The outsourcing of R&D through acquisitions in the pharmaceutical industry[†]

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Abstract

We examine the performance of 160 pharmaceutical acquisitions from 1994-2001 and find evidence that on average acquirers realize significant positive returns. These returns are positively correlated with prior acquirer access to information about the research and development activities at target firms and a superior negotiating position. A unique *Desperation Index* is employed in order to determine the current status of a firm's internal productivity. We find that firms experiencing declines in internal productivity or which are more desperate are more likely to engage in an outsourcing type acquisition in an effort to replenish their research pipelines.

Key words: acquisitions; asymmetric information; winner's curse; pharmaceutical industry
JEL: G34, D82

1.0   *Introduction*

Researchers have documented that acquirers generally realize negative returns from acquisitions or, at best, break even. We document findings indicating how acquirers have been able to avoid the winner's curse by obtaining information about the true underlying value of the target firm prior to acquisition. This information advantage for acquirers enables them to avoid the three major pitfalls that typically characterize unsuccessful acquisitions: 1) overbidding for the target firm, 2) selecting an incorrect target firm, and 3) failing at the post-acquisition integration process.

Instead of investigating a heterogeneous sample of acquisitions, we focus on research and development-directed acquisitions in the biopharmaceutical industry. This focused examination has two main advantages. First, it allows us to use the extensive publicly available data for both the acquiring and target firms involved in new drug research that are related to informational asymmetries. Secondly, it provides measures of acquirer firm performance subsequent to an acquisition directly related to R&D productivity, specifically product pipeline improvements.

We make four contributions to the literature. First, we find evidence consistent with the proposition that deteriorating R&D productivity may be the motivation underlying the acquisition of research-intensive biotech firms. An integrated data sample of four complementary data sources allows us to test *why* and *which* firms engage in outsourcing R&D-type acquisitions. Relatively few studies focus on the motivation behind a firm's acquisition decision.[1] In this paper, we find that firms that are experiencing the greatest deterioration in their R&D productivity are most likely to undertake the acquisition of a research-intensive firm.

Second, we find evidence consistent with the proposition that biopharmaceutical firms can successfully outsource R&D through acquisitions. These acquisitions appear to effectively supplement a firm's internal R&D efforts and R&D-focused alliances. Overall, we find positive announcement period cumulative abnormal returns for our acquiring companies of positive 3.91 percent.[2] This figure is greater than previous results reported in the existing literature.[3,4] In

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[1] Andrade, Mitchell & Stafford (2001) point out that "…if mergers could be sorted by their true underlying motivations, it may be those which are undertaken for good reasons do benefit acquirers, but in the average statistics, they are canceled out by those with bad reasons."

[2] Significant at the 1% level.

[3] Andrade, Mitchell & Stafford (2001) report average announcement period abnormal returns of –0.70 percent for acquiring firms across 3,688 different acquisitions from 1973–1998. These abnormal returns fell to -1.00 percent when focused on 1,864 deals from 1990-1998.

addition to the significant financial gains to our sample acquirers, we find real measures of success. For example, 71 percent of acquirers in our sample either maintain or improve their product pipelines or portfolios post-acquisition.

Third, we find that access to information by the acquirer during the pre-acquisition period leads to greater acquirer success. Most acquisition research concludes that acquiring companies pay too much for a target and little or no value is created for their shareholders when a significant portion of the target firm's value consists of intangible assets.[5] One reason for such overpayment is the difficulty in valuing intangible assets. To overcome these valuation difficulties, we hypothesize that an acquirer can obtain significant additional information through pre-acquisition alliances with the target firm or alliances with firms conducting research that is similar to that of the potential target firm. The acquirer can also obtain additional insights into the underlying value of the target by drawing upon its own internal research experience. We find that pre-acquisition information-gathering activities are positively and significantly correlated with acquirer success.

Fourth, according to Samuelson and Bazerman (1985) acquirers engaged in bilateral negotiations with a target firm that may have superior information regarding the true value of its assets tend to succumb to the winner's curse. We find, though, that acquirers can mitigate overbidding by bidding from an advantageous negotiating position. Our results indicate that acquirer gains are positively correlated with the pre-acquisition strength of the acquirer's new product pipeline and exclusive products portfolio.

The remainder of the paper is organized as follows: section 2 briefly discusses productivity trends in the pharmaceutical industry; section 3 provides a brief discussion of the relevant literature; section 4 discusses the empirical methodology and data used in our analysis; section 5 presents and discusses our empirical finding; and we conclude in section 6 by summarizing the analysis and discussing the implications of our results.

2.0 Productivity Trends in the Pharmaceutical Industry

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[4] Bruner (2002) provides a comprehensive review of the current literature on M&As and summarizes the results for acquirer shareholders in Table III, which range from −14.2 percent to +3.24 percent for non-tender offer transactions.
[5] See Rodriguez and Higgins (2003) for a notable exception among software acquisitions.

Productivity in the pharmaceutical industry -- as reflected by the overall industry exclusivity and patent horizon -- has been declining in the late 1990s, because more drugs are coming off exclusivity protection than are being replaced by new Food & Drug Administration (FDA) approved products.[6] Exclusivity refers to exclusive regulatory marketing rights granted by the FDA under 21 C.F.R. 314.108, which prevents generic products from entering the market.

