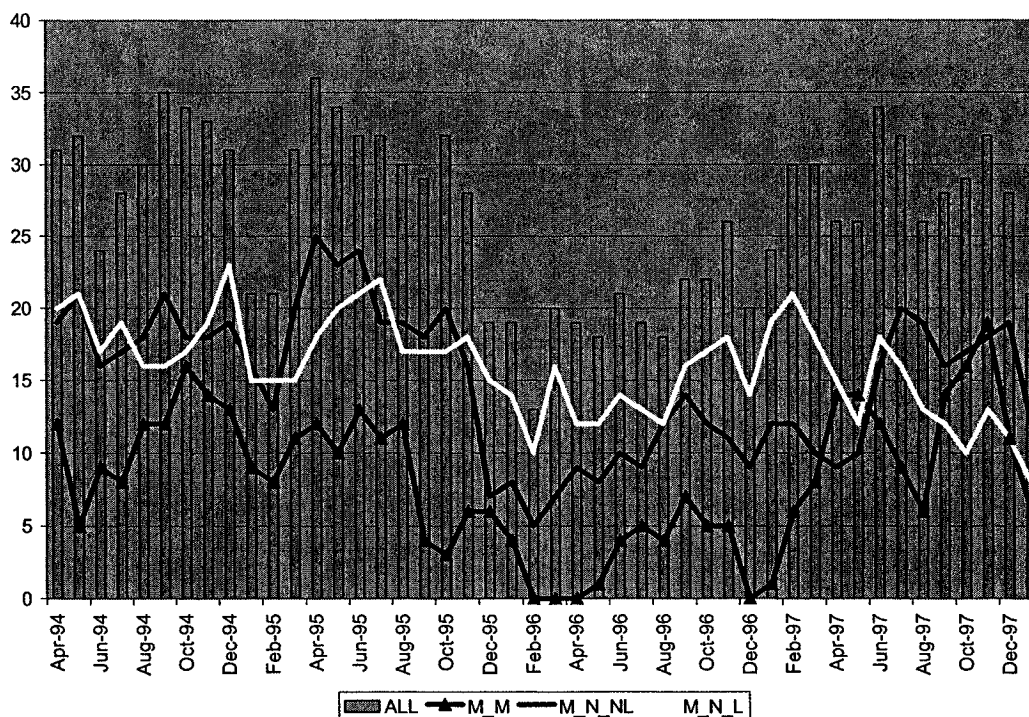
NOTE: The t-statistics are in parentheses, and N, the number of companies in the sample are in square brackets.

The above OLS estimates do not correct for the possibility of heteroscedasticity, which may exist due to the changing number of firms and events in each calendar month. As suggested by Mitchell and Stafford (2000) one way to correct for this problem is to have a minimum of ten firms in each calendar month. This is possible for the ALL event firm sample, yet when decomposing the original sample into sub-samples based on partner type this becomes difficult to achieve due to sample size. Figure 8 shows the

distribution of the event firms included in each monthly portfolio. As is evident, in the case of the ALL sample the problem of heteroscedasticity should be mitigated by the greater than 10 firms rule as stipulated by Mitchell and Stafford (2000). However, in the M_M and M_N_NL portfolios this is not the case. Hence as suggested in the methodology section a weighted least squares (WLS) regression analysis is performed (Barber, Lyon and Tsai, 1999; Kothari and Warner, 2004).

Figure 8: Monthly Distribution of Event Firms per Portfolio

A graphical representation of the varying number of event companies in each calendar month. The bars represent the overall sample's distribution of event firms and the lines represent the distribution for each of the sub-samples. In the case of the overall sub-sample, each calendar month includes more than ten firms, thereby satisfying the requirement stated by Mitchell and Stafford of 10 or more firms to solve for the potential problem of heteroscedasticity. However the sub-samples do not always satisfy this condition, making the estimation of the WLS regression necessary.



The WLS results are presented in tables 12 and 13 for the 1-factor and 3-factor models respectively. Observe that OLS results in these tables are the same as the unadjusted OLS results found in tables 10 and 11. These numbers are included in the tables to simplify the comparison between OLS and WLS results; therefore the only new information is the section under WLS. Both estimation methods yield comparable results

suggesting that heteroscedasticity is not driving the outcome of these regressions. Although the detection of abnormal returns and the sign of the a-estimate are comparable between OLS and WLS methods, the magnitude tends to differ. The WLS method consistently indicates smaller abnormal returns than do the OLS estimates, on average approximately 25% of the abnormal performance observed in the OLS results.

Table 12: WLS Regression Results of 1-Factor Model per Sample

In order to correct for heteroscedasticity equations 1 was recalculated after weighting all the variables according to the number of companies in each calendar month. The equation estimated if once again:

$$R_{p,t}/(\sqrt{w_{p,t}}) - R_{f,t}/(\sqrt{w_{p,t}}) = a_p + b_p(R_{m,t}/(\sqrt{w_{p,t}}) - R_{f,t}/(\sqrt{w_{p,t}}))$$

Where $R_{p,t}$, $R_{f,t}$, $R_{m,t}$ are defined as before, however all of these variables are weighted by $\sqrt{w_{p,t}}$ which is the square root of the weights of the number of companies in each calendar time portfolio.

	Equal Weight				Value Weight			
	OLS		WLS		OLS		WLS	
	a (t-statistic)	R ² [N]	a (t-statistic)	R ² [N]	a (t-statistic)	R ² [N]	a (t-statistic)	R ² [N]
ALL	0.10 0.20	64% [73]	0.02 0.18	64% [73]	0.40 0.85	63% [73]	0.08 0.90	62% [73]
M_M	0.005 0.01	50% [39]	0.11 0.44	45% [39]	-0.11 -0.15	50% [39]	0.02 0.05	43% [39]
M_N_NL	0.40 0.73	55% [63]	0.10 0.59	48% [63]	0.77 1.5*	58% [63]	0.21 1.39	54% [63]
M_N_L	0.57 1.12	57% [63]	0.14 1.07	57% [63]	0.52 1.01	58% [63]	0.14 1.08	56% [63]

****, ***, **, * Significant at the 1, 5, 10, and 15 percent levels, respectively

NOTE: The t-statistics are in parentheses, and N, the number of companies in the sample are in square brackets.

Table 13: WLS Regression Results of 3-Factor Model per Sample

In order to correct for heteroscedasticity equation 1 was recalculated after weighting all the variables according to the number of companies in each calendar month. The equation estimated is once again:

$$R_{p,t} / (\sqrt{w_{p,t}}) - R_{f,t} / (\sqrt{w_{p,t}}) = a_p + b_p(R_{m,t} / (\sqrt{w_{p,t}}) - R_{f,t} / (\sqrt{w_{p,t}})) + s_p(SMB_t) / (\sqrt{w_{p,t}}) + h_p(HML_t) / (\sqrt{w_{p,t}})$$

Where $R_{p,t}$, $R_{f,t}$, $R_{m,t}$, SMB_t , HML_t are defined as before, however all of these variables are weighted by $\sqrt{w_{p,t}}$ which is the square root of the weights of the number of companies in each calendar time portfolio.

	Equal Weight				Value Weight			
	OLS		WLS		OLS		WLS	
	a (t-statistic)	R ² [N]	a (t-statistic)	R ² [N]	a (t-statistic)	R ² [N]	a (t-statistic)	R ² [N]
ALL	0.73 1.81**	78% [73]	0.15 1.85**	78% [73]	0.82 2.06***	77% [73]	0.18 2.24***	77% [73]
M_M	0.58 0.86	58% [39]	0.32 1.14	50% [39]	0.16 0.20	55% [39]	0.11 0.31	45% [39]
M_N_NL	0.86 1.62**	64% [63]	0.23 1.43*	57% [63]	1.13 2.54****	73% [63]	0.31 2.35****	70% [63]
M_N_L	1.23 2.88****	74% [63]	0.30 2.80****	74% [63]	0.93 2.00***	71% [63]	0.24 2.1***	70% [63]

****, ***, **, * Significant at the 1, 5, 10, and 15 percent levels, respectively

NOTE: The t-statistics are in parentheses, and N, the number of companies in the sample are in square brackets.

5.1.2 Other Considerations in the Ordinary Least Squares Regressions for the M_M Portfolio

As mentioned previously, the M_M portfolio of R&D alliance dealings, seem to be perceived by the market as value-destroying events. Several avenues have been considered in order to verify whether this outcome is a function of the way in which the adjusted model was constructed, or if the outcome simply reveals that this type of partnership signals information which is not well-received by financial market participants.

The first possible explanation for the negative result in the M_M sub-sample using the adjusted regression model is the consideration of firms used to match to the event portfolio. Table 14 presents the number of firms distributed by market value compared to the distribution of all active publicly traded firms used in the random selection process.

Table 14: Market Value Distribution of Event Firm Samples versus Total Sample and versus Market

Market Value Groupings		M_M	M_N_NL	M_N_L	ALL	MARKET
1	<=1000	2%	7%	3%	3%	77%
2	>1000 & <=5000	25%	25%	32%	30%	15%
3	>5000 & <=20000	30%	29%	29%	31%	6%
4	>2000 & <=50000	27%	23%	22%	22%	1%
5	>50000	16%	16%	15%	14%	1%

Given that the only two criteria used to match control firms to event firms were debt-to-market and R&D-to-Sales ratio groupings, the size of the firm was not considered. However, as is shown in the table, event firms tend to be in the top quintiles of market value. Hence they tend to be larger than the average firm in the market list. In order to account for this factor, the control portfolio was re-constructed in the case of the M_M event portfolio, after excluding the bottom quintile of active market firms from the list where random selections are done. This procedure was done in the hopes of eliminating any bias in the original estimates due to size discrepancies between the event and control portfolio. Due to this additional constraint, the sample from which random draws were made to construct the control portfolio was much smaller. Therefore only two firms were matched to each event firm as opposed to the nine firms selected in the initial matching.

Table 15 summarizes the previous OLS unadjusted and adjusted results versus the new adjusted alpha calculation, accounting for size. The first two rows document the outcome of the one-factor Fama and French model and the bottom half of the table documents the outcome of the three-factor model. It reveals that negative abnormal returns are still apparent, significant at the 10 and 5% level for the one- and three-factor models respectively. The value of abnormal performance, however, is slightly lower than that observed in the initial adjusted-alpha results. A value of -1.57% in the three-factor model versus -2.07% in the initial adjusted Fama and French model. This may indicate that size is not the primary factor driving the negative and significant results

Table 15: Adjusted OLS Results for M_M Portfolio when Considering Size

For the M_M portfolio the Adjusted and Unadjusted alpha results from the initial regression from table 11 are compared to the estimated adjusted Fama and French 1-factor & 3-factor model after considering the size criteria (in the right-hand box). The following equations were therefore estimated for the 1-factor and 3-factor model respectively:

$$R_{p,t} - R_{c,t} = a_p + b_p(R_{m,t} - R_{f,t}) \text{ and } R_{p,t} - R_{c,t} = a_p + b_p(R_{m,t} - R_{f,t}) + s_p(SMB_t) + h_p(HML_t)$$

Where, $R_{c,t}$ is the return of the control portfolio, which is constructed based on similar R&D-to-Sales Ratio and Debt-to-Market Value levels as was the case in the initial adjusted alpha estimation. However, rather than selecting control firms from a list of all active companies over the period under study, in this case, all firms identified as belonging to market value grouping 1 or the ≤ 1000 grouping, were removed from the list of possible selections. The resulting control portfolio was therefore more similar in terms of size to the event portfolio.

	Value Weight					
	OLS Results		Initial Adj Alpha Results		Adj Alpha Results accting for size	
	a (t-statistic)	R ² [N]	Adjusted a (t-statistic)	Adjusted R ² [N]	Adjusted a (t-statistic)	Adjusted R ² [N]
M_M 1-Factor	-0.11 (-0.15)	0.50 [39]	-2.37 (-2.37)***	0.40 [351]	-1.87 (-1.91)***	46% [78]
M_M 3-Factor	0.16 (0.2)	0.55 [39]	-2.07 (-2.03)***	0.48 [351]	-1.57 (-1.58)**	54% [78]

****, ***, **, * Significant at the 1, 5, 10, and 15 percent levels, respectively

NOTE: The t-statistics are in parentheses, and N, the number of companies in the sample are in square brackets.

found in the M_M sample. The robustness of these results indicate that the market seems to exact a penalty on R&D alliance announcements in the three months following the event. When considering the characteristics of this sample, several explanations are possible for this unusual response. First, as was discussed earlier, the firms that make up the IRI leaderboard tend to be the largest companies in their respective industries and in the market as a whole. In addition, they have above average R&D to sales ratios and below average leverage ratios. Consequently, when examining the M_M sub-sample, one must consider that both partners are possibly market leaders, and high R&D investors, unlike the two other sub-samples where partners chosen may be smaller or may involve private companies or gov't/university institutions. Second, as is reported in table 4, the M_M sub-sample has the largest proportion of its announcements involved in multiple partnerships or joint ventures, once again with other member firms. These results suggest that there is in fact a differential response to R&D collaboration announcements in the market depending on the type of partner chosen. This is consistent with the statement

made by Hall (2002) that a company's investment decision varies not only with the type of investment but also with the source of funds. Additionally, Hagedoorn (2002) mentions that joint ventures tend to have higher organizational costs as well as higher failure rates. Note also that joint ventures are less flexible forms of partnering and are considered more long term in nature than contractual agreements and hence may require a longer period to reap benefits in the market. The fact that the M_M subsample tends to have a greater proportion of announcements involving multiple firms, may also suggest a greater difficulty in managing the collaborative relationship. In this case two top R&D spenders choosing to partner together sends a negative signal to the market. Another possible explanation is the fact that much of the output of R&D investment is knowledge and know-how, which is an intangible asset and is difficult to keep secret. Although these are problems faced by all firms entering alliances, the problem may be more pronounced for large firms since these are firms that are less willing to take high risks for high returns given their more stable structures as opposed to a smaller firm that may have a great idea but little capital to finance it. Hence partnerships between large firms may tend to suggest the lemon hypothesis where firms will outsource their information advantage on certain products or ideas that have relatively poor prospects as suggested by Pisano (1997).

Another distinction to be made with the M_M sub-sample versus the two other sub-samples is the fact that these portfolios include both partners as opposed to the case of M_N_NL and M_N_L that include only the IRI member returns. In order to address the potential differential returns that may be attributed to the partners involved, the M_M sample was separated further between dominant versus smaller partners. The dominant status in each partnership was determined according to firm's size. The following two tables (tables 16 and 17) summarize both equally-weighted and value-weighted, unadjusted and adjusted abnormal returns for both the one-factor and three-factor model. Notice that the sum of the number of firms in the dominant and small firm samples is higher than the total number of firms in this sample. The reason for this is that some of the firms in the M_M sample may be considered dominant partners for certain announcements and small partners for other announcements depending on their *relative*

size.⁶ For example, a company like Oracle is considered the smaller player when partnering with IBM, yet in an announcement of an alliance between Oracle and Compaq Computer, it is considered the dominant partner. The conclusion drawn from the regression on the sample separated according to relative size demonstrates that only in the case of the one-factor adjusted alpha, are significant negative abnormal returns evident. However it is important to note that the R^2 values of the dominant partner sample is very low, suggesting that the factors considered do not explain a great portion of the returns to these firms. Another aspect to consider is the small sample size, a consequence of taking a cross-section of an already small sample. Therefore it is difficult to draw any clear conclusions from these regressions however what is evident is that there may be differences in the returns to each partner despite the difficulty of appropriating the returns to an intangible asset such as knowledge.

Table 16: OLS Results of 1-Factor Model for M_M Portfolios of Dominant versus Small Partners

Both unadjusted and adjusted (i.e. equations 1 and 5 respectively) regressions were estimated again for two sub-samples of the M_M portfolio. Sub-samples were separated according to the identification of a dominant partner in each alliance announcement, where dominance is determined according to firm size.

$$R_{p,t} - R_{f,t} = a_p + b_p(R_{m,t} - R_{f,t}) \dots \dots \dots \text{Unadjusted 1-factor model;}$$

$$R_{p,t} - R_{c,t} = a_p + b_p(R_{m,t} - R_{f,t}) \dots \dots \dots \text{Adjusted 1-factor model.}$$

All variables are defined as in previous regressions, and control portfolios are constructed according to the same criteria, namely, R&D to sales ratio and leverage ratio groupings.

	Equal Weight				Value Weight			
	a (t-stat)	R ² [N]	Adj a (t-stat)	Adj R ² [N]	a (t-stat)	R ² [N]	Adj a (t-stat)	Adj R ² [N]
Dominant	2.22 (1.84)**	3.44% [22]	1.08 (0.76)	1% [198]	3.43 (1.73)**	0.06% [22]	1.41 (0.74)	1% [198]
Smaller Partner	0.193 (0.17)	20% [32]	-0.881 (-0.75)	11% [288]	-0.33 (-0.31)	32% [32]	-1.99 (-1.61)**	31% [288]

****, ***, **, * Significant at the 1, 5, 10, and 15 percent levels, respectively

NOTE: The t-statistics are in parentheses, and N, the number of companies in the sample are in square brackets.

⁶ Out of the 39 companies in the M_M sample, 38% or 15 firms are in both the relatively dominant and relatively small partner portfolios.

Table 17: OLS Results of Three-Factor Model for M_M Portfolios of Dominant versus Small Partners

Both unadjusted and adjusted (i.e. equations 2 and 6 respectively) regressions were estimated again for two sub-samples of the M_M portfolio. Sub-samples were separated according to the identification of a dominant partner in each alliance announcement, where dominance is determined according to firm size.

$$R_{p,t} - R_{f,t} = a_p + b_p (R_{m,t} - R_{f,t}) + s_p (SMB_t) + hp(HML_t) \dots \dots \dots \text{Unadjusted 3-factor model}$$

$$R_{p,t} - R_{c,t} = a_p + b_p (R_{m,t} - R_{f,t}) + s_p (SMB_t) + hp(HML_t) \dots \dots \dots \text{Adjusted 3-factor model}$$

All variables are defined as in previous regressions, and control portfolios are constructed according to the same criteria, namely, R&D to sales ratio and leverage ratio groupings.