The pharmaceutical industry had a combined total of approximately 1,146 years of aggregate exclusivity protection in 1998. The exclusivity horizon had fallen to just over 800 years by 2001 and the rate of decline has been fairly rapid. Figure 1 plots the total number of exclusive years for each product currently approved by the FDA[7]. The aging of the overall industry product profile is one reason for this rapid decline. In addition, new products take an average of 10-15 years to develop from initial discovery to final FDA approval. (DiMasi, 2001) From 1988-2001, the average time the FDA took to approve a new drug was approximately 20 months. (FTC, 2002) Over the same time period, the cost of developing a new drug product has increased from $231 million in 1987 to $802 million in 2000. (DiMasi, 2001) Domestic research and development expenditures have followed the same trend. In 1990, R&D expenditures for U.S. pharmaceutical companies totaled $6.8 billion and have grown to over $21.3 billion in 2000. However, as a percentage of sales, R&D expenditures have remained fairly stable at around 17 percent from 1990 to 2001, peaking at 20.4 percent of sales in 1997. (PhRMA, 2002)

In response to this decline in R&D productivity, pharmaceutical firms have pursued several options: (1) enhance their internal R&D efforts through the acquisition of smaller pharmaceutical and/or biotech companies; (2) engage in large horizontal mergers to achieve greater economies of scale and scope in their research programs; (3) acquire existing mature products through licensing agreements; (4) increase organic internal R&D efforts independently; (5) increase alliance activity; or (6) change their fundamental business model. These options are by no means mutually exclusive; in reality, companies usually engage in a number of these activities at varying levels. In this paper we explore the first response – the impact that the outsourcing of R&D through acquisition has had on individual firm R&D productivity.

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[6] One explanation put forth by industry representatives for this decline is that the "easy" drugs have already been developed – the drugs currently under development are much more sophisticated and target more difficult diseases. A second explanation, described in the Wall Street Journal ("Drug Industry's Big Push Into Technology Falls Short", February 24, 2004), suggests that the heavy reliance on combinatorial chemistry and high-throughput screening did not produce the "hits" that were initially hoped for when this technology was adopted in the 1990s.
[7] This information is publicly available in the FDA's Orange Book.

3.0   Acquisitions and the outsourcing of R&D

3.1   Relevant research on merger and acquisitions

A significant quantity of research has been dedicated to understanding for whom and how value is created through acquisitions. Many theories have emerged, for example, the monopoly theory of mergers (Mueller, 1985; Eckbo, 1992; and Ravenscraft and Scherer, 1987); the synergies approach (Bradley *et al*, 1989); economies of scale (Ravenscraft and Scherer, 1989; Houston *et al,* 2001); to gain market power (Anand and Singh, 1997; Baker and Bresnehan, 1985; Barton and Sherman, 1984); redeployment of assets (Capron, 1999); and, diversification. (Berger and Ofek, 1995)

The conclusion one draws from the bulk of the research focusing on whether value is "created" or "destroyed" is that the return to acquiring firm shareholders, on average, is essentially zero.[8] The majority of the value flows to the target firm shareholders.[9] (Jensen and Ruback, 1983; Brickley and Netter, 1988; Bruner, 2002) Relatively few studies have been able to demonstrate meaningful value gains on behalf of acquiring firms in non-tender offer acquisitions. Andrade *et al* (2001) suggests that the underlying strategic motivation for a particular transaction may provide a fruitful avenue for identifying how value is created through acquisitions for acquirer shareholders. Since companies merge for multiple reasons, it may be the case that companies engaging in mergers for "bad" reasons are negating the gains to companies engaging in mergers for "good" reasons. Mitchell & Lehn (1990) have shown empirically that there are both good and bad transactions from the viewpoint of the acquiring companies' shareholders. Andrade, Mitchell & Stafford (2001) offer five motivations for acquisition: (1) efficiency-related reasons that involve economies of scale or other synergies; (2) creation of market power; (3) market discipline; (4) self-serving attempts by acquirer management to over-expand; and (5) diversification. Each of these strategic motivations, however, has its own distinct set of problems and concerns. It may be the case then, that by grouping all transactions together we are unable to clearly look at them in any meaningful manner. By classifying acquisitions into appropriate categories of transactions, we may be able

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[8] See Kohlers and Kohlers (2001); Ecko and Thorburn (2000); Lyroudi, Lazardis and Subeniotis (1999); Schwert (1996); and Andrade, Mitchell and Stafford (2001)

to determine which strategic motivation for mergers is flawed, and thereby predisposed to destroy shareholder value. Researchers can then begin to focus on these different underlying motivations and determine why a particular strategy has been successful or unsuccessful.

3.2 Outsourcing of research and development

Mergers and acquisitions as a method for outsourcing research and development is one of the justifications for acquisition activity observed during the latter 1990s. Pharmaceutical companies, in particular, have begun to supplement internal R&D efforts through acquisition. Chesbrough (2003) discusses the importance of a company's need to address their research gaps in a timely manner. One of the methods he suggests to fill these research gaps is through the acquisition of external technologies. In addition, James (2002) discusses the role mergers and acquisitions can play in enhancing a firm's internal capability. For example, in discussing their December 2002 acquisition of Triangle Pharmaceuticals, a Gilead Sciences' spokeswoman said, "We had a need to build our pipeline. This acquisition brings to Gilead not only a late-stage product that could launch next year, but a pipeline of other drugs in development."[10] Merck provides another interesting example of this trend. In March 2002 Merck's CEO lauded the company's pipeline of products which numbered 11 potential treatments that were slated to launch over the next few years. However, as of November 2003, only two of the products have launched. A third product was in the process of being filed. Two product's filings have been delayed until 2006 and six products have either been canceled or delayed indefinitely.[11] These cancellations and failures have caused Merck's pipeline to deteriorate significantly. Subsequently, in February 2004, Merck acquired Aton Pharmaceuticals Inc., a privately held biotechnology company. In describing the acquisition Merck said "The acquisition…will enhance its [Merck] internal research efforts to develop potential new medicines for the treatment of cancer…"[12]

In addition to having an understanding of what they are purchasing, acquiring companies must also have the absorptive capacity to integrate the acquired research into their own R&D

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[9] See Houston, James, and Ryngaert (2001); DeLong (2001); Eckbo and Thorburn (2000); and Bruner (2001)
[10] Smartmoney.com, "If you can't beat em, buy em", December 4, 2002.
[11] Wall Street Journal, November 28, 2003.
[12] Wall Street Journal, "Merck to Buy Aton Pharmaceuticals", February 23, 2004.

program. Cohen and Levinthal (1989) postulate that a firm's absorptive capacity will be based on their own internal research and development efforts. As a result, regardless of the external R&D activities that an acquiring company may engage in, it will still be important for the firm to continue to pursue a comprehensive internal research program. Chesbrough (2003)

One challenge that acquirers face in these types of acquisitions is holding on to essential target firm employees who may represent a significant portion of firm value at the target. In contrast to the primary findings in the extant literature -- for example, Andrade (2001) and Myers and Majluf (1984) -- equity deals may be preferable to cash deals. Equity deals may be more effective in aligning the interests of employees at the target firm with those at the acquiring firm. This type of moral hazard problem is discussed by Jensen and Thursby (2001) within the context of university licensing agreements. They find that the use of equity in order to induce scientists to continue to remain committed to a project is an effective measure for reducing the moral hazard problem. Additionally, the willingness of the target firm in these transactions to accept equity payment also serves as a signal to the market regarding their on-going commitment to their research post-acquisition.

3.3   Information gathering and the winner's curse

Asymmetric information in acquisitions is potentially a significant problem. For our specific example of acquisitions, this problem is compounded given the knowledge-intensive nature of the industry. Knowledge-based assets, in general, are more difficult to assess than tangible ones. One of the concerns for an acquiring company is their ability to accurately value the target firm. Firms that attempt to make acquisitions outside of their core competencies may have difficulty adding value to the firm. (Williamson, 1975) Given this potential difficulty, it makes sense for knowledge-intensive firms to pursue targets with similar competencies.[13] Chatterjee and Wernerfelt (1991) and Samuelson and Bazerman (1985) suggest that when acquiring firms engage in negotiations with target firms that have superior information regarding the true value of its assets, the acquiring firm will tend to succumb to the winner's curse and overpay for the target. The winner's curse arises due to the uncertainty over the value of the target firm's assets.

We propose that firms pursuing knowledge-intensive acquisitions must engage in *some* pre-acquisition information gathering, besides normal corporate due diligence, in order to diminish the amount of asymmetric information between the acquirer and the target firms. The pre-acquisition information activities that we consider include: alliances prior to an acquisition with the target firm, alliances with other firms within the same therapeutic category as the acquisition, and internal research and prior sales experience within the same therapeutic category as the target firm. These activities function as a feedback mechanism which allows acquiring companies to generate information on a potential target. The pharmaceutical acquirers in our sample have been and continue to be heavily focused upon research and development; we can presume they are experts in evaluating the future profitability of basic research. As such, if an acquiring firm is engaged in similar research as a target firm, it should be able to place a more accurate value on the target research, potentially avoiding the typical overpayment associated with the winner's curse. Additionally, prior contact with the target firm through alliances gives the two firms an opportunity to "learn" about each other's research and also meet and work with key scientists and management.[14] In the current analysis, each acquiring firm has, on average, four prior alliances with the target firm *prior* to the acquisition. This contact should provide the acquiring firm with sufficient information regarding the human capital of the target firm. Combined, these pre-acquisition activities should provide enough information to the acquirer so that it "knows what it is buying." This type of organizational learning perspective is broadly similar to that suggested by Hayward (2002).

In addition to providing information, Rothaermel (2001) finds that alliances with providers of new technologies are positively correlated with new product development for the incumbent firm and, in turn, new product development is positively associated with firm performance. This finding is supported elsewhere in the literature, for example, Shan et al (1994) and Deeds and Hill (1997).

Acquirers in the pharmaceutical industry are able to negotiate more effectively with the target firm when the exclusivity and patent horizon of their own product portfolios and their product pipelines are strong. We argue they undertake acquisitions to supplement their slowing

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[13] In fact, 82 percent of the acquisitions in the current project are ones that involve firms with complementary research.

[14] Anand and Khanna (2000) show that firms can *learn* to create value as their alliance experience accumulates over time.

R&D productivity as evidenced by an increase in their *Desperation Index* (our unique quantitative measure of firm level desperation), which will be discussed more fully below. Firms are able to capture value from their acquisition activities by improving their stock of knowledge or information about the target prior to the time of the acquisition. As such, we make the following predictions: (1) the probability that a given firm undertakes a R&D acquisition will be positively related its level of desperation just prior to an acquisition; (2) given that a firm makes an acquisition, the cumulative abnormal return, *CAR*, realized from the acquisition will be positively related to the stock of information accumulated by the acquirer in the period prior to an acquisition; (3) the *CAR* realized from an acquisition will be negatively related to the acquirer's level of desperation; (4) post-acquisition improvements in R&D productivity or pipeline health of an acquirer will be positively related to acquirer's pre-acquisition information gathering activities; and, (5) post-acquisition improvements in pipeline health of an acquirer will be positively related to the acquirer's level of desperation prior to an acquisition.

4.0   *Empirical Methodology and Data Sample*

4.1   *Empirical Methodology*

We use event study methodology to compute the cumulative abnormal returns around the time of the acquisition announcement. Acquisition dates for the sample were gathered from Securities Data Corporation (SDC) and verified using publicly available media reports from *The Wall Street Journal* and other business publications. We ran the event study utilizing an event window of three days. The three day window includes the day of the announcement as well as the day before and after. As a robustness check, we re-ran the event study utilizing a five day window. The five day window includes the three days prior to an acquisition announcement, the day of the announcement as well as the day after. Finally, we checked for confounding events for each transaction with *The Wall Street Journal*.[15]

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[15] Major corporate events including: litigation, naming of new CEO or senior management, new product announcements, earnings and dividend announcements, major news relating to success or failure of a drug in clinical trials, rulings by the FDA and other mergers, joint venture or alliance announcements were considered confounding events. Firms for which confounding events are identified were excluded from our sample.