	Equal Weight				Value Weight			
	a (t-stat)	R ² [N]	Adj a (t-stat)	Adj R ² [N]	a (t-stat)	R ² [N]	Adj a (t-stat)	Adj R ² [N]
Dominant	2.05 (1.82)**	4% [22]	1.15 (0.74)	3% [198]	4.11 (1.91)**	2% [22]	2.17 (1.05)	5% [198]
Smaller Partner	1.309 (1.19)	36% [32]	-0.121 (-0.10)	26% [288]	0.732 (0.74)	52% [32]	-0.86 (-0.76)	52% [288]

****, ***, **, * Significant at the 1, 5, 10, and 15 percent levels, respectively

NOTE: The t-statistics are in parentheses, and N, the number of companies in the sample are in square brackets.

5.1.3 Ordinary Least Squares Results for Overall Sample, Considering Experience in R&D Alliances

The sample of ALL event firm announcements was further divided into two groups, the first involving firms classified as frequent announcers during the period studied and the second is composed of infrequent event firms. Method of separating the sample into these two groups was described in the methodology section. The frequency variable is used as a proxy for the level of experience IRI member firms have in participating in collaborative activities. Tables 18 and 19 report the results of the regular and adjusted alphas, for the 1-factor and the 3-factor models respectively. As before, I will focus on the three-factor model in the discussion of the results. Firms that are more frequently involved in R&D alliances result in intercepts that are positive and significant at the 1% level. In the equally-weighted case, the abnormal return is equivalent to 1.42% and in the value-weighted instance it is 1.7% per month, both of which are statistically

significant at the 1% level. In the case of the infrequent sample, intercept results of both the equally- and value-weighted regressions, are negative and insignificant.

In contrast to the regular intercept estimation, the adjusted intercept produces different results in both the frequent and infrequent portfolios of event firms. Insignificant results are generated in the case of the frequent sample, which was previously found to be positive using the unadjusted Fama and French intercept. For the infrequent portfolio of firms, negative and significant intercepts result, at approximately -1.8% and -2.23% corresponding to the equally- and value-weighted regressions. If we focus primarily on the adjusted intercept outcomes, the frequent event firms seem to be in line with the efficient market hypothesis, whereas the infrequent event firms tend to destroy value. This suggests that lack of experience in R&D partnering, may have an impact on the market's reaction to this type of news. Similar to Anand and Khanna (2000) and Baum, Calabrese and Silverman (2000), both unadjusted and adjusted outcomes show that more frequent announcers do result in more favorable outcomes relative to their infrequent counterparts.

Table 18: OLS Results of 1-Factor Model of Frequent versus Infrequent Event Firms

Both unadjusted and adjusted (i.e. equations 1 and 5 respectively) regressions were estimated again for two sub-samples of the overall portfolio. Sub-samples were separated according to the frequency of event firms' participation in R&D alliances. Frequency was determined according to each firm's yearly number of announcements relative to the average number of announcements made per company per year. For example, if a company made more announcements than the average for a given year it would be classified as frequent. This is carried out for each year over the four-year period under study (1994-1998) therefore a company is part of the frequent event firm portfolio if it is classified as frequent in more than 2 of the 4-years and infrequent if it made less than the average number of yearly announcements in more than 2 of the 4 years. This resulted in 17 companies recognized as frequent and 46 as infrequent, the remainder falling in neither category according to the methodology used to distinguish between the two groups.

$$R_{p,t} - R_{f,t} = a_p + b_p(R_{m,t} - R_{f,t}) \dots \dots \dots \text{Unadjusted 1-factor model;}$$

$$R_{p,t} - R_{c,t} = a_p + b_p(R_{m,t} - R_{f,t}) \dots \dots \dots \text{Adjusted 1-factor model.}$$

All variables are defined as in previous regressions, and control portfolios in the adjusted regression model, are constructed according to the same criteria, namely, R&D to sales ratio and leverage ratio groupings.

	Equal Weight				Value Weight			
	a (t-stat)	R ² [N]	Adj a (t-stat)	Adj R ² [N]	a (t-stat)	R ² [N]	Adj a (t-stat)	Adj R ² [N]
Frequent	0.69 1.09	53% [17]	-1.39 0.23	24% [17]	1.01 1.49*	47% [17]	-1.06 -1.08	30% [17]
Infrequent	-0.813 -1.32	51% [46]	-2.263 -2.23***	28% [46]	-0.46 -0.85	47% [46]	-2.46 -3.37****	41% [46]

****, ***, **, * Significant at the 1, 5, 10, and 15 percent levels, respectively

NOTE: The t-statistics are in parentheses, and N, the number of companies in the sample are in square brackets.

Table 19: OLS Results of 3-Factor Model of Frequent versus Infrequent Event Firms

Both unadjusted and adjusted (i.e. equations 2 and 6 respectively) regressions were estimated for two sub-samples of the overall portfolio. Sub-samples were separated according to the frequency of event firms' participation in R&D alliances. See the previous table description of frequency determination.

$$R_{p,t} - R_{f,t} = a_p + b_p (R_{m,t} - R_{f,t}) + s_p (SMB_t) + hp(HML_t) \dots \dots \dots \text{Unadjusted 3-factor model}$$

$$R_{p,t} - R_{c,t} = a_p + b_p (R_{m,t} - R_{f,t}) + s_p (SMB_t) + hp(HML_t) \dots \dots \dots \text{Adjusted 3-factor model}$$

All variables are defined as in previous regressions, and control portfolios are constructed according to the same criteria, namely, R&D to sales ratio and leverage ratio groupings.

	Equal Weight				Value Weight			
	(t-statistic)	R2 [N]	a (t-)	Adjusted R2 [N]	(t-statistic)	R2 [N]	a (t-)	Adjusted R2 [N]
Frequent	1.42 2.55****	69% [17]	-0.61 -0.54	37% [17]	1.70 2.92****	66% [17]	-0.17 -0.19	50% [17]
Infrequent	-0.241 -0.41	62% [46]	-1.794 -1.69**	32% [46]	-0.48 -0.83	47% [46]	-2.23 -2.93****	45% [46]

****, ***, **, * Significant at the 1, 5, 10, and 15 percent levels, respectively

NOTE: The t-statistics are in parentheses, and N, the number of companies in the sample are in square brackets.

5.2 Results by Industry

Taking each of the four portfolio samples presented above separately, this section reveals the abnormal performance experienced by firms in the various industries represented in the IRI listing. Note that in this section only value-weighted results are presented since, as was observed in the previous sections, equally-weighted regressions yield the same conclusions but with smaller magnitudes of abnormal returns. Table 20 demonstrates the OLS results per industry using the Fama and French one-factor market model (the three factor model was also examined and yielded similar findings). The market benchmarks used are the value-weighted average return on all stocks in each of the industries analyzed (as highlighted in Table 5). These include: business services; computers; drugs; chips; laboratory equipment; household; telecommunications; chemicals; and auto industries.

Regular one-factor OLS Results of all IRI firms presented in table 20, indicate that the only industry that experienced significant abnormal performance in the three months

following the alliance announcement is the business services industry. A 1.41% monthly abnormal return is presented in Table 20 for the ALL portfolio or 4.24% over the three-month period. The key companies involved in announcements in this industry include companies such as Microsoft, Oracle, Compaq Computer, Computer Associates, Automatic Processing, BMC Software, Electronic Arts, Cadence Design Systems, and Peoplesoft. These companies also make up a large proportion of the total announcements made, as was indicated in table 5, with approximately 21 announcements per firm. Only the laboratory equipment and telecommunications industries have a higher average number of announcements per firm than the business services industry. However only 2 companies as opposed to the 9 companies found in business services, are represented in the laboratory equipment and telecommunications industries. Another key observation from table 20, is the fact that the business services industry is much more diverse in its selection of partnering firms. With the exception of the Chips industry, it is the only other industry, which chooses to partner with both public and non-public companies/organizations, as well as with other IRI member firms. Given that business services represents such a large proportion of the alliance activity of the entire portfolios, this may explain the reason the overall portfolio return results from table 11 in the first section, were positive and significant in the unadjusted OLS model.

Industry Concentration ratios are presented in table 21 using the widely accepted CR₄ measure. The second measure of concentration described in the methodology section (HHI), was also calculated, however outputs are not presented since similar conclusions resulted. Both indices imply that most of the firms are focused in low concentration or highly competitive environments. Consistent with the Schumpeterian hypothesis on market concentration and the findings of Doukas and Switzer (1992), the results provide evidence that a differential market response to the formation of R&D partnerships may exist. The Business Services industry is among one of the industries with the lowest concentration ratios, implying that announcements of R&D alliances are perceived as positive information by the market when partnering companies are found in highly competitive industries. This may be considered support for the Schumpeterian hypothesis, since it states that industries with low concentration levels are not in a

position to gain from spending on R&D. Hence forming alliances with other firms may be the alternative for companies in these types of industries to reap benefits and grow. Nonetheless, the fact that not all low concentration industries are responding in the same fashion may imply that there are other factors influencing the market response to these events. Note that unlike R&D in-house spending, R&D alliance formation requires much more attention to several factors outside of the R&D project itself. Hence concentration levels alone cannot determine fully the effectiveness of an alliance event. Another interesting finding from the concentration ratio table, is that those more highly concentrated industries not only are consistent with the market efficiency hypothesis with no abnormal returns in the three months following the event, but they also are the industries that are more likely to partner with non-public companies or public companies that are not among the top R&D spenders.

Table 20: Portfolio Returns by Industry – 1-factor model

Abnormal returns are estimated for the 3-month post-announcement horizons for the combined sample of alliance announcements as well as for each of the sub-samples from the period 1994-1998 by industry. Value-weighted (rebalanced monthly) calendar time portfolio returns are calculated each month from all firms involved in an R&D collaborative activity in the previous 3 months, for each industry. The monthly excess returns to the calendar time portfolios, $R_{p,t} - R_{f,t}$, are regressed on the Fama and French 3 factor market model in order to calculate the unadjusted intercept:

$$R_{p,t} - R_{f,t} = a_p + b_p(R_{m,t} - R_{f,t}) + s_p(SMB_t) + h_p(HML_t)$$

$R_{m,t}$, the excess return on the market (note different market used for each industry regression to take only those active firms in the same industry as event firms), is the value-weight return on all NYSE, AMEX, and NASDAQ stocks separated by industry (from CRSP) minus the one-month Treasury bill rate (from Ibbotson Associates). SMB_t is the difference between the returns of value weighted portfolios of small and big firm stocks, and HML_t is the difference between the returns of value-weighted portfolios of high and low book-to-market stocks. See Fama and French (1993) for a complete description.

	ALL			M_M			M_N_NL			M_N_L		
	Alpha	R ²	# of Firms	# of Events	Alpha	R ²	# of Firms	# of Events	Alpha	R ²	# of Firms	# of Events
Business Services Industry	1.41 (1.75)**	56%	9	181	1.37 (1.37)	52%	5	33	3.10 (3.63)***	40%	8	71
Computer Industry	0.09 (0.2)	84%	10	176	1.97 (1.79)**	49%	8	32	0.96 (0.92)	39%	7	74
Drug Industry	-0.07 (-0.16)	76%	14	144	NA	NA	NA	NA	-0.26 (-0.45)	69%	14	69
Chips Industry	0.28 (0.48)	81%	7	102	-0.61 (-0.56)	55%	5	29	0.63 (0.66)	53%	5	39
Laboratory Equipment Industry	-0.33 (-0.65)	88%	2	66	-0.07 (-0.17)	94%	2	16	NA	NA	NA	NA
Household Industry	-0.27 (-0.5)	68%	5	54	NA	NA	NA	NA	1.33 (1.48)*	37%	4	21
Telecommunications Industry	0.62 (0.62)	31%	2	49	NA	NA	NA	NA	NA	NA	NA	NA
Chemicals Industry	0.74 (1.07)	50%	3	27	NA	NA	NA	NA	-0.03 (-0.03)	43%	2	2
Auto Industry	-0.61 (-0.84)	41%	4	15	NA	NA	NA	NA	NA	NA	NA	NA

***, **, *, Significant at the 1, 5, 10, and 15 percent levels, respectively
NOTE: The t-statistics are in parentheses, and N_i the number of companies in the sample are in square brackets.

Table 21: : Industry Concentration Ratios

Calculated based on the CR₄ methodology $CR_4 = s_1 + s_2 + s_3 + s_4$,

where s_i = the market share of the i th firm.

If CR₄ is close to 0, then the industry is considered to be extremely competitive, since the four largest firms have an insignificant market share. The generally accepted rule by economists is that if the CR₄ measure is less than 40%, then the industry is considered to be very competitive, with several firms competing but none dominating the market. If CR₄ is more than 90%, the industry is considered a monopoly. Also presented is the number of event firms in each industry and the average number of announcements per company

Industry	CR ₄	Concentration Level	# of Companies	Avg Announcements Per Company
Household Industry	52%	High Concentration	5	11
Computer Industry	46%	High Concentration	10	18
Auto Industry	43%	High Concentration	4	4
Chemicals Industry	37%	Low Concentration	3	9
Drug Industry	36%	Low Concentration	14	10
Laboratory Equipment Industry	34%	Low Concentration	2	34
Business Services Industry	28%	Low Concentration	9	21
Chips Industry	27%	Low Concentration	7	15
Telecommunications Industry	21%	Low Concentration	2	25

Table 20 also presents the results of the regressions by industry for each of the portfolios of differing choice of partners. The M_M Portfolio includes only firms that were on the IRI list of top R&D spenders and are publicly traded on an American exchange. Due to the small number of announcements in this category, only four industries included sufficient amount of data to be included in the analysis, namely, the computer, chips, laboratory equipment, and business services industries. Only the computer industry sample results in positive abnormal returns at the 10% significance levels. Unlike in the overall results, the computer industry is a relatively more concentrated industry and yet is indicating positive abnormal performance in the months following an R&D alliance announcement. The fact that the results of the per industry samples indicate a more positive impact on the M_M portfolio does not necessarily contradict the initial findings of the overall M_M portfolio, which indicated a negative or insignificant overall impact. The industries considered in this section are those for which the most data points are available. Consequently, the per industry samples are comprised of those firms that frequently make announcements, since each industry on it's own does

not include enough firms to perform a regression analysis. According to the results regarding level of frequency in table 18 and 19, the sample of firms frequently participating in alliances tends to result in positive and significant abnormal returns, whereas the infrequent participants result in significantly negative abnormal returns. Subsequently, the results per industry in the M_M sub-sample indicate positive or insignificant results since the regression analysis is focused on the more frequent participants.

The industry breakdown of the sample of IRI firms that engaged in R&D collaboration with non-member and non-listed firms or organizations are presented under M_N_NL of the same table. This set of regressions indicates that both the household and business services industries demonstrate positive abnormal returns in the three months following the alliance announcement, at 15% and 1% levels of significance for the respective industries.

M_N_L includes the final sub-sample of firms, in particular the alliance announcements between IRI member firms with non-member public firms. It also exhibits positive abnormal returns solely in the business services industry at a 5% level of significance with a monthly abnormal return of 1.79%.

It is important to note that the R^2 of these regressions varies between sub-samples and by industry. There are several reasons that may explain this phenomenon, the most important being the fact that each of the industry portfolios are represented by 14 or less companies that are very actively announcing R&D alliances. Small sample size was also the case when splitting the M_M portfolio between Dominant and Small partner firms. In that case the dominant partner sample included fewer companies and was the sample with the higher average market value. As a result, the market industry portfolio, which is comprised of 600-800 firms over the period studied, may not entirely describe the return structure of these companies. Hence the few data points, coupled with the fact that the member companies are among the largest in their respective industries may explain the reason for such small R^2 values.

Since the business services industry resulted in positive abnormal performance consistently across all sub-samples, there is interest in verifying if these results hold when

taking into consideration the potential mispricing of the Fama and French (1993) model. Similar to the findings of the M_M sample earlier, table 22 demonstrates that when using a portfolio of control firms to evaluate potential abnormal performance, regression outcomes indicate a -2.06% estimate of alpha significant at the 10% level. This negative performance may be another explanation for the overall negative result found in the M_M industry since the business services companies make up a large proportion of the announcements in this particular sub-sample. In the case of the two other sub-samples, the negative performance of this industry is offset by other industries since business services, in particular, is not over-represented in the other sub-samples.

Table 22: Business Service Industry Adjusted alpha versus regular OLS alpha results

For the Business Services industry portfolio the Unadjusted alpha results from the initial regression in table 20 are compared to the estimated adjusted Fama and French 1-factor. The following equation was estimated:

$$R_{p,t} - R_{c,t} = \alpha_p + b_p(R_{m,t} - R_{f,t})$$

Where, $R_{c,t}$ is the return of the control portfolio, which is constructed based on similar R&D-to-Sales Ratio and Debt-to-Market Value levels as was the case in the initial adjusted alpha estimation.

	Value Weight			
	a (t-statistic)	R ² [N]	Adjusted a (t-statistic)	Adjusted R ² [N]
Business Services	1.41	56%	-2.06	40%
(1-Factor)	(1.75)**	[9]	-1.70**	[9]
Business Services	1.25	66%	-1.81	48%
(3-Factor)	(1.43)*	[9]	-1.30	[9]

****, ***, **, * Significant at the 1, 5, 10, and 15 percent levels, respectively

NOTE: The t-statistics are in parentheses, and N, the number of companies in the sample are in square brackets.