One of the challenges in analyzing mergers and acquisitions is to find appropriate measures of transactions success, in addition to the widely accepted cumulative abnormal returns. Healey, Palepu, and Ruback (1992) use post-acquisition accounting data to test directly for changes in operating performance that result from mergers. This approach would not be appropriate for the current analysis, because it overlooks the health of the acquiring company's product pipeline, which represents potential future significant cash flows that are not recorded in available accounting data. We examine two measures of acquisition success in addition to cumulative abnormal returns. First, we look at the post-acquisition change in the product pipeline for the year following the acquisition. We quantitatively measure each company's pipeline using a unique "*Score*" value, which will be discussed below. If pipeline products were included in the acquisition, the company's post acquisition product pipeline *Score* value should increase. This would be one indication that the company was successful in making improvements to its product pipeline as a result of R&D acquisitions. Second, we look at post-acquisition changes in revenues in the year following the acquisition. This measure is less precise for two reasons. First, since many of the acquisitions are smaller in size, even if a company acquired a mature product with existing sales, those added sales may not be enough to counteract the firm's existing loss in sales due to current products coming off patent. Second, pipeline products that are acquired by a firm will most likely not have sales in the following year, unless the product has already been submitted for FDA approval.[16] To test our primary predictions, we employ regression analysis controlling for firm characteristics and transaction characteristics expected to affect the value creation resulting from acquisitions in our sample using our standard measure of acquirer success, *CARs*, and two industry-specific measures of success, improved product pipeline and new drug product sales.

4.2   *Acquisition identification*

We obtained acquisitions data from Thomson Financial's Securities Data Corporation (SDC) database for the years 1994-2001. We identified transactions representative of the new

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[16]   The inability to extend this beyond one year post-acquisition is a function of our data range. Since our data ends in 2001, we are limited to the number of years we can extend the analysis post-acquisition without losing data points. Our current research project is looking at the status of the acquired pipeline products in the post-acquisition period.

product-focused biotechnology industry acquisitions by the primary acquirer SIC code and by SDC's "high-tech" search variable. SIC codes 2833-2836 cover the pharmaceutical industry. The "high-tech" industry classification by SDC identified firms within the biotechnology industry, but with SIC codes other than 2833-2836. This search method also identified high-tech companies in different sectors. As a result, we filtered the data set using SDC's "business description" and "sector" variables. Acquisitions that clearly were outside of the biopharmaceutical sector were deleted from the data set. Unrelated acquisitions were considered to be those that included over-the-counter or generic drugs, consumer products, medical devices and products, and manufacturing facilities. In addition to filtering the sample to verify the relevance of the acquisition in question, we collected additional information from news stories from Factiva. First, we verified the value and method of payment of the acquisition, when disclosed. Second, we noted the company's stated reason for entering into the acquisition. Third, the relatedness of the firms was coded. Firms were coded as "related" if the target company's research or products were within the same therapeutic category as the acquiring company.[17] The purpose of this classification is determine whether firms were making acquisitions within their current competency or whether they were venturing to build a new competency. This filtering process left approximately 180 transactions spanning 15 countries, with the majority of the acquirers and targets, 76 percent and 80 percent, respectively, being based in the United States. We obtained domestic stock market returns data from CRSP and international returns data from Data Stream. Twenty transactions were dropped from the final sample due to inadequate data; in some of these cases, both parties were private entities and information about the transaction was severely limited or not available.

4.3   Exclusivity horizon and patent profiles

4.3.1   Implications of Hatch-Waxman

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[17] Firms were categorized into broad therapeutic categories based upon the Uniform Standard of Classification. For coding purposes we looked at several sources for therapeutic information about firms. For example, we utilized the therapeutic coding available from our proprietary sales data set, the NDA pipeline, company websites and the news releases about the acquisition itself.

Two types of patent protection exist for pharmaceutical companies. The first are traditional patents granted and processed by the United States Patent and Trademark Office (USPTO). The Uruguay Round Agreements Act of 1994 extended patent lengths from 17 years from the date the patent was granted to 20 years from the date the application is filed. Traditional patents can be filed anywhere along the development lifeline of a drug and they can encompass a wide range of claims. In fact, most approved pharmaceutical products have several patents attached to them. For example, the new Eli Lilly drug *Cialis*™ which was approved on November 21, 2003, has two separate patents associated with their new drug application (NDA).[18]

The second type of protection is regulatory in nature and granted by the FDA upon actual approval of a new chemical entity (NCE). This type of protection is termed *exclusivity* and may run concurrent with traditional patent protection. For a NCE, exclusivity is granted for a period of five years from the date of FDA approval.[19] Exclusivity came about as an important provision in the Drug Price Competition and Patent Term Act of 1984 – more commonly referred to as the Hatch-Waxman Act. The purpose of exclusivity was to provide pharmaceutical companies five years of marketing protection during which other manufacturers were prohibited from filing an application to sell a generic product. Exclusivity does not, however, prevent other manufacturers from seeking approval for a drug that uses the same therapeutic mechanism as an already approved drug. These products are often referred to as "me-too" drugs and are required to undergo the same rigorous clinical testing in order to garner FDA approval.[20] For example, the erectile dysfunction drugs *Cialis™* and *Levitra*™ -- direct competitors of the already marketed drug *Viagra*™ -- were approved on November 2, 2003 and August 19, 2003 respectively. The exclusivity provision was designed to help firms that had no patent protection, or had very little time left under patent by the time a NCE was finally approved by the FDA.

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[18] Two patents -- numbers 5859006 and 6140329 expiring on January 12, 2016 and July 11, 2016, respectively – were attached to the NDA in the FDA Orange Book.