5.3 Results of Non-Event Portfolio Simulations and Mean Calendar Time Abnormal Returns (MCTARs)

This last section conveys the results of the simulations of control portfolios in order to confirm the robustness of the initial Fama and French 3-factor estimation model, for each of the sub-samples of partnering portfolios (i.e. M_M, M_N_NL, and M_N_L). Moreover the final methods of calculating abnormal performance, more specifically the CTARs, are presented here. There are several implications for the construction of the

1000 pseudoportfolios, matched based on leverage and R&D intensity. The first is that it permits the construction of an empirical distribution of non-event alphas for each of the main sub-samples of this study (M_M, M_N_NL, and M_N_L). This allows for testing of the original OLS estimates of alpha in a more representative empirical distribution constructed based on 1000 random draws. Here the null hypothesis is that $\alpha_{(OLS)} = \hat{\alpha}$, where $\hat{\alpha}$ is the mean intercept of the 1000 non-event pseudoportfolios. Second, constructing the simulated portfolios provides evidence regarding the distribution characteristics of the sample, hence the null hypothesis $\hat{\alpha} = 0$ is also important to assess. Third, the 1000 simulated portfolios are also used in the calculation of MCTAR as presented in the methodology section and as calculated in previous papers (Lyon, Barber, and Tsai, 1999; Mitchell and Stafford, 2000; Boehme and Sorescu, 2002; Andre, Kooli, and L'Her, 2004). This enabled the construction of an empirical distribution of event portfolio alphas, where control portfolio returns are subtracted from event portfolio returns and regressed on the three Fama & French factors. In this case the null hypothesis is that MCTAR = 0, or that the mean abnormal return of event firms is 0 in the 3 months following the R&D alliance announcement. Finally, the careful construction of the portfolios accounting for overlap of alphas makes the comparison of abnormal returns between portfolios possible. Consequently, this section also validates whether the abnormal return related to one form of partnering is more significant than that of another form of partnering. This is performed for both the comparison of original OLS estimates tested in the non-event distribution of the difference of intercepts, as well as for the difference of MCTARs between samples. These simulation methods help mitigate some of the statistical problems potentially existent in the initial regression results, which assumes that the data is normally distributed. Given the small sample of firms used in this study, it is likely that this assumption may not be accurate.

5.3.1 OLS Alpha Estimates using Empirically Constructed Distribution

The empirical distribution of the alphas for each sub-sample, generated from the 1000 non-event control portfolios and their respective cumulative distribution's, are presented in figures 9 to 11 for the equally-weighted regressions and figures 12 to 14 for

the value-weighted regressions. Each of the figures includes the descriptive statistics of the empirical distribution clearly indicating that control firm alphas are not normally distributed. The kurtosis measures reveal that in all six equally-weighted and value-weighted sub-samples the distribution is more peaked than is the normal distribution with a value greater than 3 in all cases. Moreover, the skewness measures are positive in all six figures, demonstrating that data is skewed to the right. *Note all results discussed in the text and figures that follow are summarized at the end of section 5.3.2 in table 25.*

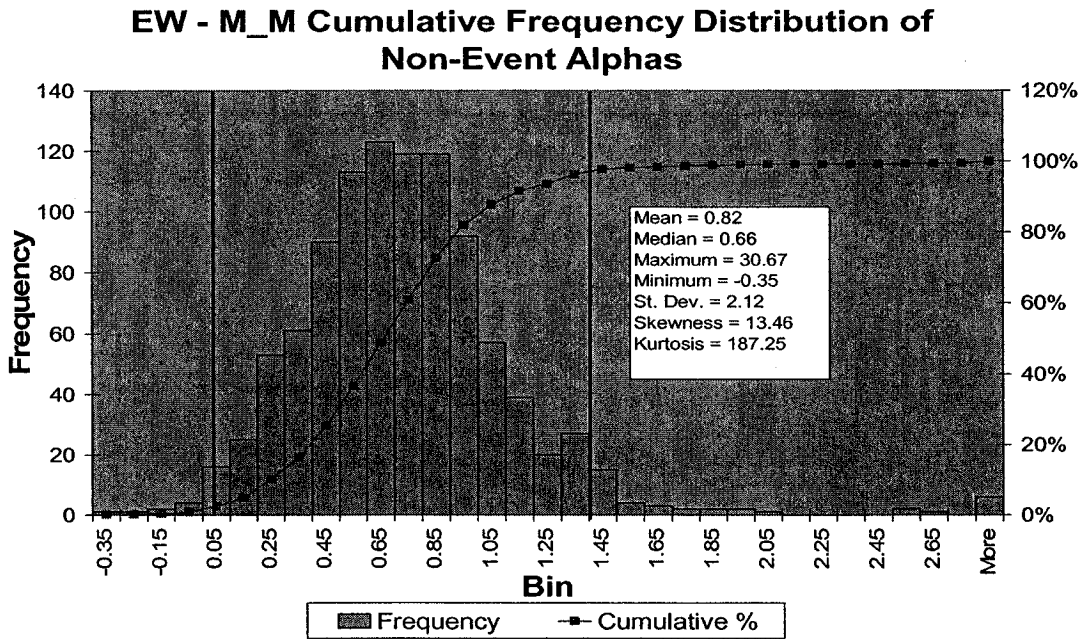


Figure 9: Equally-Weighted Cumulative Frequency Distribution of Non-Event Alphas for M_M Sub-sample

1000 non-event alphas were generated from the following three factor regression model:

$$R_{c,t} - R_{f,t} = a_p + b_p (R_{m,t} - R_{f,t}) + s_p (SMB_t) + h_p (HML_t)$$

Where $R_{c,t}$ is the return of the matched non-event portfolio and the other variables are as defined previously. a_p thereby represents the non-event intercept for the group of firms matched to the M_M equally weighted monthly event firm portfolios. This is reiterated 1000 times in order to generate the empirical distribution above. Graph includes descriptive statistics of the distribution. Also displayed on the graph are the upper and lower limits beyond which the original OLS event alphas will be considered significantly different from zero (note limits are represented by black bold lines at either end of the distribution and correspond to the 95% level of confidence).

Looking at the equally weighted matched M_M portfolio intercepts in figure 9, the bold black lines at either end of the distribution indicate that an alpha value less than 0.05% or greater than 1.45% will result in the rejection of the null that $a_{(OLS)}$ is equal to \hat{a} . That

being established, the *original equally weighted 3-factor OLS model* resulted in an alpha estimate of 0.577 from table 11, which according to the empirical distribution generated from the 1000 non-event repetitions, is not significantly different from zero. Note that the critical values presented are for a two-tailed test. This is consistent with the OLS regression estimates, which indicated insignificant positive abnormal returns when estimated with a standard normal distribution. With the aim of determining whether the simulation is a better approximation of the distribution than the standard normal, I test whether the mean of the empirical distribution is equal to zero, $\hat{\alpha} = 0$. Calculated z-values indicate that the null hypothesis in this case is rejected since the calculated z-value falls outside of the acceptance region. Hence, the $\hat{\alpha}$ of 0.82 is positive and significant thereby confirming the importance of testing alpha with a simulated empirical distribution.

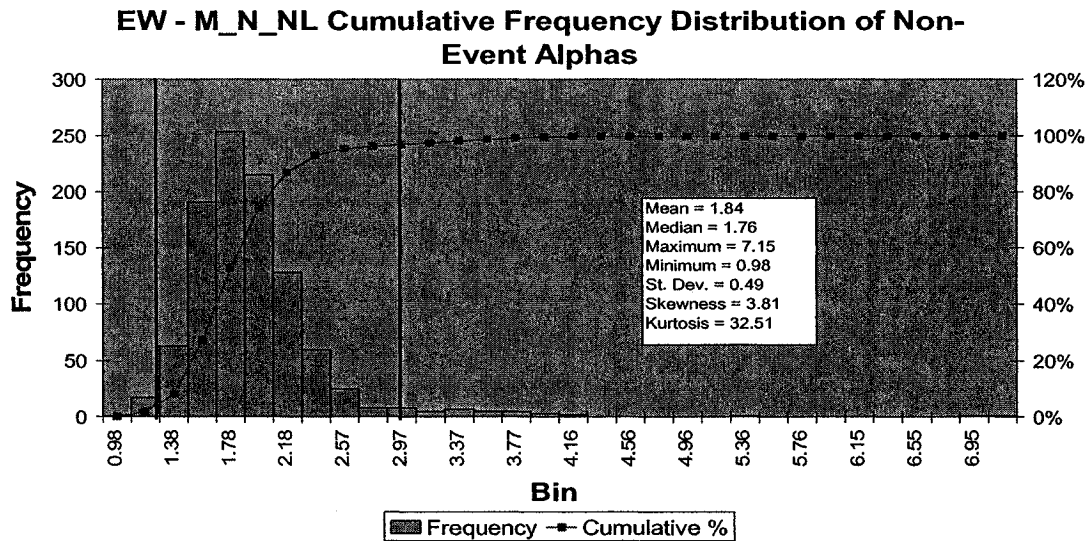


Figure 10: Equally-weighted Cumulative Frequency Distribution of Non-Event Alphas for M_N_NL Sub-sample

1000 non-event alphas were generated from the following three factor regression model:

$$R_{c,t} - R_{f,t} = a_p + b_p (R_{m,t} - R_{f,t}) + s_p (SMB_t) + h_p (HML_t)$$

Where $R_{c,t}$ is the return of the matched non-event portfolio and the other variables are as defined previously. a_p thereby represents the non-event intercept for the group of firms matched to the M_N_NL equally weighted monthly event firm portfolios. This is reiterated 1000 times in order to generate the empirical distribution above. Graph includes descriptive statistics of the distribution. Also displayed on the graph are the upper and lower limits beyond which the original OLS event alphas will be considered significantly different from zero (note limits are represented by black bold lines at either end of the distribution and correspond to the 95% level of confidence).

The next figure displays the resulting empirical distribution for the 1000 equally-weighted matched portfolios of the M_N_NL event portfolio. For alpha values falling

between 1.22% and 2.97%, the null that $a_{(OLS)} = \hat{a}$ cannot be rejected. In the original OLS regression from table 11 the estimated abnormal return was 0.86%, thereby falling outside the limits and generating significant positive abnormal returns. This is in-line with original findings which indicate positive and significant abnormal performance in the three months following the R&D alliance announcement. When testing whether the mean is significantly different from zero, again the mean value of the distribution is not equal to zero therefore making tests using the simulated distribution more reliable than those using a standard normal distribution.

The last of the equally-weighted non-event pseudoportfolios, M_N_L subsample, is displayed in figure 11. The original OLS estimate of 1.23 is below the upper limit of 1.36% and above the lower limit of 0.2%, therefore the null that $a_{(OLS)}$ is equal to the \hat{a} cannot be rejected. Moreover, the hypothesis that $\hat{a}=0$ in this case is rejected, again providing support for the use of the simulation.

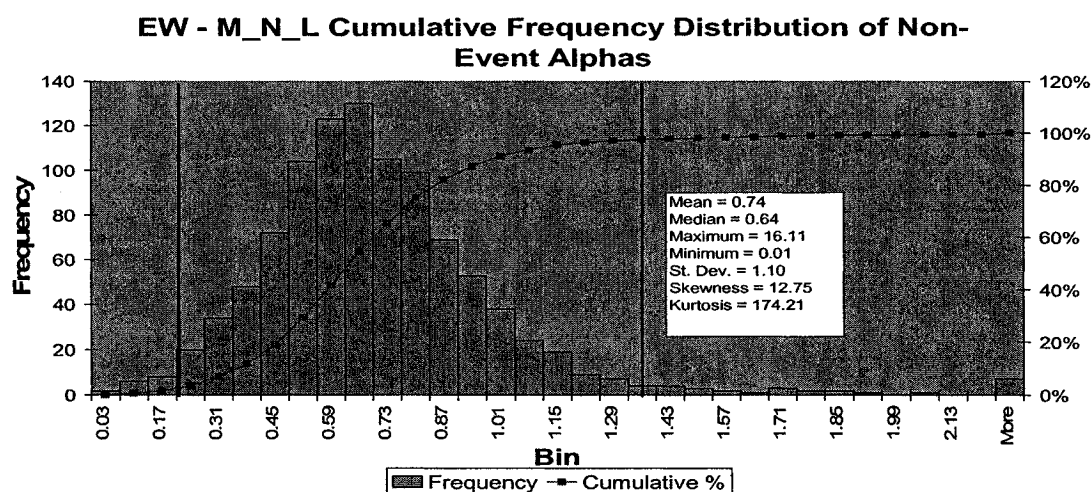


Figure 11: Equally-Weighted Cumulative Frequency Distribution of Non-Event Alphas for M_N_L Sub-sample

1000 non-event alphas were generated from the following three factor regression model:

$$R_{c,t} - R_{f,t} = a_p + b_p (R_{m,t} - R_{f,t}) + s_p (SMB_t) + h_p (HML_t)$$

Where $R_{c,t}$ is the return of the matched non-event portfolio and the other variables are as defined previously. a_p thereby represents the non-event intercept for the group of firms matched to the M_N_L equally weighted monthly event firm portfolios. This is reiterated 1000 times in order to generate the empirical distribution above. Graph includes descriptive statistics of the distribution. Also displayed on the graph are the upper and lower limits beyond which the original OLS event alphas will be considered significantly different from zero (note limits are represented by black bold lines at either end of the distribution and correspond to the 95% level of confidence).

The next three figures demonstrate the shape of the distributions for the value-weighted regressions of the 1000 non-event portfolios. Similar to the equally-weighted findings, the moments of the value-weighted distributions also indicate that the control portfolios are not normally distributed, with positive skewness measures and kurtosis values greater than 3. The latter suggesting a more peaked distribution than the standard normal. That being said, the resulting tests of original alphas in this distribution should yield more accurate results. In the case of the portfolio of member firms partnering together (M_M), the α -value of 0.16% falls within the limits displayed in figure 12 therefore cannot reject the null that $\alpha_{(OLS)} = \hat{\alpha}$. For the member firms partnering with private non-members (M_N_NL), in figure 13, the original value of 1.13% falls within the acceptance region, hence value-weighted alpha estimate is positive but insignificant. This is inconsistent with both original value-weighted OLS estimates as well as with the equally weighted findings previously mentioned. Both these methods had generated positive and significant abnormal returns. This may suggest that the relatively smaller firms in the samples may be driving the abnormal return performance since this abnormal return disappears when regressions are value-weighted. Finally in the case of members partnering with public non-members (figure 14), the 0.93 value that resulted from the OLS regression, is also found to be insignificant as was the case in the equally weighted results however opposite the findings of the original OLS estimate when approximated under the normality assumption. Note that in all three of the value-weighted cases as in the equally weighted simulations, the null that $\hat{\alpha} = 0$ is rejected, revealing the importance of testing intercepts in an empirically constructed distribution as opposed to standard theoretical distributions.

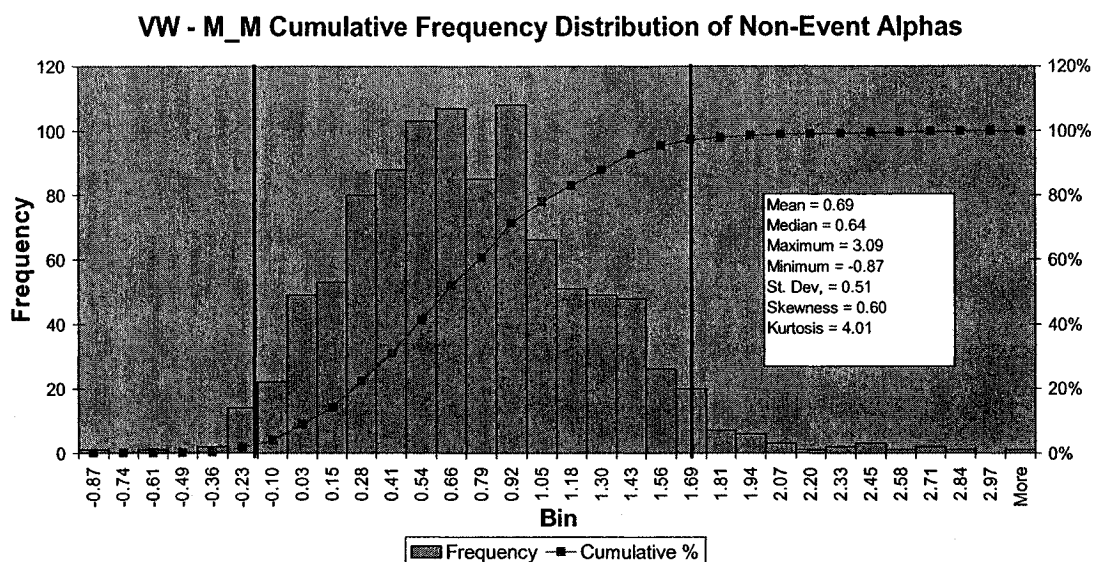


Figure 12: Value-Weighted Cumulative Frequency Distribution of Non-Event Alphas for M_M Sub-sample

1000 non-event alphas were generated from the following three factor regression model:

$$R_{c,t} - R_{f,t} = a_p + b_p (R_{m,t} - R_{f,t}) + s_p (SMB_t) + h_p (HML_t)$$

Where $R_{c,t}$ is the return of the matched non-event portfolio and the other variables are as defined previously. a_p thereby represents the non-event intercept for the group of firms matched to the M_M value weighted monthly event firm portfolios. This is reiterated 1000 times in order to generate the empirical distribution above. Graph includes descriptive statistics of the distribution. Also displayed on the graph are the upper and lower limits beyond which the original OLS event alphas will be considered significantly different from zero (note limits are represented by black bold lines at either end of the distribution and correspond to the 95% level of confidence).