[19] Orphan (for rare diseases and disorders) and pediatric drugs are granted longer exclusivity periods due to their more limited use. For example, orphan drugs are granted 7 years of exclusivity protection.

[20] This is in contrast to generic drugs which, according to the Hatch-Waxman Act, only need to demonstrate "bio-equivalence" to an already approved brand name drugs in order to get FDA approval. Bioequivalence means that the active ingredient in the generic drug is absorbed at the same rate as the brand name drug. The test required to demonstrate bioequivalence are much less costly than those undertaken by brand name drugs. This provision in Hatch-Waxman has allowed generics to enter the market quickly and at much lower cost. For example, prior to Hatch-Waxman in 1983, only 35 percent of top-selling drugs with expired patents faced generic competition. By 1998, that number was close to 100 percent. (CBO, 1998)

Our goal is to construct an exclusivity and patent profile for each pharmaceutical company with an approved product. The purpose of such an exercise is to provide a measure of the health of an individual company's patented product profile. The FDA Orange Book indicates when a NCE is formally approved by the FDA. Along with this approval is the granting of exclusivity by the FDA. According to 21 C.F.R. § 314.53, upon submission of a new drug application (NDA) for consideration by the FDA, pharmaceutical firms are required to submit relevant and supporting patent information. For patents issued after the approval of an NDA, firms are required to submit relevant patent information within 30 days.

Unfortunately, several issues arise when trying to use the FDA Orange Book to construct our exclusivity and patent profiles which must be taken into consideration. First, exclusivity and patent lengths are not static. That is to say there are ways in which companies are allowed to extend the length of both their exclusivity and patent protection. The allowances for both of these extensions flow from the Hatch-Waxman Act. In terms of patent protection, companies that have received approval for a NCE by the FDA can apply to have half the time the drug spent in clinical trials (approximately four to eight years) plus all of the time spent having the FDA review (usually two years) its new drug application added onto its patent length. There are three limitations. First, the extension cannot be longer than five years. Second, the total granted patent length of a drug cannot exceed 14 years after the drug has been approved and, third, companies must apply for this extension within 60 days of FDA approval. (CBO, 1998) Additionally, only one patent is eligible for the Hatch-Waxman extension. As a result, most firms will choose to extend the patent that covers the drug's chemical compound or in the alternative, the patent that covers the use of the drug. (CBO, 1998)

The Hatch-Waxman Act also provides for extensions to exclusivity protection. The act allows for the granting of three additional years of exclusivity for a supplemental NDA if the application required additional clinical testing. Manufacturers will often use this provision in order to obtain approval for new dosages of previously approved products. Schering used these provisions effectively in the follow-up introductions of *Claritin-D*™ and *Claritin-D 24 Hour*™ to there hit allergy medicine *Claritin*™, which was originally approved on April 4, 1993. The logic behind this provision is to provide an incentive for manufacturers to continually improve brand-name products. (CBO, 1998)

When a generic manufacturer makes an application (called an Abbreviated New Drug Approval or ANDA) to the FDA the ANDA must contain a certification regarding each of the patents listed in the Orange Book. There are four possible certifications that can be made.[21] Of relevance to the current discussion as it relates to the extension of exclusivity are "Paragraph IV Certifications". With this certification a generic manufacturer is challenging that a listed patent is either invalid or will not be infringed upon by the generic drug. The manufacturer making this claim must provide the patent holder with their factual and legal basis for their filing. The patent holder then has 45 days in which to file an infringement suit. By filing an infringement suit, the FDA sets aside the approval process for the ANDA until the earliest of: (1) the date the NDA patent being challenged expires, (2) there is a court ruling invalidating the patent, (3) a court ruling of non-infringement, or (4) 30 months after the patent holder was originally notified of the ANDA Paragraph IV certification. The Federal Trade Commission (FTC) estimates that Paragraph IV challenges, on average, take approximately 25 months to adjudicate. (FTC, 2002) In effect, brand-name manufacturers are able to tack on another two and one-half years of additional exclusivity protection thereby increasing their effective exclusivity period to seven and one-half years.[22]

Unfortunately, these provisions to extend exclusivity and patent protection have been increasingly used in an effort to stave off generic competition by the brand-name manufacturers.[23] Bulow (2003) provides a more complete discussion of the type of "gaming" that has taken place. As a result, the FDA Orange Book, which provides an accurate picture of new drug approvals, may be missing relevant patent data. We next discuss the construction of our variables and the potential biases, we feel, that may be introduced as a result of the above discussion.

4.3.2   Exclusivity & Patent Profiles

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[21] See Bulow (2003) for a description of the four certifications.

[22] In their report, the FTC noted that the prevalence of infringement suits increased after 1998. (FTC, 2002)

[23] This process appears to have been abused in the past. For example, Bristol Meyers Squibb (BMS) announced that they would pay a total of $670 million to settle anti-trust suits relating to *Buspar* and *Taxol*. One of the allegations made was that the improperly listed a patent in the Orange Book extending their exclusivity. (*In re Busprinoe Patent Litigation*, MDL No. 1410 (S.D.N.Y.))

Three separate data sources are utilized in generating our firm and industry exclusivity and patent profiles. Since there is the possibility of underreporting in the FDA Orange book, two other sources, Thomson Derwent and NERAC, are used in an attempt to identify additional patents that could be used by the firm in order to extend protections. The goal in utilizing these added data sets is to attempt to capture additional, unreported patents that are relevant to a particular approved product. The net result of using this combination of data is that we create a bound for each of our profile measures. A lower bound is created by the use of the FDA Orange Book since there is potential underreporting of patents. An upper bound is created by the combination of Derwent and NERAC. We make the claim that an upper bound is generated since theses datasets attempt to identify additional patents tied to a particular approved product that are not identified in the FDA Orange book. Since this process of attaching additional patents to a particular approved product is rather subjective it is *possible* that some of the patents identified and attached to a product *may* not be useable by the firm in efforts to increase patent protection or stave off generic competition.[24]

In addition to these raw patent and exclusivity profiles a third measure is created. This measure is a sales-weighted exclusivity horizon. Since not all approved products are worth the same in terms of revenues, it makes sense that not all patents are worth the same. By sales-weighting our exclusivity measure we are able to discern the status of the most important patents to the firm, in terms of revenues. We constructed this by obtaining proprietary sales data from IMS Health for every patented drug in the FDA's Orange Book files from 1994-2001.[25] We combined the two data sets for each product to obtain a weighted product exclusivity horizon. Each product was weighted according to the proportion of sales represented by the average product life cycle of all drugs in the FDA Orange Book. The average product life cycle was determined as the proportion of sales in each year of exclusivity through three years following loss of exclusivity protection. Over the entire Orange Book file, 74.19 percent of sales occurred during the five-year exclusivity protection period, while an additional 15 percent of sales were realized in the three years following the loss of exclusivity. We chose this weighting technique in an effort to reflect each product's position correctly within its individual product sales life

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[24] We thank a patent attorney specializing in biopharmaceutical patents, who requested to remain anonymous, for spending countless hours answering questions relating to these issues.
[25] 150 patented products identified in the Orange Book files did not have sales data identified in IMS Health's data set; this left 398 patented products with sales data.

cycle. This life-cycle measure also provides some empirical insight into the previous discussion relating to potential "gaming" in the FDA Orange Book. Since 74.19 percent of sales across the FDA Orange book are occurring within a drug's first five years of sales, this suggests that the impact of "gaming" may not yet be that significant. On average, the vast majority of pharmaceutical sales for a product are still occurring within their first five years of approval.

The exclusivity horizon for the sector, regardless of the measure used, indicates that the cumulative horizon is declining. Figure 1 plots the cumulative number of years of exclusive marketing rights remaining for all patented products for the years 1991-2002. The range was extended beyond our sample length of 1994-2001 to demonstrate the longer run trend. Two potential extensions of the number of exclusive years were discussed; this graph takes into consideration one of those concerns. When companies apply for a supplemental NDA as a result of a new dosage or use, those products are listed separately and as a result, are captured in this measure.[26] It is possible that *some* firms for *some* products may have a longer exclusivity horizon.

The cumulative patent profile for the sector also follows a similar pattern as the exclusivity profile. The cumulative exclusivity horizon peaked in 1998, while the overall patent profile peaked in 1999. There are two possible reasons the cumulative years for the patent profile exceed the cumulative years in the exclusivity profile. First, exclusivity protection is only granted to products that have been approved by the FDA. There are many projects in earlier stage testing that have received regular patent protection, but are ineligible for exclusivity protection. Second, an approved product is granted exclusivity only once, while at the same time an approved product may have a series of patents tied to it that extend back to the early-stage discovery process. For example, product "X" will be given five years of exclusivity protection (excluding any possible extensions), but may have several patents associated with it with varying lengths of protected time remaining.

4.3   New Drug Approval (NDA) pipeline

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[26]   These products were also listed separately in our proprietary sales data.

In an effort to determine what products are in development for acquirer firms, we use the NDA Pipeline files from 1994-2001. These files contain information relating to the various stages of product development. For purposes of this study we focus on the following phases: pre-clinical, Phase I, Phase II, Phase III and FDA filed. Phase I involves safety testing, Phase II focuses on small-scale human efficacy trials and Phase III focuses on large-scale human efficacy trials. We group all pre-Phase I research into the "pre-clinical" category. We were also able to identify the broad therapeutic categories where this research is focused.[27] For example, over the entire time period, 18.56 percent of all treatments in various stages of development are related in some way to oncology. While the sheer numbers of potential treatments has grown, the number of treatments actually being taken to the last stage – filing with the FDA – has remained relatively constant. The ratio of treatments that make it to FDA filing over the number of treatments in Phase III has declined from 29 percent to 17 percent throughout the 1990s.

Clinical probabilities are subsequently assigned to each of the various phases of research. These assigned clinical probabilities, based on existing research, reflect the chance a potential treatment has of receiving FDA approval (Krieger and Ruback, 2001). We subsequently employ these values to construct a weighted value of each company's pipeline products, which we refer to as the *Score*. A relatively high *Score* indicates a healthy product pipeline, in that higher *Score* values are reflective of a greater number of later stage products in the pipeline. For example, a firm with a small number of Phase II or Phase III products would have a higher *Score* value that a firm with a large number of pre-clinical or Phase I products. The more important element, however, is not necessarily the level of the *Score* in any given year, but rather the trend of the *Score* in the years prior to and after an acquisition. A declining *Score* in the years prior to an acquisition would be indicative of a company whose product pipeline was deteriorating.

The overall industry *Score* value shows a marked increase in the mid-1990s and is reflective of an underlying increase in the number of products in the NDA pipeline. Figure 2 plots the cumulative number of products in their various stages of pipeline research over our sample period. The number of early-stage pipeline products dramatically increased in the late 1990s as did, to a lesser extent, the number of late-stage products. Actual FDA approvals throughout this time period, however, have remained fairly constant at around 50. Reflecting

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[27]   According to the Uniform Standard of Classification.

back to Figure 1, the increase in pipeline products has yet to produce sufficient numbers of new products to stem the decline in industry-wide firm exclusivity horizons.

In the analysis that follows we utilize the raw *Score* values in the two years prior to the acquisition, the year of the acquisition and the year following an acquisition. In addition, two changes in *Score* value are considered. First, we look at the change in the *Score* value between the year of the acquisition and the year prior. Second, we look at the change between the year after the acquisition and year of the acquisition. By using these different combinations we can look at both levels and changes in the *Score*.