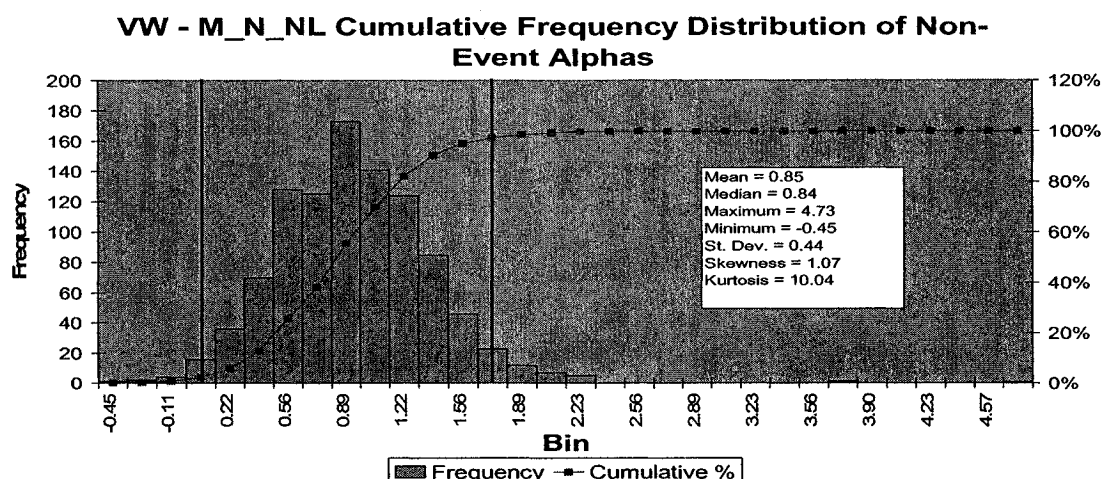


Figure 13: Value-Weighted Cumulative Frequency Distribution of Non-Event Alphas for M_N_NL Sub-sample

1000 non-event alphas were generated from the following three factor regression model:

$$R_{c,t} - R_{f,t} = a_p + b_p (R_{m,t} - R_{f,t}) + s_p (SMB_t) + h_p (HML_t)$$

Where $R_{c,t}$ is the return of the matched non-event portfolio and the other variables are as defined previously. a_p thereby represents the non-event intercept for the group of firms matched to the M_N_NL value weighted monthly event firm portfolios. This is reiterated 1000 times in order to generate the empirical distribution above. Graph includes descriptive statistics of the distribution. Also displayed on the graph are the upper and lower limits beyond which the original OLS event alphas will be considered significantly different from zero

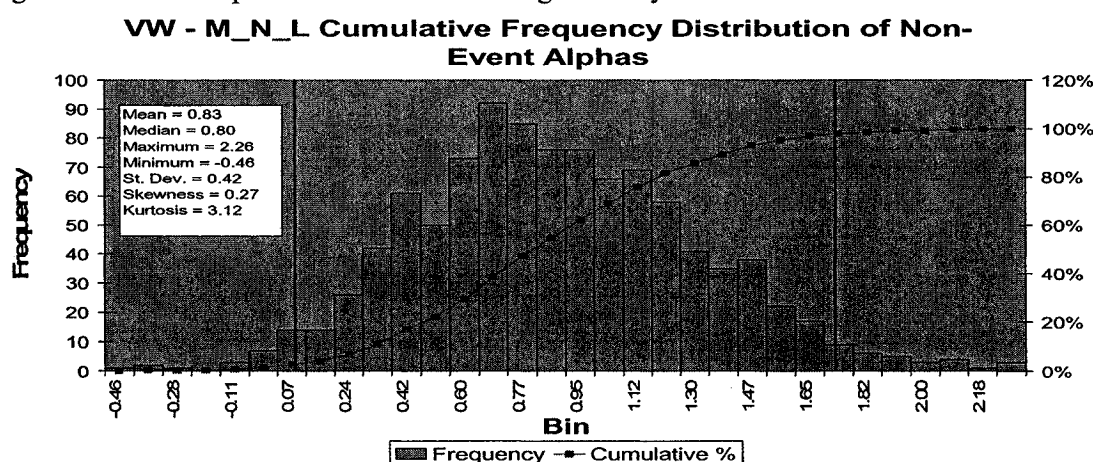


Figure 14: Value-Weighted Cumulative Frequency Distribution of Non-Event Alphas for M_N_L Sub-sample

1000 non-event alphas were generated from the following three factor regression model:

$$R_{c,t} - R_{f,t} = a_p + b_p (R_{m,t} - R_{f,t}) + s_p (SMB_t) + h_p (HML_t)$$

Where $R_{c,t}$ is the return of the matched non-event portfolio and the other variables are as defined previously. a_p thereby represents the non-event intercept for the group of firms matched to the M_N_L value weighted monthly event firm portfolios. This is reiterated 1000 times in order to generate the empirical distribution above. Graph includes descriptive statistics of the distribution. Also displayed on the graph are the upper and lower limits beyond which the original OLS event alphas will be considered significantly different from zero.

The conclusions of this section appear to indicate support for the market efficiency hypothesis that, in the long run, the market adjusts to new information relatively quickly and should not result in abnormal performance. The only exceptions are the equally-weighted results of the two sub-samples of IRI member firms partnering with non-IRI member firms (M_N_NL and M_N_L). The fact that these positive and significant abnormal return disappear when calculated using value-weighted regressions implies that the relatively smaller firms in these sub-samples may be driving the abnormal performance observed in the equally-weighted regressions. The lack of significant abnormal performance of large firms may eliminate any benefits generated by small firms when weighting according to firm size. This is further supported by the fact that the phenomenon of differential results between equally-weighted and value-weighted regressions, is not observed for the subsample of IRI member firms that partner with other members (i.e. M_M). Given that the IRI member firms tend to be among the largest in their respective industries, the market seems to adjust their price accordingly in the long-run probably associated to the greater flow of information and press coverage surrounding these firms. Hence for the M_M sub-sample, whether weighting according to size or not, results in similar findings.

The size of the t-values are also examined in this section, since they give further evidence of the usefulness of estimating simulated portfolios. This method was also employed by Barber, Lyon, and Tsai (1999). Table 23 presents the percentage of times the null hypothesis, that $\hat{\alpha}_i = 0$, is rejected when examining each of the 1000 matched portfolios. It is the probability of rejection given no event. Panel A displays the equally-weighted results and panel B indicates the value-weighted results. Both panels reveal that using the normal distribution is not an accurate approximation of the samples being studied. Namely, using conventional levels of confidence of 95%, we would reject the null less frequently if the normal distribution was used versus the empirical distribution. This may suggest that controlling for leverage and R&D/Sales ratios, may be important in trying to eliminate factors other than the event itself when calculating abnormal performance. It also indicates the importance of a good model to estimate returns so that the alpha is capturing mispricing and not model misspecification.

Table 23: Specification (Size) of Monthly Calendar-Time Portfolio Abnormal Returns of Non-Event Pseudo Portfolios

The analysis of this table is based on 1000 random samples of 46 event months. Each of the matched group of securities is included in the calendar-time portfolio for 3-months following the event of the event firm. The following regression was estimated:

$$R_{c,t} - R_{f,t} = \hat{a}_i + b_i (R_{m,t} - R_{f,t}) + s_i (SMB_t) + h_i (HML_t)$$

Where $R_{c,t}$ is the simple return on the calendar-time portfolio (equally-weighted in Panel A and value weighted in Panel B), $R_{f,t}$ is the return on 3-month Treasury bills, $R_{m,t}$ is the return on a value-weighted market index, SMB_t is the difference in the returns of a value-weighted portfolio of small stocks and big stocks and low book-to-market stocks, and HML_t is the difference in the returns of a value-weighted portfolio of high book to market stocks and low book-to-market stocks. The estimate of the intercept term (\hat{a}_i) provides a test of the null hypothesis that the mean of the simulated distribution is zero. The numbers presented in the first row of each panel represent the percentage of the 1000 random samples that reject the null hypothesis of the mean equal to 0, when the holding period is three months, at a theoretical significance level of 5% in favor of the alternative hypothesis of a significantly negative intercept (i.e. calculated p-value is less than 2.5% at the 5% significance level) or a significantly positive intercept (i.e. calculated p-value is greater than 97.5% at the 5% level of significance). The rows in each panel represent the rejection levels for each of the partnering sub-samples studied, namely, M_M, M_N_NL, and M_N_L.

Samples	Theoretical Cumulative Density Function (%)	
	2.50%	97.50%
Panel A: Equally-Weighted Calendar Time Portfolios		
M_M	0.10%	0.00%
M_N_NL	0.00%	1.80%
M_N_L	0.00%	1.30%
Panel B: Value-Weighted Calendar Time Portfolios		
M_M	2.40%	0.00%
M_N_NL	0.70%	2.70%
M_N_L	1.70%	0.60%

5.3.2 MCTAR Results

In this section, the mean abnormal returns calculated from the 1000 3-factor model regressions are tested and compared to findings from the previous section. Basically the distributions presented in figures 15-20 display the event alphas for 1000 iterations of the regression model that controls for leverage levels and R&D intensity. Here the MCTAR is the mean of the distribution and the null hypothesis is whether $MCTAR = 0$ for each of the sub-samples of partnering firms. Before examining the

MCTARs notice that once again the distributions of event intercepts are not normally distributed as shown by the negative skewness values and the high kurtosis values. This is true in each of the methodologies used, namely equally- and value-weighted. Although skewness and kurtosis values of equally-weighted and value-weighted methodologies both indicate that the frequency distributions do not possess the standard characteristics of a normal distribution, in the case of the value-weighted alphas, skewness and kurtosis measures seem to be closer to the levels associated to a normal distribution. Yet still are slightly more negatively skewed and more peaked than a standard normal distribution.

In the M_M sub-samples, both equally-weighted and value-weighted event portfolio intercepts result in negative MCTARs, -0.48 and -0.55 respectively (see figures 15 and 16). The critical value to test the null hypothesis is calculated as stated in the methodology section is:

$$\frac{\text{Mean}}{\sigma/\sqrt{n}}; \text{ where } \sigma = \text{Standard deviation and } n = \text{the 1000 portfolios.}$$

This tests the significance of the null hypothesis assuming normality. The graphs presented in this section display the distribution of the CTARs or event portfolio abnormal returns, however testing the mean requires the distribution of the MCTARs. In order to construct such a distribution, the exercise of drawing 1000 samples of non-event firms and taking the difference of event minus non-event returns and regressing them on the three factor model, would have to be reiterated 1000 times in order to be able to plot 1000 mean abnormal returns (MCTARs), each of which was calculated from a sample of 1000. Given the very large samples involved in this exercise, it can be assumed that the distribution of MCTARs will approach normality and therefore can use the normal test to determine the significance. For the M_M sub-sample the calculated z-value is -6.48 and -31 for equally- and value-weighted methods respectively. Therefore I conclude that the $\text{MCTAR}_{[M_M]}$ is significantly different from 0. Hence contrary to the original OLS results, which indicate that member firms partnering together produce positive and insignificant results, after accounting for leverage levels and R&D intensity of the sample, this group of firms results in negative abnormal performance in the three months following the R&D alliance announcement. This is, however, consistent with the

adjusted Fama and French model used earlier in this paper (refer to results of table 11 under adjusted-alpha).

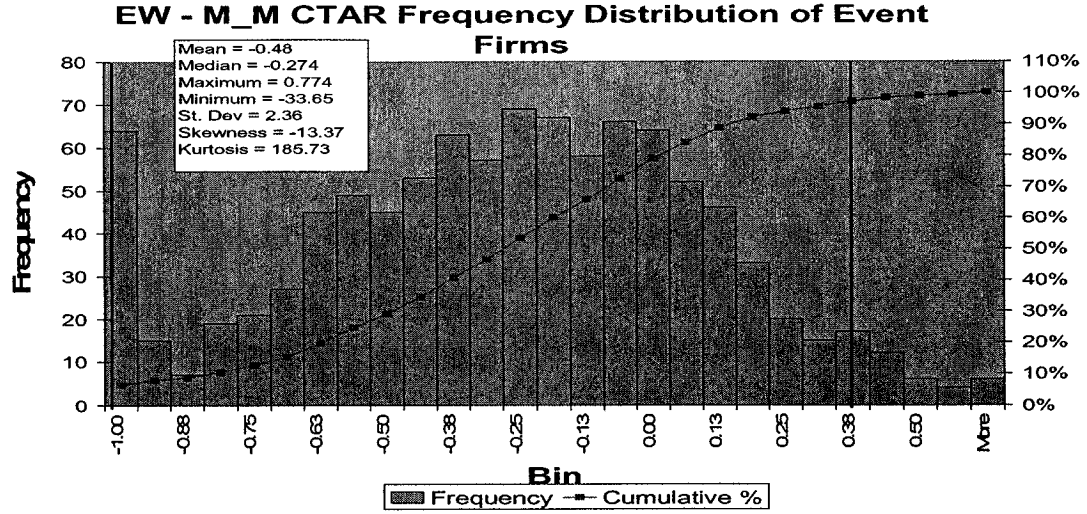


Figure 15: Equally-Weighted Cumulative Frequency Distribution of Event Alphas (i.e. CTARs) for the M_M Sub-Sample

1000 event alphas were generated from the following three factor regression model:

$$R_{p,t} - R_{ic,t} = a_{ip} + b_{ip}(R_{m,t} - R_{f,t}) + s_{ip}(SMB_t) + h_{ip}(HML_t) \text{ where } i = 1000$$

Where $R_{ic,t}$ is the return of the matched non-event portfolio and $R_{p,t}$ is the return of the event portfolio. The other variables are as defined previously. a_i thereby represents the CTAR or event intercept for the group of firms matched to the M_M equally weighted monthly event firm portfolios. This is reiterated 1000 times in order to generate the empirical distribution above. Graph includes descriptive statistics of the distribution. Also displayed on the graph are the upper and lower limits for a 95% confidence interval (note limits are represented by black bold lines at either end of the distribution).

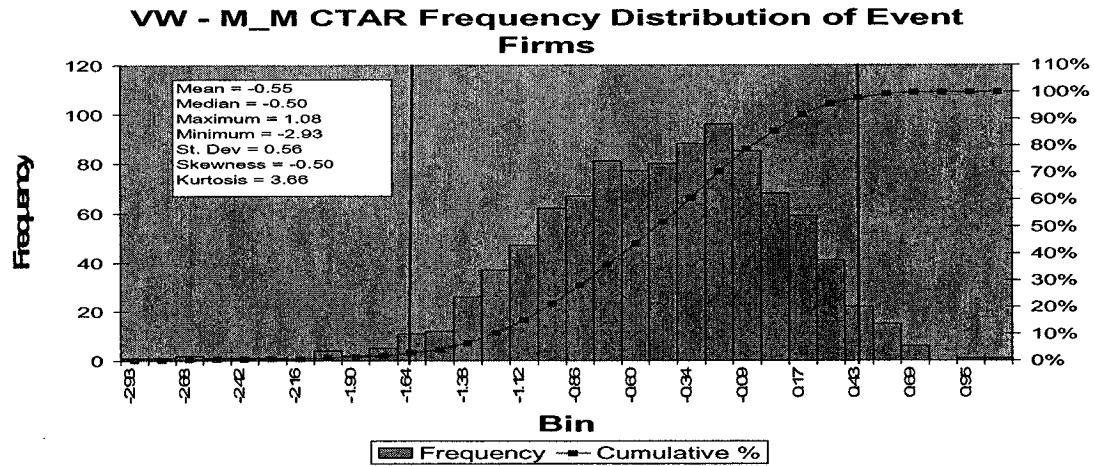


Figure 16: Value-Weighted Cumulative Frequency Distribution of Event Alphas (i.e. CTARs) for the M_M Sub-Sample

1000 event alphas were generated from the following three factor regression model:

$$R_{p,t} - R_{ic,t} = a_{ip} + b_{ip}(R_{m,t} - R_{f,t}) + s_{ip}(SMB_t) + h_{ip}(HML_t) \text{ where } i = 1000$$

Where $R_{ic,t}$ is the return of the matched non-event portfolio and $R_{p,t}$ is the return of the event portfolio. The other variables are as defined previously. a_i thereby represents the CTAR or event intercept for the group of firms matched to the M_M value-weighted monthly event firm portfolios. This is reiterated 1000 times in order to generate the empirical distribution above. Graph includes descriptive statistics of the distribution. Also displayed on the graph are the upper and lower limits for a 95% confidence interval.

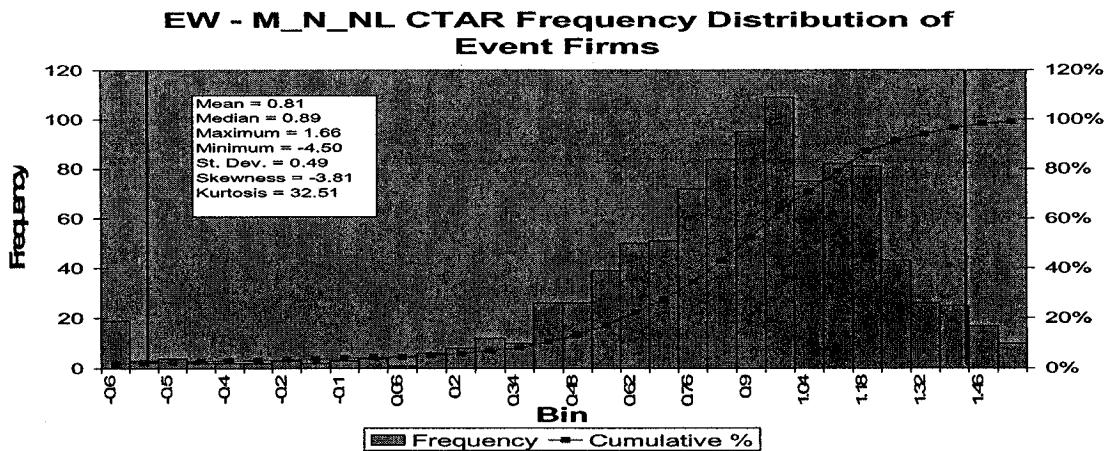


Figure 17: Equally-Weighted Cumulative Frequency Distribution of Event Alphas (i.e. CTARs) for the M_N_NL Sub-Sample

1000 event alphas were generated from the following three factor regression model:

$$R_{p,t} - R_{ic,t} = a_{ip} + b_{ip}(R_{m,t} - R_{f,t}) + s_{ip}(SMB_t) + h_{ip}(HML_t) \text{ where, } i = 1000$$

Where $R_{ic,t}$ is the return of the matched non-event portfolio and $R_{p,t}$ is the return of the event portfolio. The other variables are as defined previously. a_i thereby represents the CTAR or event intercept for the group of firms matched to the M_N_NL equally weighted monthly event firm portfolios. This is reiterated 1000 times in order to generate the empirical distribution above. Graph includes descriptive statistics of the distribution. Also displayed on the graph are the upper and lower limits for a 95% confidence

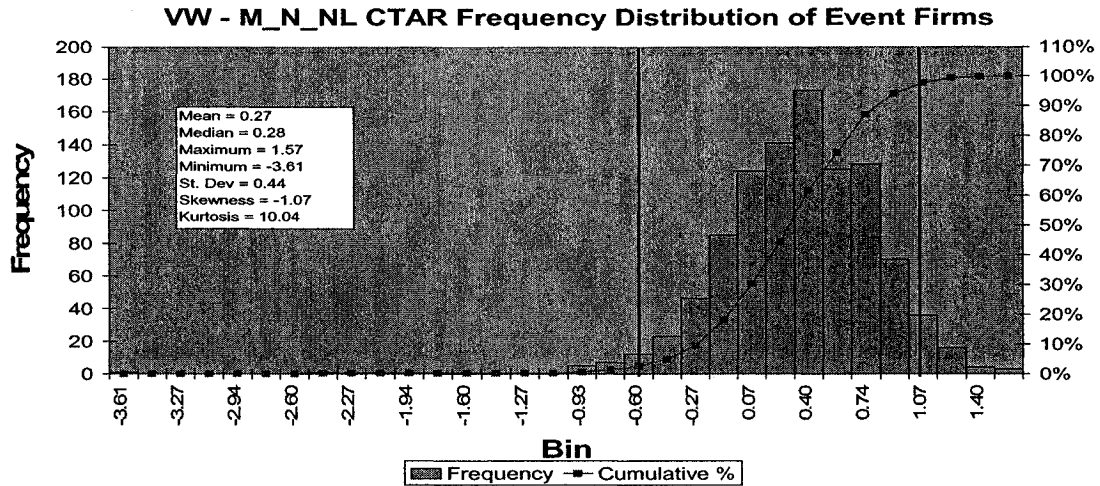


Figure 18: Value-Weighted Cumulative Frequency Distribution of Event Alphas (i.e. CTARs) for the M_N_NL Sub-Sample

1000 non-event alphas were generated from the following three factor regression model:

$$R_{p,t} - R_{ic,t} = a_{ip} + b_{ip}(R_{m,t} - R_{f,t}) + s_{ip}(SMB_t) + h_{ip}(HML_t) \text{ where } i = 1000$$

Where $R_{ic,t}$ is the return of the matched non-event portfolio and $R_{p,t}$ is the return of the event portfolio. The other variables are as defined previously. a_i thereby represents the CTAR or event intercept for the group of firms matched to the M_N_NL value-weighted monthly event firm portfolios. This is reiterated 1000 times in order to generate the empirical distribution above. Graph includes descriptive statistics of the distribution. Also displayed on the graph are the upper and lower limits for a 95% confidence interval (note limits are represented by black bold lines at either end of the distribution).