4.4   Alliances

For our analysis we use a proprietary set of alliance data provided by Recombinant Capital. This data identifies alliances in the biopharmaceutical industry from 1973 through 2003. It also provides a general description of the nature of these alliances. This information provides two important acquirer firm attributes for our present analysis: (1) whether the acquiring company had any alliances with the target company prior to the acquisition; and, (2) what type of alliances these were for example, licensing, research, development, co-development, co-marketing, distribution, or manufacturing. We are also able to determine whether an alliance was for an early or late stage product. In addition to alliances between our acquirer and target, we also specify two other categories of alliances. The first category is whether or not the acquiring company engaged in *any* alliances prior to the acquisition with other firms other than the target. The second category of alliances is whether the acquiring company engaged in any other alliances within the same therapeutic category as the target, but with a firm other than the target. We believe prior alliance activity with the target provides the most specific opportunity for an acquiring company to "learn" about the target firm. In fact, 67 percent of the sample acquirers engaged in, on average, four alliances with the target prior to the acquisition.[28]

4.5   Desperation Index

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[28] Target firms, on average, had six alliances with firms *other* than the acquiring firm prior to the acquisition.

Through the combination of these data we construct a categorical *Desperation Index*. We place each firm in the sample into one of four categories of desperation based upon whether or not the change in their *Score* value and sales-weighted exclusivity horizon is increasing or decreasing in the year immediately prior ($year_t – year_{t-1}$) to an acquisition. The categories reflect an increasing level of desperation. Category I (strongest position) represents firms that have an increasing *Score* value and an increasing sales-weighted exclusivity horizon. Category II represents firms that have increasing *Score* values, but a declining sales-weighted exclusivity horizon. In contrast, a Category III firm is generating increasing sales, but has a declining *Score* value. Finally, Category IV (weakest position) represents firms that have both decreasing *Score* values and a decreasing sales-weighted exclusivity horizon. We place Category II firms ahead of those in Category III since they have greater potential for generating future products and as a result future sales. For example, a firm in the second category is one that is experiencing a decline in sales prior to an acquisition, but it is also experiencing an increase in *Score* value. The prospect exists for the firm to be able to replace declining sales products with new ones in the future. In contrast, a category three firm is generating increasing sales but their *Score* value is declining. This would be indicative of firm whose product pipeline is deteriorating. Thus, this firm would have a lower prospect for being able to replace current products with new ones in the near future. Firms were assigned to corresponding desperation index categories prior to and subsequent to each acquisition. As we will discuss below in Table 8, 60 percent of firms were categorized as either Category III or IV in the period prior to the acquisition. This is in contrast to the post-acquisition period, where only 32 percent of firms were categorized as Category III or IV. Approximately 28 percent of the acquiring firms in our sample were able to remove themselves completely from these lower classifications. Whereas 59 percent of acquiring firms were able to improve their categorical classification by at least one level while only 12 percent of these firms remained at their pre-acquisition desperation level.

In addition to our base definition, we consider other variations and combinations of the variables in our *Desperation Index* in order to test the robustness of our results. First, we parse the *Desperation Index* into its two component parts – the *Score* value and sales-weighted exclusivity horizon. This will allow us to test the *levels* of these variables versus their *change*. Next, we replace the sales-weighted exclusivity horizon variable with three other alternatives. First, we test the raw number of exclusivity years remaining in the portfolio. This is a simple

summation of exclusivity years as reported in the FDA Orange Book. Second, as we discussed above, firms are potentially able to "game" the number of exclusive years for a product. As a result, the first measure may well understate the actual exclusivity horizon. Assuming that a firm will not engage in a patent infringement suit unless the marginal benefit of doing so exceeds the marginal cost of litigation, we add 30 months of exclusivity protection to drugs that have sales equal to or in excess of $100 million in the year they would lose exclusivity protection.[29] A new summation of the exclusivity variable is then generated based on this extension. While not a perfect measure, it should mimic more closely the response of companies. Finally, we replace the sales-weighted exclusivity horizon with a summation of regular patent years. Again, due to potential gaming of patents in the FDA Orange book, we use our second patent measure generated from NERAC and Thomson Derwent. These data attempt to identify relevant data not identified in the FDA Orange book. As a result, there is the possibility that this variable could possibly be overstated. As such, this measure serves as an upper-bound, while the exclusivity horizon will serve as a lower bound.

5.0 Empirical analysis

5.1 Assessing acquirer desperation and propensity to engage in acquisitions

Pharmaceutical firms experiencing declines in either their research pipeline or patented product portfolio can respond in several ways. We focus our analysis here on the propensity of firms to engage in outsourcing acquisitions using probit regressions. Our sample for this analysis includes firms contained in Recombinant Capital's alliance data set from 1994-2001 and that have both sales and pipeline data available. This allows for a homogenous sample of firms engaged in similar activities and facing potentially similar constraints. The dependent variable is an indicator variable, y_{it} that assumes a value of one for a given firm, i, in a specific year, t, if that firm undertakes an acquisition in a given year, and is zero otherwise. For independent variables we use the change in *Score*, R&D intensity, the log of market capitalization, a count variable identifying the number of alliances undertaken prior to the current year (includes all firms, not just target firms), indicator variables corresponding to each category of our potential

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[29] This process was repeated for drugs with $50 million and $75 million in revenues in the final year of exclusivity.

acquirer desperation index and a time trend. As a robustness check, we include the three other definitions and constructions of the components of the *Desperation Index* discussed previously. We also refine the variable *Count* to include only alliances with the target firm. See Table 1 for variable definitions; Table 2 summarizes the variables and Table 3 presents the variable correlations.