The group of IRI member firms partnering with private non-member firms (M_N_NL) in figures 17 and 18 for the equally-weighted and value-weighted methods respectively result once again in significantly positive results.

Finally Figures 19 and 20 present the distributions of the CTARs of the IRI member firms that chose to partner with public non-member firms (M_N_L) for the equally- and value-weighted regression intercept estimates. Similar to the results of the M_N_NL sub-sample, the M_N_L portfolios generate positive and significant results.

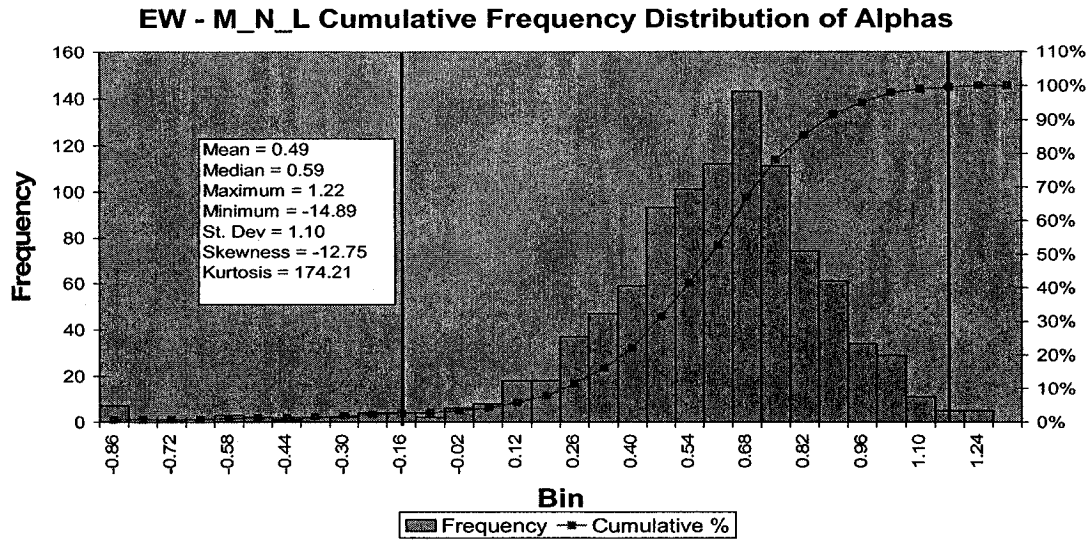


Figure 19: Equally-Weighted Cumulative Frequency Distribution of Event Alphas (i.e. CTARs) for the M_N_L Sub-Sample

1000 non-event alphas were generated from the following three factor regression model:

$$R_{p,t} - R_{ic,t} = a_{ip} + b_{ip}(R_{m,t} - R_{f,t}) + s_{ip}(SMB_t) + h_{ip}(HML_t) \text{ where, } i = 1000$$

Where $R_{ic,t}$ is the return of the matched non-event portfolio and $R_{p,t}$ is the return of the event portfolio. The other variables are as defined previously. a_i thereby represents the CTAR or event intercept for the group of firms matched to the M_N_L equally weighted monthly event firm portfolios. This is reiterated 1000 times in order to generate the empirical distribution above. Graph includes descriptive statistics of the distribution. Also displayed on the graph are the upper and lower limits for a 95% confidence interval (note limits are represented by black bold lines at either end of the distribution).

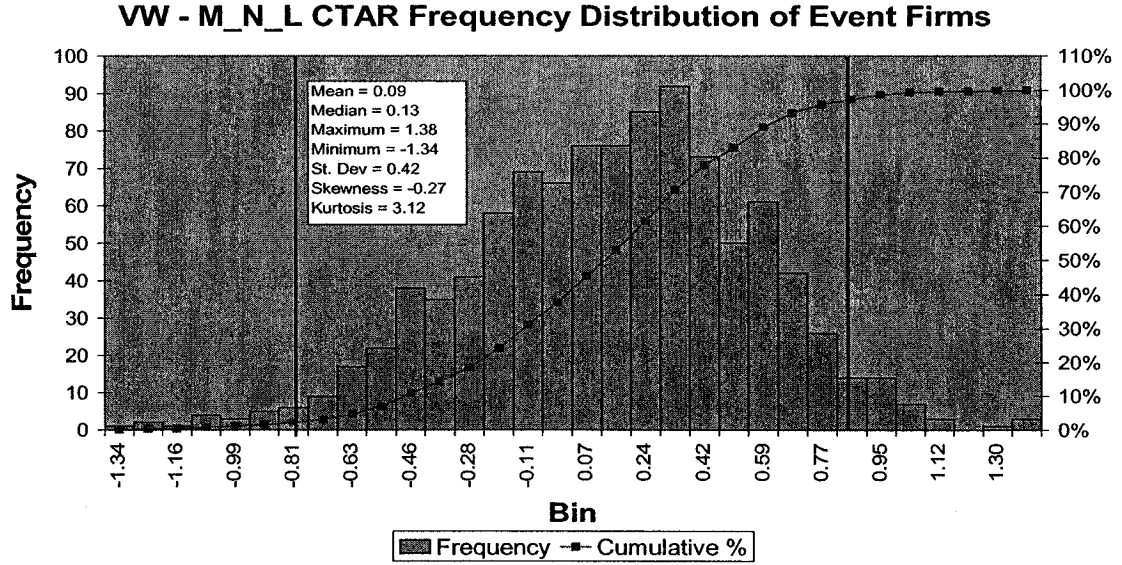


Figure 20: Value-Weighted Cumulative Frequency Distribution of Event Alphas (i.e. CTARs) for the M_N_L Sub-Sample

1000 non-event alphas were generated from the following three factor regression model:

$$R_{p,t} - R_{ic,t} = a_{ip} + b_{ip} (R_{m,t} - R_{f,t}) + s_{ip} (SMB_t) + h_{ip} (HML_t)$$

Where $R_{ic,t}$ is the return of the matched non-event portfolio and $R_{p,t}$ is the return of the event portfolio. The other variables are as defined previously. a_i thereby represents the CTAR or event intercept for the group of firms matched to the M_N_L value-weighted monthly event firm portfolios. This is reiterated 1000 times in order to generate the empirical distribution above. Graph includes descriptive statistics of the distribution. Also displayed on the graph are the upper and lower limits for a 95% confidence interval (note limits are represented by black bold lines at either end of the distribution).

These outcomes are consistent with earlier results of adjusted alpha calculations from table 10, that the MCTAR is negative in the case of M_M and positive in the other two sub-samples. Nonetheless, unlike the adjusted alpha results, the MCTAR outcomes are all significant at the 1% level. This thereby provides evidence of rejection of the efficient market hypothesis, when factors such as leverage levels and R&D/Sales ratios are taken into consideration. Moreover, consistent with previous simulation findings the magnitude of the abnormal performance is more pronounced in the equally-weighted cases than in the value weighted cases, suggesting that smaller firms may be driving the positive abnormal return results. Once again, this may also reflect the fact that larger firms tend to have a lot more press coverage surrounding R&D alliance announcements given their large size, therefore less surprise in the market regarding the outcome of the alliance over the long-run. Additionally, smaller firms may be viewed by the market as

making more risky investment choices in order to grow more rapidly, thereby resulting in greater abnormal returns.

Table 24 summarizes the size of the t-values for the event portfolio simulations (i.e. CTARs), providing more support for the use of estimating simulated portfolios. Displayed is the percentage of times the null hypothesis, that $\alpha = 0$, is rejected when examining each the 1000 matched portfolios. It is the probability of rejection given the R&D alliance event. Panel A displays the equally-weighted results and panel B indicates the value-weighted results. Both panels reveal that using the normal distribution is not an accurate approximation of the samples being studied. Namely, using conventional levels of confidence of 95%, we would reject the null more frequently if the normal distribution was used versus the empirical distribution.

Table 24: Specification (Size) of Monthly Calendar-Time Portfolio Abnormal Returns of Event Pseudo Portfolios

The analysis of this table is based on 1000 random samples of 46 event months. Each of the matched group of securities is included in the calendar-time portfolio for 3-months following the event of the event firm. The following regression was estimated:

$$R_{p,t} - R_{ic,t} = a_{ip} + b_{ip} (R_{m,t} - R_{f,t}) + s_{ip} (SMB_t) + h_{ip} (HML_t) \text{ where, } i = 1000$$

Where $R_{ic,t}$ is the simple return on the calendar-time portfolio (equally-weighted in Panel A and value weighted in Panel B), $R_{p,t}$ is the return on the event portfolio of firms, $R_{f,t}$ is the return on 3-month Treasury bills, $R_{m,t}$ is the return on a value-weighted market index, SMB_t is the difference in the returns of a value-weighted portfolio of small stocks and big stocks and low book-to-market stocks, and HML_t is the difference in the returns of a value-weighted portfolio of high book to market stocks and low book-to-market stocks. The estimate of the intercept term (a_i) provides a test of the null hypothesis that the grand mean monthly abnormal return (i.e. MCTAR) is zero. The numbers presented in the first row of each panel represent the percentage of the 1000 random samples that reject the null hypothesis of no mean excess return, when the holding period is three months, at a theoretical significance level of 5% in favor of the alternative hypothesis of a significantly negative intercept (i.e. calculated p-value is less than 2.5% at the 5% significance level) or a significantly positive intercept (i.e. calculated p-value is greater than 97.5% at the 5% level of significance). The rows in each panel represent the rejection levels for each of the partnering sub-samples studied, namely, M_M, M_N_NL, and M_N_L.

Samples	Theoretical Cumulative Density Function (%)	
	2.50%	97.50%
Panel A: Equally-Weighted Calendar Time Portfolios		
M_M	0.00%	12.50%
M_N_NL	0.00%	32.00%
M_N_L	0.00%	17.50%
Panel B: Value-Weighted Calendar Time Portfolios		
M_M	0.00%	35.30%
M_N_NL	0.00%	60.90%
M_N_L	0.00%	59.00%

P-values and alpha estimates of the original OLS 3-factor model and the MCTARs generated from the 1000 pseudoportfolios are summarized in table 25. This table compiles the key findings from Figures 9 to 20, discussed in the last two sections. Namely that in the case of testing the OLS alpha results in the empirical distribution of non-event control firm alphas (i.e. simulated distribution), equally-weighted indicates significantly positive results with the exception of the M_M sub-sample of firms. Value-weighted, on the other hand, indicates positive and insignificant results for all sub-samples. The MCTARs, on the other hand, generate significantly negative abnormal returns in the case of M_M portfolios and significantly positive abnormal returns in the

case of the two other sub-samples of event firms. This is the case for both the equally- and value-weighted regressions.

Table 25: Equally-Weighted and Value-Weighted CTAR Results vs Simulation Results

This table summarizes the results from figures 9 to 20. For each section, namely left-hand-side is equally Weighted and right-hand-side is value-weighted results, the first row represents the test of the following hypotheses:

$\alpha_{(OLS)} = \hat{\alpha}$, where $\hat{\alpha}$ is the mean intercept of the 1000 non-event pseudoportfolios and $\alpha_{(OLS)}$ is the original alpha estimated in the three-factor Fama/French unadjusted model in table 11. The second rows of each of these sections displays the grand mean of the monthly calendar-time event portfolios (i.e. MCTAR). In this latter case, the null hypothesis is that the mean abnormal return is equal to 0 (MCTAR = 0) in the three months following the R&D alliance announcement. In square brackets are the respective p-values of these tests.

	Equally Weighted		Value-Weighted	
	$\alpha_{(OLS)}$	$\alpha_{(MCTAR)}$	$\alpha_{(OLS)}$	$\alpha_{(MCTAR)}$
	$H_0: \alpha_{(OLS)} = \hat{\alpha}$	$H_0: MCTAR = 0$	$H_0: \alpha_{(OLS)} = \hat{\alpha}$	$H_0: MCTAR = 0$
M_M	0.577 [.74]	-0.48 [<.01]****	0.16 [0.28]	-0.55 [<.01]****
M_N_NL	0.86 [.40]	0.81 [<.01]****	1.13 [0.16]	0.27 [<.01]****
M_N_L	1.13 [0.13]*	0.49 [<.01]****	0.93 [0.16]	0.09 [<.01]****

****, ***, **, * Significant at the 1, 5, 10, and 15 percent levels, respectively
Number in square brackets is the p-value

Abnormal return results, considering certain characteristics of the sample firms demonstrate evidence against the efficient market hypothesis when examining CTARs for both the equally-weighted and value-weighted regressions, in that in the long run, the market does not adjust all information into the price of the firm thereby generating the potential for abnormal performance. Considering the nature of this topic this would not be surprising since alliance activities deal with great uncertainty for long periods of time following the announcement. The process in research and development activities can be very long and outcomes are not always tangible or attached to generally accepted levels of value. Hence this increased uncertainty may be driving the results of abnormal performance in either direction. This abnormal performance, however, is no longer apparent in the case of examining value-weighted returns, when characteristics such as leverage levels and R&D intensity are not considered. This may suggest that the relatively smaller firms may experience abnormal performance in the long run, however when grouped with large firms this performance is eliminated by either the lack of or

negative abnormal returns of the larger firms. Although not the main topic of this research the M_M sub-sample was separated earlier to examine whether abnormal performance of original regression analysis was related to relative size of partnering firms. The explanation I suggest for the difference in results between value-weighted and equally-weighted results is not consistent with the results of the M_M sample analysis in table 17. In particular the M_M sample indicated that in separating the sample, the relatively dominant partners generated positive and significant results while the smaller partners generated no significant abnormal performance in the 3 months following the event announcement. This, however, may be associated to the fact that some of the firms appear in both dominant and small partner sub-samples since in one event the firm may be relatively large and in another event the firm may be relatively small. Future research should examine this more closely with a larger sample. Given the small size of the M_M sample in particular, the results may be driven by one or two firms and therefore affect the value-weighted results significantly. Nonetheless provided that results were highly dependant on method of calculation, more research in this area needs to be conducted possibly considering different approaches to calculating long-run abnormal performance. A larger sample would also help in generating more accurate results.

5.3.3 Test of Difference of Alphas between Sub-Samples

Given that the MCTARs produced significant abnormal returns in the long run for the three sub-samples another interesting question to further understand is the choice of partner in R&D alliances. More specifically whether one set of partnering firms has a significantly different abnormal performance versus another set of partnering type. For example, is the abnormal performance associated with the M_M firms significantly different from the abnormal performance of M_N_NL firms? This allows us to better understand the signaling impact of choice of partner in an alliance relationship. In order to test whether CTARs of one sub-sample are more significant than those of another sub-sample, figures 21-26 presented in appendix III, graphically display the results. The main hypotheses being tested in this final section are the following:

$$H_0: \text{MCTAR}_{[M_M]} - \text{MCTAR}_{[M_N_NL]} = 0$$

$$H_0: \text{MCTAR}_{[M_N_NL]} - \text{MCTAR}_{[M_N_L]} = 0$$

$$H_0: \text{MCTAR}_{[M_N_L]} - \text{MCTAR}_{[M_M]} = 0$$

The same question was evaluated using the simulated non-event alpha distributions presented in figures 27-32 of appendix III. In this case the hypotheses being tested are the following:

$$H_0: a_{(OLS)[M_M]} - a_{(OLS)[M_N_NL]} = \hat{a}_{(OLS)[M_M]} - \hat{a}_{(OLS)[M_N_NL]}$$

$$H_0: a_{(OLS)[M_N_NL]} - a_{(OLS)[M_N_L]} = \hat{a}_{(OLS)[M_N_NL]} - \hat{a}_{(OLS)[M_N_L]}$$

$$H_0: a_{(OLS)[M_N_L]} - a_{(OLS)[M_M]} = \hat{a}_{(OLS)[M_N_L]} - \hat{a}_{(OLS)[M_M]}$$

The results of these six hypotheses are presented in table 26, for both equally- and value-weighted regressions. The twelve graphical representations of the frequency distributions of alpha differences between sub-samples, are presented in Appendix III.

Table 26: Equally-Weighted and Value-Weighted Difference of CTAR Results Between Sub-Samples

This table summarizes the results from figures 21 to 32 presented in appendix III. For each section, namely left-hand section is equally-weighted and right-hand section is value-weighted results, the first row represents the test of the following hypotheses:

$a_{(OLS)n} - a_{(OLS)n} = \hat{a}_{i(OLS)n} - \hat{a}_{i(OLS)n}$, where $a_{(OLS)}$ is the original alpha estimated in the three-factor Fama/French unadjusted model in table 10 and the n subscript is defined as the sub-sample identifier (i.e. M_M , M_N_NL , or M_N_L); and $\hat{a}_{(OLS)}$ are the alpha's generated from the 1000 non-event pseudo-portfolios. The second rows of each of these sections displays the difference between the alphas of event portfolio simulations, hence it is the difference of the grand means (MCTARs). In this latter case, the null hypothesis is that the difference of the mean abnormal returns between sub-samples is equal to 0 in the three months following the R&D alliance announcement. Hypothesis is presented as: $\text{MCTAR}_{[n]} - \text{MCTAR}_{[n]} = 0$.

In square brackets are the respective p-values of these tests.

	Equally Weighted		Value Weighted	
	a(OLS)	a(MCTAR)	a(OLS)	a(MCTAR)
	H0: $a_{(OLS)n} - a_{(OLS)n} = 0$	H0: $\text{MCTAR}_n - \text{MCTAR}_n = 0$	H0: $a_{(OLS)n} - a_{(OLS)n} = 0$	H0: $\text{MCTAR}_n - \text{MCTAR}_n = 0$
[M_M] - [M_N_NL]	-0.283 [.046]***	-1.29 [<.01]****	-0.97 [.05]***	-0.82 [<.01]****
[M_N_NL] - [M_N_L]	-0.37 [<.01]****	0.32 [<.01]****	0.2 [0.53]	0.18 [<.01]****
[M_N_L] - [M_M]	0.653 [.05]***	0.97 [<.01]****	0.77 [0.108]**	0.64 [<.01]****

****, ***, **, * Significant at the 1, 5, 10, and 15 percent levels, respectively
Number in square brackets is the p-value

The estimates of the differences illustrate that the sub-samples of IRI member firms partnering with non-members, whether public or not, seem to yield more favorable results that partnerships among IRI members. This result is consistent across methodologies, whether using equal- or value-weighted regressions and whether examining alphas from

simulations of non-event firms versus CTAR distributions. The differences between M_N_NL and M_N_L sub-samples, are less conclusive. Nonetheless, results appear to suggest that the M_N_NL sub-sample yields higher abnormal returns than does the M_N_L sub-sample. Hence the least favored choice of partnership suggested by this analysis is the partnership among IRI member firms, which are generally large firms with high investment in R&D and lower levels of leverage than the market average. These findings may reveal the need for alternatives to in-house R&D spending, such as R&D alliances, for firms spending less on R&D than the top 100 R&D spenders, possibly due to lack of other types of resources. Moreover given their smaller size these firms may also be less covered by the press making details of the R&D alliance less clear and having a greater potential to generate abnormal returns in the long run. Finally, these partnerships may be considered more efficient since the larger firms may be plagued by their size making quick decision-making more tedious and thereby lengthening the R&D development process. Future research should vary the holding period beyond four months, in order to determine whether one type of partnership may result in prices adjusting more quickly than others.

6. CONCLUDING REMARKS AND FUTURE RESEARCH AVENUES

The importance of leading-edge research to economic development has been recognized across industrialized countries. Consequently research collaboration has become imperative in order for firms to maintain their competitive edge in the global economy. As Dr. Emily Yaung Ashworth, professor at Texas A&M University, points out, “research thrives on openness and suffers in isolation.” (pp. 2) This statement encompasses the idea of research & development partnerships and the importance of studying their implications on firm value.

This analysis brings new insights on the study of long-term stock price performance of the top US R&D spenders, by empirically testing long-run abnormal stock returns surrounding the announcement of an R&D alliance. No published studies to date have examined the long-term impacts of these events and only a few management journals have published results on short-term abnormal performance (Chan, Kensinger,

Keown, and Martin, 1997; Das, Sen and Senguta, 1998; Neill, Pfeffer, and Young-Ybarra, 2001; Anand and Khanna, 2000; Park Mezas and Song, 2004). Moreover, these studies tend to focus on the late 80s and early 90s, the period immediately following legislation that facilitated the formation of R&D alliances. Other research is industry-specific, and still others tend to focus on one type of R&D alliance (i.e. often joint ventures). Results focused solely on one type of agreement may not fully reflect the market's perception of alternative forms of partnering, among which the degree of flexibility varies greatly.

The goal of this study was to address the following questions regarding the long term impact of R&D alliance announcements: Do R&D alliance events made by the top US R&D spenders create value in the long-run? Does type of partner chosen influence the possibility of long run abnormal performance? Does level of experience in R&D alliance formation, result in a differential response from investors? Does industry of the top US R&D spenders affect the value-creation or value-destruction of R&D collaborations?

As pointed out by Barber, Lyon, and Tsai (1999) 'analysis of long run abnormal returns is treacherous.' Hence this paper also deals with the problems associated with inferences in long-run studies by considering several alternatives. The methodology employed is the calendar-time portfolio approach, which solves for the cross-sectional dependence among sample firms by creating portfolios of event firms in each calendar month. This model is estimated with OLS using both the one-factor and three-factor Fama and French (1993) model. In order to test whether the normal distribution is an appropriate assumption in the evaluation of long run abnormal returns of the sample firms addressed in this paper, a distribution of non-event alphas is also constructed. Moreover, to solve for the joint test problem associated with the traditional Fama and French model, an adjusted alpha was estimated based on 1000 control portfolios. These control portfolios were matched based on leverage levels and R&D to sales ratios, two factors deemed important when selecting non-event firms of similar characteristics. Finally, mean calendar-time portfolios (Lyon, Barber, and Tsai, 1999; Mitchell and Stafford, 2000; Boehme and Sorescu, 2002) were estimated in order to construct empirical

distributions of event firm abnormal returns and test whether the grand mean abnormal returns equal 0 in the long run.

Results indicate that first, unadjusted alpha estimates yield positive and significant abnormal returns for the sample of all events as well as for all sub-samples of partnering firms, with the exception of the group of IRI member firms partnering with other members. This sub-sample experiences no significant abnormal performance. These results are robust to the WLS estimates that take into consideration potential biases due to the existence of heteroscedasticity. Second, when accounting for the joint test or bad model problem, adjusted alpha results for the ALL sample and the M_N_NL and M_N_L show no signs of significant abnormal performance in the three months following the announcement. These results are consistent with the efficient market hypothesis. The M_M sub-sample on the other hand, indicates negative and significant abnormal returns, hence requiring further investigation. One possibility considered is the fact that unlike the other sub-samples, the M_M portfolio is the only group of event firms that includes both partners. Hence, firms are further split between dominant and smaller partner, based on relative market value. Results from this cross section are inconclusive due to the small sample size. However, dominant versus smaller firms do seem to indicate a differential response, thereby, warranting further investigation in future research using a larger sample.

Other potential explanations for the negative M_M abnormal returns may be associated to some of the characteristics of this particular sub-sample. More specifically, the fact that this group of R&D alliances includes a greater proportion of joint ventures and multiple partner collaborations. Both of these factors can be associated with less favorable impacts on firm value since they are less flexible forms of partnerships. Additionally, the fact that both firms involved are large in size relative to the market may also explain the lack of or negative abnormal returns of the M_M subsample in the long run. It is possible that their large size may result in greater press coverage regarding the R&D collaborative agreement or venture thereby allowing the market to react more quickly to the information than in cases where one or more of the firms involved are small or private firms/institutions. As can be seen in appendix II, although firms within

the M_M sub-sample are among the most frequent firms to engage in alliance activities, they also tend to make the fewest of their connections with fellow members. Hence announcements within the M_M portfolio are also considered less frequent. Although not an indication of experience in this case, it is probably more associated with the greater difficulty in adopting a common culture among the two major players, as opposed to the case where one player more clearly dominates the partnership. Parkhe (1993) mentions that the potential for opportunistic behavior in alliance formation is less likely when the alliance partners see prospects of continued cooperation. Hence it may be that the IRI member firms are perceived as more opportunistic when collaborating with other members, thereby destroying shareholder value.

Results considering IRI members' level of experience demonstrates, in the unadjusted alpha case, that frequent announcers are associated with positive abnormal returns, however, after adjusting for leverage and R&D to sales ratios, this abnormal return disappears. Infrequent announcers, on the other hand, show no significant abnormal performance in the unadjusted case but after adjustments, results indicate that infrequent announcers are perceived as value destroying in the long run. This is not surprising since as noted by De Man, 2002; Hagedoorn, 2002, and Powell, Koput and Smith, 1996, prior alliance experience influences a firm's choice when considering new partnerships. Consequently, investors have more information available when dealing with frequent announcers based on past experience therefore may adjust prices more quickly, creating no long-term abnormal returns. By the same token, firms that engage sporadically in collaborative activity may lack the expertise in the management of these forms of investment, or may be driven by hubris reasons, hence are perceived more often as value-destroying transactions.

Finally considering industry classification, the business services industry is the only industry consistently displaying positive and significant abnormal performance for the ALL sample as well as for the three sub-samples of partnering firms. Noteworthy is the fact that the business services industry is one of the least concentrated industries in my sample, providing support for the Shumpeterian hypothesis. This hypothesis is interpreted in this context as: industries with low concentration levels are in a less

favorable position to gain from in-house spending, hence their motive for choosing alternative methods to increase their innovativeness and remain competitive. When adjusted alphas are calculated however, the positive abnormal performance experienced by the business services industry becomes negative but insignificant, thereby continuing to be consistent with the efficient market hypothesis.

Dealing more specifically with the methodology challenges associated with long term studies, the simulation of non-event alphas provides further insight on initial results, indicating the difficulty in drawing one single conclusion. In this case, I still find positive and significant abnormal returns in the equally weighted- case for the two sub-samples partnering with non-IRI members (i.e. M_N_NL and M_N_L) and no significant results for the M_M sub-sample. The value-weighted methodology however, shows no signs of abnormal performance when adjusting for the assumption of normality. One possible explanation is that the smaller firms are driving the positive abnormal performance, which is offset by the zero or negative abnormal returns of relatively larger firms that are weighted more heavily in the value-weighted regressions. This is consistent with some of the short run study findings that smaller firms tend to generate higher abnormal returns surrounding the announcement of an R&D alliance.

The final method employed to verify the robustness of initial results is the MCTAR. In this case both equally-weighted and value-weighted methods go against the efficient market hypothesis and result in significant abnormal performance in the three months following the R&D alliance announcement. Consistent with the adjusted alpha results, the M_M sub-sample indicates that the market exacts a penalty on IRI members collaborating on R&D activities. In contrast, the M_N_NL and M_N_L sub-samples both show value enhancing results in the long run consistent with the unadjusted alpha and simulation findings.

In order to better grasp the findings that partner choice influences the value the market attaches to the announcement of an R&D alliance in the long run, I also examine the difference in abnormal performance between different partner subsamples. The findings are consistent with some of the earlier discussion, in that the M_M sub-sample is clearly the least favored partnership choice. In the cases where IRI members partner with

other public firms or with private firms or institutions, no clear conclusions can be drawn, although there appears to be more support for the M_N_NL being the dominant type of partnership. This is probably explained by less conflict between public and private members, given that their roles may be better defined and their motivations may less often be driven by opportunistic behavior, in favor of more cooperative behavior that may influence future relationships. Repeat business may be of considerable importance especially to private firms/organizations, since large firms often help in providing the means for them to conduct and implement certain research projects.

Given these results, it is difficult to conclude that R&D alliances do in fact have a staying impact on the market in the three months following the announcement since different methodologies do not consistently generate the same results. Nonetheless, there is evidence that type of partner chosen may have an impact on the perception of the announcement in the market as was seen in the case of IRI-member firms partnering with other IRI firms. The M_M sub-sample consistently indicated zero or negative performance in the long run. Moreover, the frequency or level of experience firms have with respect to R&D alliances also indicate a different response between frequent and infrequent announcers. Investors seem to favor those firms with experience, which is not surprising since the lack of a better understanding of the success factors of alliances may mean that investors will place more importance on past experience than on the single event in question. Finally the industry variable also reveals different responses among industries of different levels of concentration. Although inconclusive due to the small sample size of the industry portfolios the business services industry exhibits a very different response than do the other industries possibly suggesting a link between the low level of concentration in this group of SIC codes and abnormal returns following an R&D partnership.

The results of this study bring rise to new questions in the area of strategic alliances, an area that is expanding at a very rapid pace and needs to be better understood. This study contains a number of limitations that suggest meaningful directions for future research. The focus on top US R&D spenders from the IRI leaderboard, limited the sample size making data points in further decompositions of sub-samples, insufficient to

draw inferences from. Hence beginning with a larger sample will allow a more in depth analysis of cross sections of data that can bring more insight to the results of my paper. Moreover, studying alliances on a larger scale would allow statements, regarding the perception of alliances in the market and partner choice, to be more universally accepted. A larger sample would especially help the industry analysis which was very limiting in this paper due to sample size.

Imperative in long term studies is the determination of a proper method of calculating abnormal returns. The best way to determine the robustness of results is to perform several methods. This was in part accomplished in this paper, but an examination of the BHAR method may provide further insights on the topic.

Varying the length of time that the companies are evaluated, following an alliance, would also be very interesting for future researchers to pursue. More specifically studying whether one type of partnership (i.e. M_M vs M_N_NL vs M_N_L) results in the reflection of the event in market prices more quickly than other types. Comparing outcomes from different long term windows may shed more light on the results from partnerships between IRI members (i.e. M_M) found in this paper.

Lastly, an interesting area to pursue given the rising importance of alliances at the expense of mergers and acquisitions, is the study of the tradeoffs between these two options which is imperative to determine for managers attempting to select the best method of increasing innovativeness. Examining a group of firms engaging in both alliances and M&As versus firms focused more on one type of collaborative form, using the same methodology of calculating abnormal returns, will provide a better understanding of the different perceptions of these type of corporate actions. This understanding would in turn enable managers to make more informed decisions and government to implement the appropriate policies to encourage the most value enhancing option for the economy.

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8. APPENDICES

APPENDIX 1

Table 27: An overview of motives for (strategic) interfirm technology corporation

I. Motives related to basic and applied research and some general characteristics of technological development:

- *Increased complexity and intersectoral nature of new technologies. Cross-fertilization of scientific disciplines and field of technology, monitoring of evolution of technologies, technological synergies, access to scientific knowledge or to complementary technology:* Mariti and Smiley (1983), Harrigan (1985), Ohmae (1985), OECD (1986a, b), Porter and Fuller (1986), Fufeld (1986), Haklisch (1986), Mariotti and Ricotta (1986) Auster (1987) Hladik (1988), Klepper (1988), Mowery (1988a, b), Ouchi and Bolton (1988) Obeiros and Macdonald (1988). Pisano, Russo and Teece (1988). Pisano, Shan and Teece (1988). Steinmuller (1988), Womack (1988), Hagedoorn and Schakenraad (1990a, b).

- *Reduction, minimizing and sharing of uncertainty in R&D:* Berg. Duncan and Friedman (1982). Ohmae (1985). Harrigan (1985, 1988). Mariotti and Ricotta (1986). Porter and Fuller (1986). Auster (1987). Mytelka and DelaPierre (1987), Hladik (1988). Mowery (1988b). Obleros and MacDonald (1988).

- *Reduction and sharing costs of R&D:* Ohmac (1985), Harrigan (1985, 1988). OECD (1986a), Mariotti and Ricotta (1986), Auster (1987), Mytelka and Delapierre (1987). Hladik (1988). Mowery (1988b). Obleros and MacDonald (1988), Steinmueller (1988). Link and Bauer (1989).

II. Motives related to concrete innovation processes:

- *Capturing of partner's tacit knowledge of technology, technology transfer, technological leapfrogging:* Mariti and Smiley (1983). Harrigan (1985), Hamel, Doz and Prahalad (1986). Lynn (1988), Pisano, Shan and Teece (1988), Hagedoorn and Schakenraad (1990a, b).

- *Shortening of product life cycle, reducing the period between invention and market introduction:* OECD (1986a), Mariotti and Ricotta (1986).

III. Motives related to market access and search for opportunities:

- *Monitoring of environmental changes and opportunities:* Mariotti and Ricotta (1986). Obleros and MacDonald (1988).

- *Internationalization, globalization and entry to foreign markets:* Ohmae (1985). OECD (1986a), Porter and Fuller (1986) Harrigan (1988), Lynn (1988), Mowery (1988b), Pisano, Russo and Teece (1988), Steinmueller (1988), Womack (1988), Vonortas (1989).

- *New products and markets, market entry, expansion of product range:* Hladik (1985, 1988), Harrigan (1985, 1988). OECD (1986 a, b), Mariotti and Ricotta (1986), Porter and Fuller (1986), Klepper (1988), Mowery (1988a), Steinmueller (1988), Pisano, Shan and Teece (1988), Womack (1988), Hagedoorn and Schakenraad (1990a, b).

SOURCE: HAGEDOORN (1993)

APPENDIX II

Table 28: List of the 73 Firms used in this study, from the Industrial Research Institutes (IRI) 4th Annual R&D Leaderboard

Firms are listed in order of R&D spending. Presented in this table are firm characteristics such as industry name, industry classification service vs non-service and high-, mid-, or low- technology industry. Also displays average number of announcements made by each of the IRI member firms by sub-sample and overall.

IRI Companies	Industry	Service/ Non Service Industry	High/ Mid/ Low Tech	Avg # of R&D Alliance Announcements per company			
				M_M	M_N_NL	M_N_L	TOTAL
Ford Motor Co	Autos	NS	M	-	1.00	1.50	2.50
General Motors	Autos	NS	M	0.25	0.50	0.50	1.25
Int'l Business Machines Corp	Comps	NS	H	2.50	8.50	6.50	17.50
Pfizer Inc	Drugs	NS	H	-	2.50	1.50	4.00
Microsoft Corp	Bussv	S	H	4.00	8.50	9.00	21.50
Motorola Inc	Chips	NS	H	2.25	4.25	1.50	8.00
Cisco Systems	Comps	NS	H	1.50	2.00	1.75	5.25
Intel Corp	Chips	NS	H	3.50	3.50	3.00	10.00
Johnson & Johnson	Medeq	NS	M	-	1.00	1.00	2.00
Lucent Technologies Inc	Telcm	S	H	0.50	1.25	0.75	2.50
Hewlett-Packard Co	Labeq	NS	M	4.00	4.00	8.25	16.25
Merck & Co	Drugs	NS	H	-	1.75	1.75	3.50
Bristol Myers Squibb	Hshld	NS	M	-	2.50	1.25	3.75
Lilly (Eli) & Co	Drugs	NS	H	0.50	2.25	3.25	6.00
Sun Microsystems Inc	Comps	NS	H	2.25	2.00	3.25	7.50
General Electric Co	Hshld	NS	M	0.50	0.25	0.75	1.50
Boeing Co	Aero	NS	H	0.25	0.25	-	0.50
Wyeth	Drugs	NS	H	-	0.50	0.50	1.00
Proctor & Gamble Co	Hshld	NS	M	-	-	1.50	1.50
Texas Instruments	Chips	NS	H	1.00	1.00	3.50	5.50
Du Pont (E I) De Nemours	Chems	NS	M	0.75	1.75	0.25	2.75
Abbott Laboratories	Drugs	NS	H	-	1.75	2.50	4.25
Compaq Computer Corp	Bussv	S	H	2.50	1.50	1.75	5.75
United Technologies Corp	Aero	NS	H	-	0.50	0.25	0.75
Applied Materials Inc	Mach	NS	M	-	0.50	-	0.50
3M Co	Boxes	NS	L	0.25	1.25	0.50	2.00
Oracle Corp	Bussv	S	H	2.00	3.75	4.50	10.25
Dow Chemical Co	Chems	NS	M	0.25	0.25	1.00	1.50
Xerox Corp	Hshld	NS	M	0.75	0.25	1.25	2.25
Amgen Inc	Drugs	NS	H	0.25	1.25	0.75	2.25
Honeywell International Inc	Aero	NS	H	-	0.25	0.50	0.75
Eastman Kodak Co	Hshld	NS	M	1.25	2.25	1.25	4.75
Caterpillar Inc	Mach	NS	M	-	0.25	-	0.25
Computer Associates Int'l Inc	Bussv	S	H	1.50	1.25	1.50	4.25
Advanced Micro Devices	Comps	NS	H	0.50	1.00	0.75	2.25
Medtronic Inc	Medeq	NS	M	0.25	0.50	1.25	2.00
Exxon Mobile Corp	Enrgy	NS	H	-	0.50	-	0.50
LSI Logic Corp	Chips	NS	H	0.50	0.75	0.25	1.50
Monsanto Co	Chems	NS	M	1.00	0.50	1.50	3.00

Table 28 Continued

IRI Companies	Industry	Service/ Non Service Industry	High/ Mid/ Low Tech	Avg # of R&D Alliance Announcements per company			
				M_M	M_N_NL	M_N_L	TOTAL
Genentech Inc	Drugs	NS	H	0.25	0.75	1.75	2.75
Automatic Data Processing	Bussv	S	H	-	-	0.50	0.50
Micron Technology Inc	Comps	NS	H	1.00	-	-	1.00
BMC Software Inc	Bussv	S	H	0.25	0.25	0.25	0.75
Raytheon Co	Chips	NS	H	0.75	0.25	0.50	1.50
Analog Devices	Eleeq	NS	M	-	0.25	0.25	0.50
Maxtor Corp	Comps	NS	H	-	-	0.25	0.25
Apple Computer Inc	Comps	NS	H	1.75	2.25	3.00	7.00
Baxter International Inc	Drugs	NS	H	1.00	0.25	0.75	2.00
Tellabs Inc	Chips	NS	H	-	-	0.25	0.25
ITT Industries Inc	Eleeq	NS	M	-	-	0.25	0.25
Qualcomm Inc	Eleeq	NS	M	-	1.25	0.75	2.00
Millennium Phamactels Inc	Drugs	NS	H	0.75	0.25	-	1.00
Electronic Arts Inc	Bussv	S	H	-	1.25	0.25	1.50
Guidant Corp	Medeq	NS	M	0.50	-	0.25	0.75
NCR Corp	Comps	NS	H	0.50	-	0.25	0.75
Chiron Corp	Drugs	NS	H	0.50	2.50	1.00	4.00
Northrop Grumman	Aero	NS	H	-	-	0.50	0.50
Unisys Corp	Comps	NS	H	0.50	2.25	1.00	3.75
AT&T Corp	Telcm	S	H	1.50	3.50	4.75	9.75
Biogen Inc	Drugs	NS	H	-	0.50	0.50	1.00
Cadence Design Sys Inc	Bussv	S	H	-	0.25	0.75	1.00
Peoplesoft Inc	Bussv	S	H	-	1.00	0.75	1.75
Kimberly-Clark Corp	Paper	NS	L	-	0.25	-	0.25
Rockwell Collins Inc	Aero	NS	H	-	0.25	0.25	0.50
Teradyne Inc	Labeq	NS	M	0.25	-	0.25	0.50
3Com Corp	Comps	NS	H	-	0.50	0.75	1.25
ADC Telecommunications Inc	Eleeq	NS	M	-	0.50	0.25	0.75
Boston Scientific Corp	Drugs	NS	H	-	0.50	0.75	1.25
Novellus Systems Inc	Steel	NS	L	-	0.25	-	0.25
Atmel Corp	Chips	NS	H	-	-	0.25	0.25
PPG Industries Inc	Bldmt	NS	L	-	0.25	-	0.25
Genzyme Corp- Consolidated	Drugs	NS	H	-	1.75	1.50	3.25
Allergan Inc	Drugs	NS	H	-	0.75	-	0.75

APPENDIX III

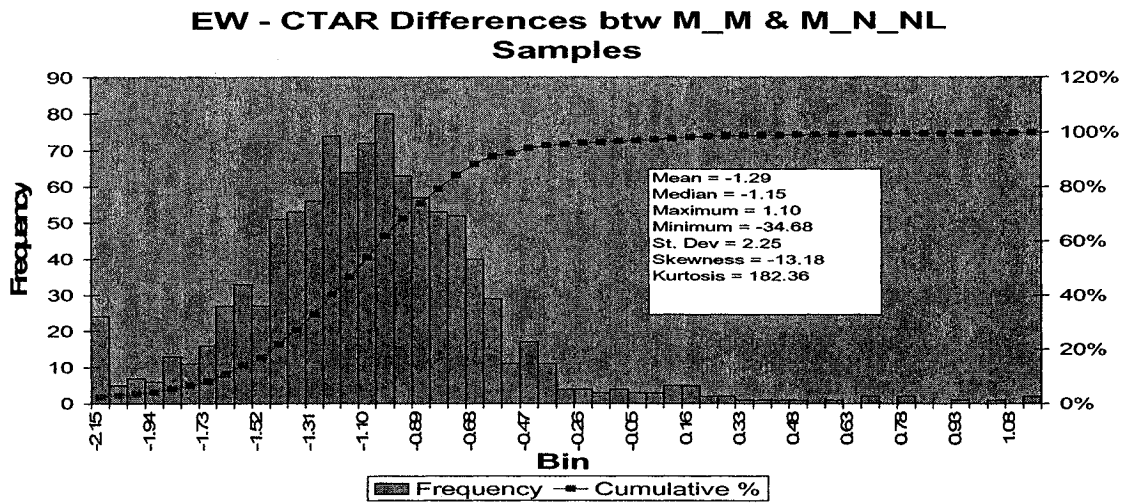


Figure 21: Equally-Weighted Distribution of Difference of CTARs (i.e. event alphas) between Sub-Samples M_M and M_N_NL

Displayed are the 1000 differences of event alphas calculated as $a_{i[M_M]} - a_{i[M_N_NL]}$ where $a_{i[M_M]}$ is one observation of alpha for the M_M subsample and $a_{i[M_N_NL]}$ is one observation of the alpha for the M_N_NL subsample. The distribution generated from these differences allows the test of the hypothesis that $\hat{a}_{[M_M]} = \hat{a}_{[M_N_NL]}$.

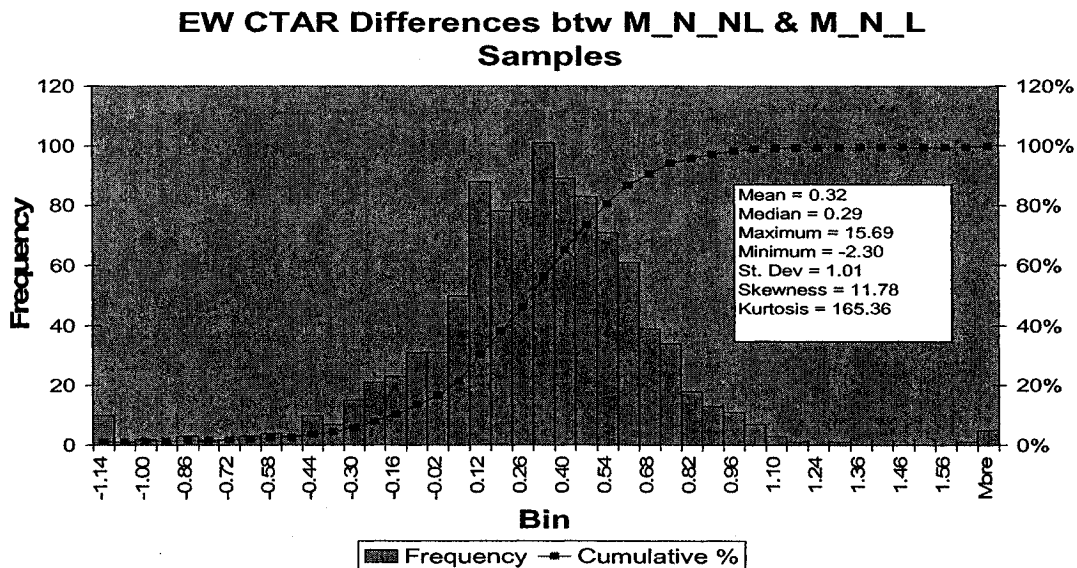


Figure 22: Equally-Weighted Distribution of Difference of CTARs (i.e. event alphas) between Sub-Samples M_N_NL and M_N_L

Displayed are the 1000 differences of event alphas calculated as $a_{i[M_N_NL]} - a_{i[M_N_L]}$ where $a_{i[M_N_NL]}$ is one observation of alpha for the M_N_NL subsample and $a_{i[M_N_L]}$ is one observation of the alpha for the M_N_L subsample. The distribution generated from these differences allows the test of the hypothesis that $\hat{a}_{[M_N_NL]} = \hat{a}_{[M_N_L]}$.

EW CTAR Differences btw M_N_L & M_M Samples

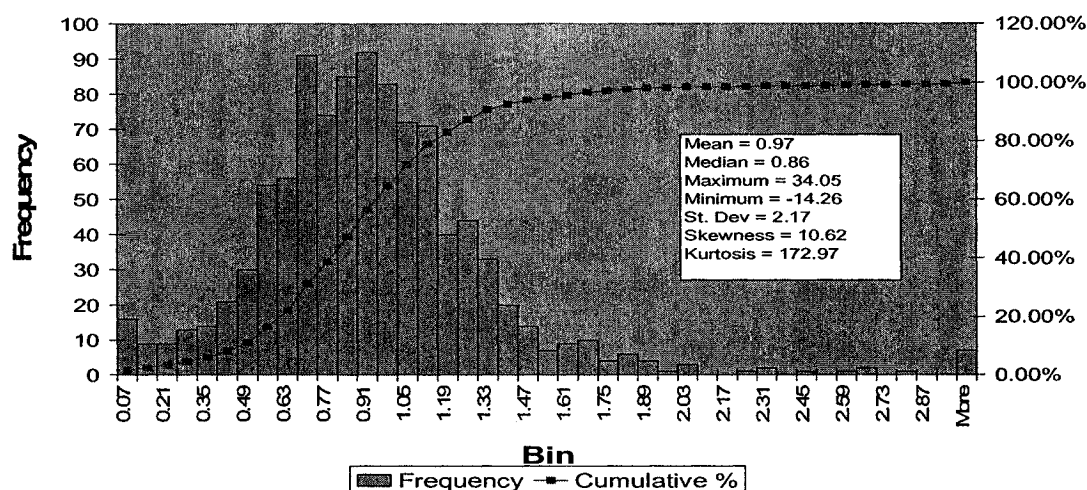


Figure 23: Equally-Weighted Distribution of Difference of CTARs (i.e. event alphas) between Sub-Samples M_N_L and M_M

Displayed are the 1000 differences of event alphas calculated as $a_{i[M_N_L]} - a_{i[M_M]}$ where $a_{i[M_N_L]}$ is one observation of alpha for the M_N_L subsample and $a_{i[M_M]}$ is one observation of the alpha for the M_M subsample. The distribution generated from these differences allows the test of the hypothesis that $\hat{a}_{[M_N_NL]} = \hat{a}_{[M_N_L]}$.

VW - CTAR Differences btw M_M & M_N_NL Samples

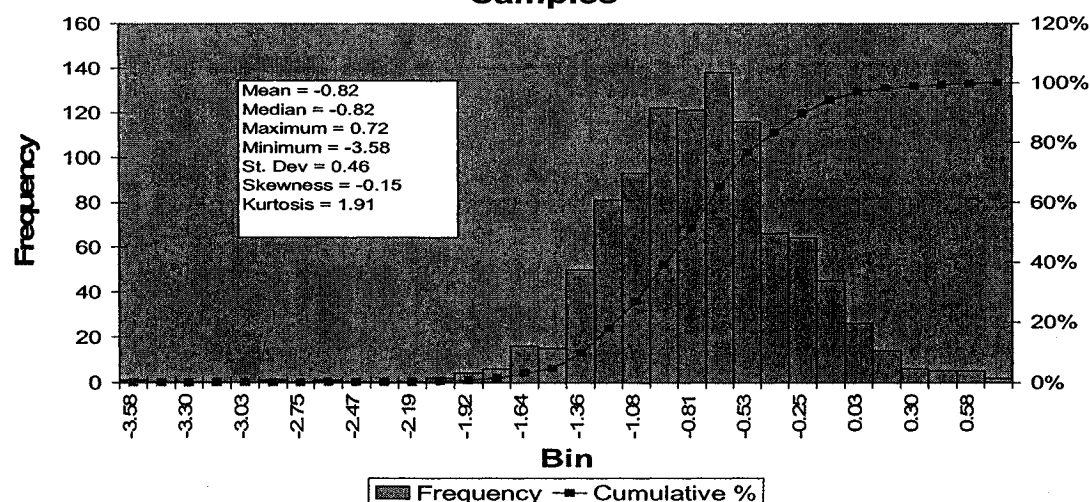


Figure 24: Value-Weighted Distribution of Difference of CTARs (i.e. event alphas) between Sub-Samples M_N_L and M_M

Displayed are the 1000 differences of value-weighted event alphas calculated as $a_{i[M_M]} - a_{i[M_N_NL]}$ where $a_{i[M_M]}$ is one observation of alpha for the M_M subsample and $a_{i[M_N_NL]}$ is one observation of the alpha for the M_N_NL subsample. The distribution generated from these differences allows the test of the hypothesis that $\hat{a}_{[M_M]} = \hat{a}_{[M_N_NL]}$.

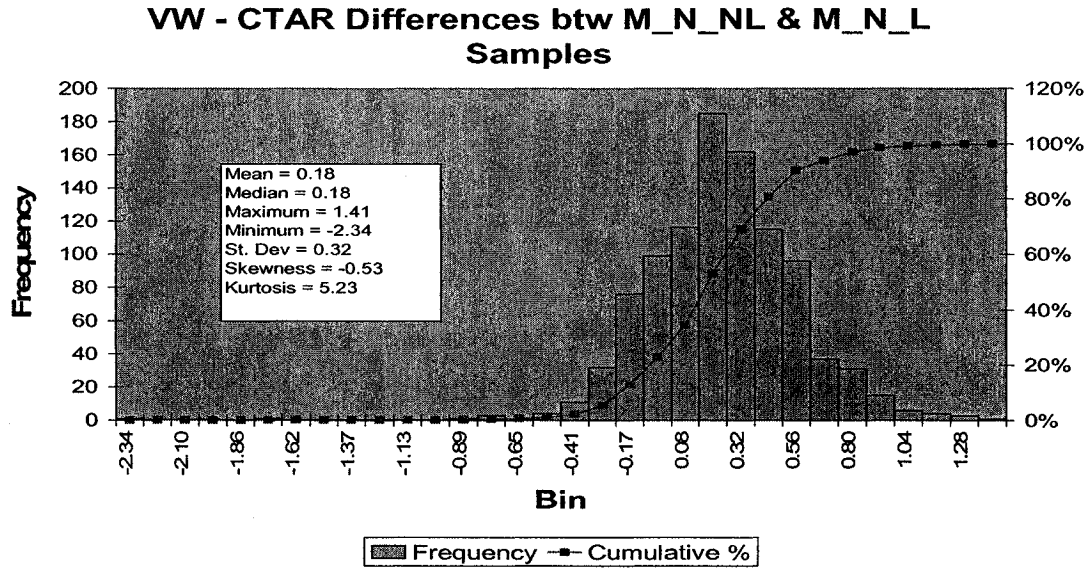


Figure 25: Value-Weighted Distribution of Difference of CTARs (i.e. event alphas) between Sub-Samples M_N_NL and M_N_L

Displayed are the 1000 differences of value-weighted event alphas calculated as $a_{i[M_N_NL]} - a_{i[M_N_L]}$ where $a_{i[M_N_NL]}$ is one observation of alpha for the M_N_NL subsample and $a_{i[M_N_L]}$ is one observation of the alpha for the M_N_L subsample. The distribution generated from these differences allows the test of the hypothesis that $\hat{a}_{[M_N_NL]} = \hat{a}_{[M_N_L]}$.

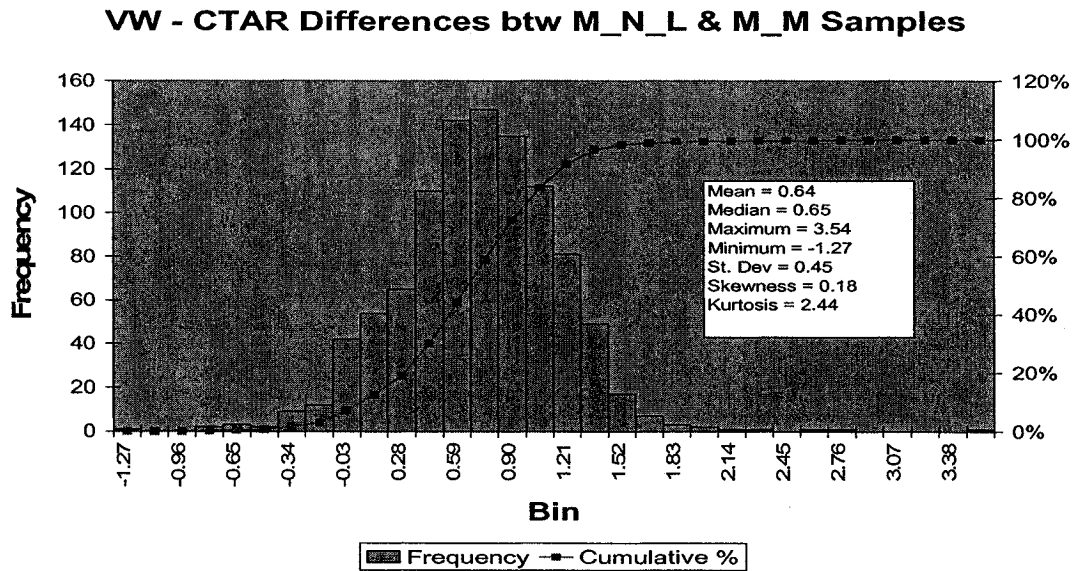


Figure 26: Value-Weighted Distribution of Difference of CTARs (i.e. event alphas) between Sub-Samples M_N_L and M_M

Displayed are the 1000 differences of value-weighted event alphas calculated as $a_{i[M_N_L]} - a_{i[M_M]}$ where $a_{i[M_N_L]}$ is one observation of alpha for the M_N_L subsample and $a_{i[M_M]}$ is one observation of the alpha for the M_M subsample. The distribution generated from these differences allows the test of the hypothesis that $\hat{a}_{[M_N_L]} = \hat{a}_{[M_M]}$.

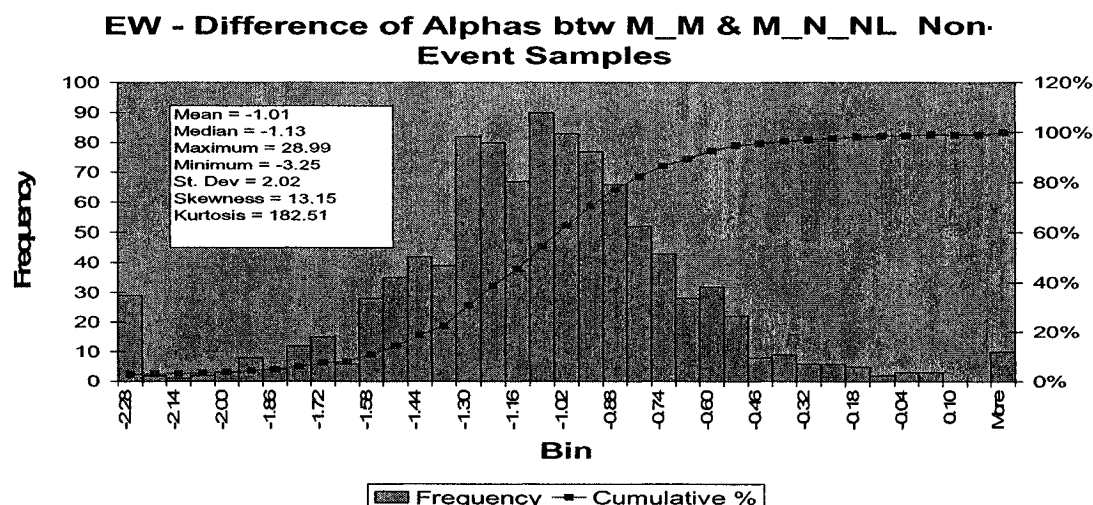


Figure 27: Equally-Weighted Distribution of Difference of Non-Event Alphas between Sub-Samples M_M and M_N_NL

Displayed are the 1000 differences of equally-weighted non-event alphas calculated as $a_{i[M_M]} - a_{i[M_N_NL]}$ where $a_{i[M_M]}$ is one observation of alpha for the M_M subsample and $a_{i[M_N_NL]}$ is one observation of the alpha for the M_N_NL subsample. The distribution generated from these differences allows the test of the hypothesis that $a_{(OLS)[M_M]} - a_{(OLS)[M_N_NL]} = \hat{a}_{(OLS)[M_M]} - \hat{a}_{(OLS)[M_N_NL]}$, where $a_{(OLS)}$ values are the original OLS estimates of alpha for each sub-sample from the 3-factor model in table 11.

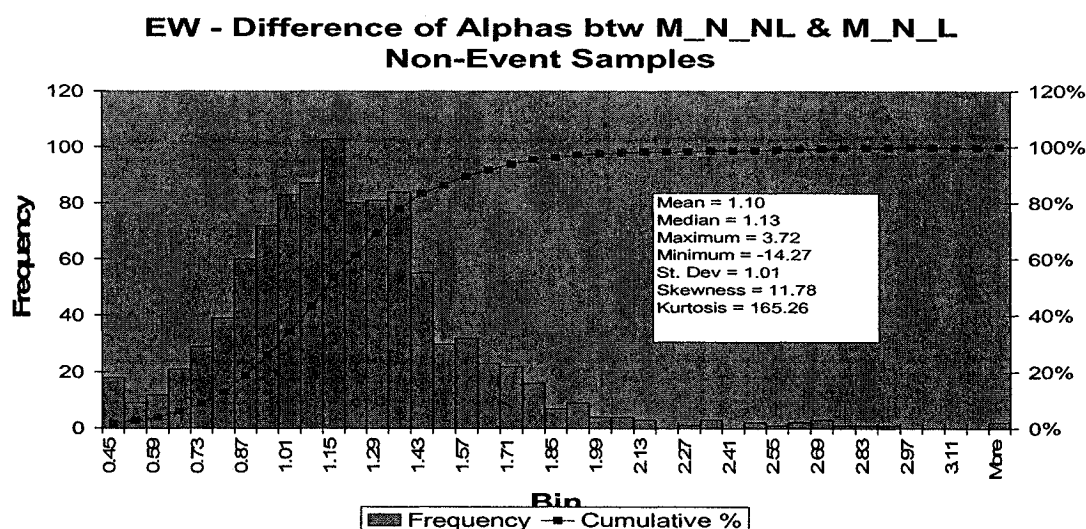


Figure 28: Equally-Weighted Distribution of Difference of Non-Event Alphas between Sub-Samples M_N_NL and M_N_L

Displayed are the 1000 differences of equally-weighted non-event alphas calculated as $a_{i[M_N_NL]} - a_{i[M_N_L]}$ where $a_{i[M_N_NL]}$ is one observation of alpha for the M_N_NL subsample and $a_{i[M_N_L]}$ is one observation of the alpha for the M_N_L subsample. The distribution generated from these differences allows the test of the hypothesis that $a_{(OLS)[M_N_NL]} - a_{(OLS)[M_N_L]} = \hat{a}_{(OLS)[M_N_NL]} - \hat{a}_{(OLS)[M_N_L]}$, where $a_{(OLS)}$ values are the original OLS estimates of alpha for each sub-sample from the 3-factor model in table 11.

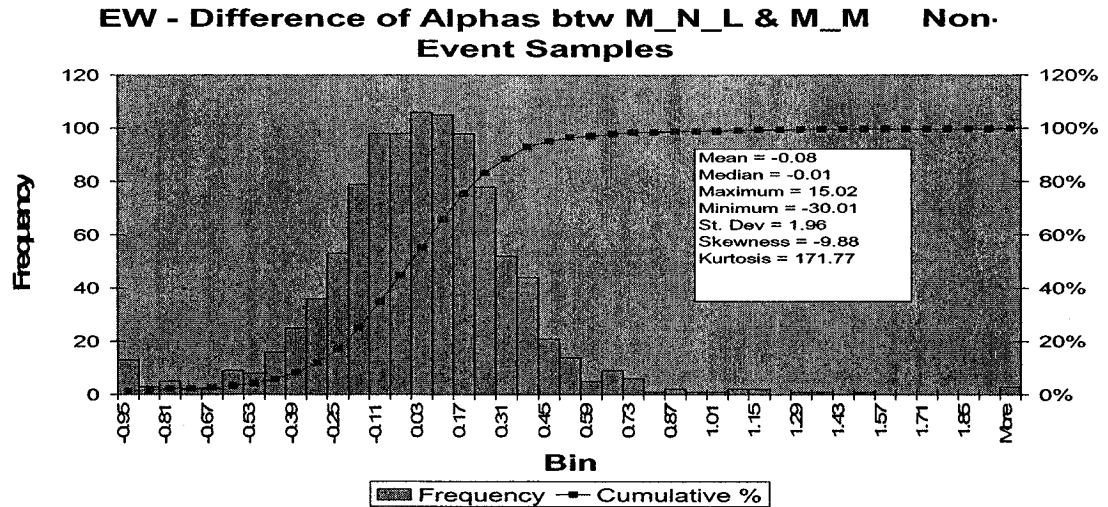


Figure 29: Equally-Weighted Distribution of Difference of Non-Event Alphas between Sub-Samples M_N_L and M_M

Displayed are the 1000 differences of equally-weighted non-event alphas calculated as $a_{i[M_N_L]} - a_{i[M_M]}$ where $a_{i[M_N_L]}$ is one observation of alpha for the M_N_L subsample and $a_{i[M_M]}$ is one observation of the alpha for the M_M subsample. The distribution generated from these differences allows the test of the hypothesis that $a_{(OLS)[M_N_L]} - a_{(OLS)[M_M]} = \hat{a}_{(OLS)[M_N_L]} - \hat{a}_{(OLS)[M_M]}$, where $a_{(OLS)}$ values are the original OLS estimates of alpha for each sub-sample from the 3-factor model.

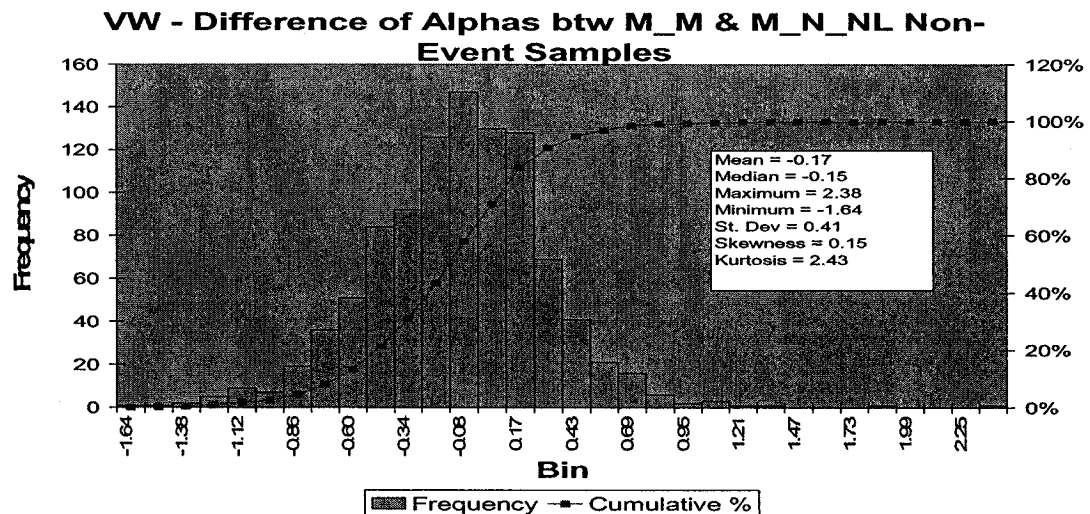


Figure 30: Value-Weighted Distribution of Difference of Non-Event Alphas between Sub-Samples M_M and M_N_NL

Displayed are the 1000 differences of value-weighted non-event alphas calculated as $a_{i[M_M]} - a_{i[M_N_NL]}$ where $a_{i[M_M]}$ is one observation of alpha for the M_M subsample and $a_{i[M_N_NL]}$ is one observation of the alpha for the M_N_NL subsample. The distribution generated from these differences allows the test of the hypothesis that $a_{(OLS)[M_M]} - a_{(OLS)[M_N_NL]} = \hat{a}_{(OLS)[M_M]} - \hat{a}_{(OLS)[M_N_NL]}$, where $a_{(OLS)}$ values are the original OLS estimates of alpha for each sub-sample from the 3-factor model in table 11.

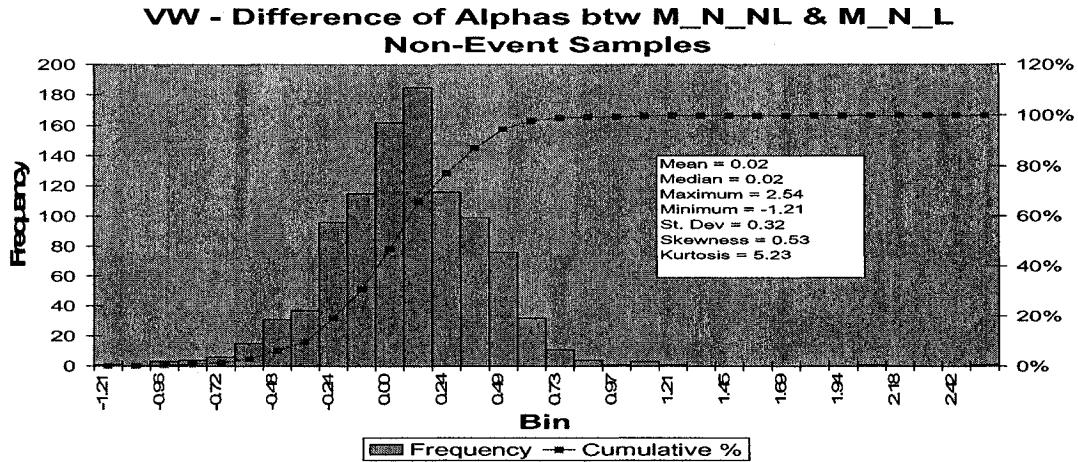


Figure 31: Value-Weighted Distribution of Difference of Non-Event Alphas between Sub-Samples M_N_NL and M_N_L

Displayed are the 1000 differences of value-weighted non-event alphas calculated as $a_{i[M_N_NL]} - a_{i[M_N_L]}$ where $a_{i[M_N_NL]}$ is one observation of alpha for the M_N_NL subsample and $a_{i[M_N_L]}$ is one observation of the alpha for the M_N_L subsample. The distribution generated from these differences allows the test of the hypothesis that $a_{(OLS)[M_N_NL]} - a_{(OLS)[M_N_L]} = \hat{a}_{(OLS)[M_N_NL]} - \hat{a}_{(OLS)[M_N_L]}$, where $a_{(OLS)}$ values are the original OLS estimates of alpha for each sub-sample from the 3-factor model in table 11.

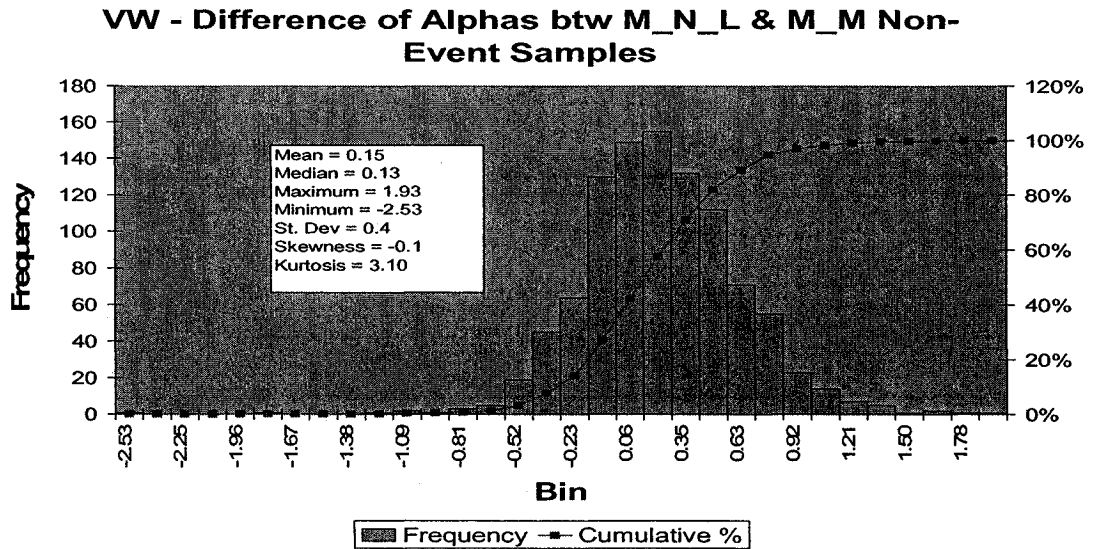


Figure 32: Value-Weighted Distribution of Difference of Non-Event Alphas between Sub-Samples M_N_L and M_M

Displayed are the 1000 differences of value-weighted non-event alphas calculated as $a_{i[M_N_L]} - a_{i[M_M]}$ where $a_{i[M_N_L]}$ is one observation of alpha for the M_N_L subsample and $a_{i[M_M]}$ is one observation of the alpha for the M_M subsample. The distribution generated from these differences allows the test of the hypothesis that $a_{(OLS)[M_N_L]} - a_{(OLS)[M_M]} = \hat{a}_{(OLS)[M_N_L]} - \hat{a}_{(OLS)[M_M]}$, where $a_{(OLS)}$ values are the original OLS estimates of alpha for each sub-sample from the 3-factor model.