We present the results of our probit regressions with White-Huber heteroscedasticity-consistent standard errors in Table 4.[30] Consistent with our hypothesis, we find that firms that are more "desperate" are *more* likely to engage in acquisitions. Recall that our *Desperation Index* is comprised of two components; the change in *Score* value (representing progress in the firm's new product pipeline) and the change in the sales-weighted exclusivity horizon (representing the state of the firm's current product portfolio). Model 1 takes just one of the component values, the change in *Score*, and uses it as an independent variable. We report a negative and significant correlation between the change in *Score* value and the probability that a firm engaged in an acquisition. This result suggests that firms with improving product pipelines are less likely to undertake an outsourcing acquisition. In models 2 and 3, we incorporate each of our four classifications of the *Desperation Index*. Category III and IV firms -- our most desperate firms -- are experiencing a declining sales-weighted exclusivity horizon and declining pipeline *Score* values in the case of Category IV. Of significant interest are the coefficient estimates on x_7 and x_8 which correspond to Categories III and IV of the *Desperation Index*. In model 2, both Category III and Category IV firms were *more* likely than Category I firms to engage in an acquisition. Category III firms were 11.41 percent and Category IV firms were 16.01 percent more likely to engage in acquisitions. This result suggests that as firms fall from Category III to IV, their probability of engaging in an acquisition increases by approximately 4.6 percent. In model 3, when the number of previous alliances indicator variable (*Count*) is removed, the coefficients and resulting probabilities remain fairly stable. Again, Category III and IV firms were more likely than Category I firms to engage in acquisitions. Category III firms were 11.77 percent more likely and Category IV firms were 16.38 percent more likely. Model 4 takes two of the desperation categories and combines them into a single indicator variable, *Desperation Index*, which equals one if the firm is either a Category III or IV firm.

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[30] The same analyses were performed with logit regressions. Unreported results are consistent with the probit analyses reported in the paper. A Hausman test was run and rejected the hypothesis that the individual-level effects were adequately modeled using a random effects approach. As such, a fixed effects model is utilized.

Using this specification, desperate firms were 13.86 percent more likely to engage in an acquisition than Category I and II firms. These findings support recent work by Danzon *et al* (2004). They find a positive relationship between the motivation to merge and a percentage of a firm's drugs that are old and at risk of losing patent protection.

These results suggest that we might anticipate lower or even negative abnormal returns for acquiring firms at higher levels of desperation. However, as we discuss in the next section, we do not find that target firms are able to extract all of the acquiring firm gains, even when the acquirer is particularly desperate to supplement its R&D program.

In unreported regressions we test the robustness of the above results to a change in definition of the *Desperation Index*. First, we parse the *Desperation Index* into its two essential component parts – the *Score* and sales-weighted exclusivity horizon. We then use the *levels* of these variables in the year prior to the acquisition to test whether a firm was more or less likely to engage in an acquisition. In a series of regressions, using the same independent variables as Table 4, we consistently find a negative and significant relationship between our *Score* and *Acquisition* variables. These findings suggest that firms with large *Score* values – or relatively healthy research pipelines – are less likely to engage in an acquisition. Likewise, firms with low *Score* values – or relatively unhealthy research pipelines – were more likely to engage in an acquisition in the following calendar year. The sales-weighted exclusivity horizon variable did not produce the same result. The variable was consistently not significant across the additional specifications. This finding may suggest that the decision to engage in a research type acquisition is mainly driven by what is happening with a firm's research pipeline and not their sales or revenues. This is consistent with the findings of Danzon *et al* (2004).

When we replace the sales-weighted exclusivity horizon with our patent horizon generated from our combination of NERAC and Thomson Derwent data sources we find results similar to those reported in Table 4. Category II was not significant across any specification. Categories III and IV were both negative and significant. Marginal probabilities were slightly larger, on average, than the results we report. Category III firms were around 13 percent more likely to engage in an acquisition than Category I firms while Category IV firms were around 19 percent more likely. When we combine Category III and IV firms together in Model 4 the marginal probability increases slightly to 15 percent. All results using this modified definition of the *Desperation Index* are significant at least at the 5 percent level of significance.

There are several other results of note in this analysis. Firms with greater R&D intensity have a greater propensity to undertake R&D outsourcing acquisitions. This result is consistent with the notion that higher levels of absorptive capacity on the part of research-focused firms are necessary for those firms to incorporate new research into their R&D programs effectively (Cohen and Levinthal, 1989). This view is supported by Chesbrough (2003) who stresses the importance of maintaining internal competencies even while considering the use of outsourced research and development. Additionally, we find that smaller firms have a greater tendency to undertake acquisitions. This is demonstrated by the consistently negative and significant coefficient estimates for our log of market capitalization variable in Table 4. This result is consistent with the notion that pharmaceutical R&D programs require increasing economies of scale (Cockburn and Henderson, 1996). In order for smaller firms to improve the productivity of their research programs, they can engage in R&D acquisitions to increase their scale. Finally, Andrade and Stafford (2004) find that firms with a high Tobin Q are significantly more likely to undertake both merger and non-merger investment. In unreported regressions, we do not find, for the current sample, any statistically significant relation between Tobin's Q and the probability that a firm engaged in an acquisition. High Q firms may very well engage in non-merger investment, however, that question is beyond the scope of the present study.

5.2   Assessing stock market returns

We present univariate *CAR*s against various independent variables in Table 5. We focus on five specific independent variables: the relatedness of the transaction, financing method, alliance activity, sales experience, and research experience. As discussed above, the relatedness of the transaction measures if both the acquirer and target operate within the same therapeutic category. Next, we focus on whether the deal was financed with stock or cash. Mixed financing deals were included in the overall sample, but not in this specific analysis given the inability to attribute any potential *CAR* to a specific financing method. The alliance variable is an indicator that equals one if the acquiring firm had an alliance with the target prior to the acquisition. The sales experience variable is an indicator that equals one if the acquiring firm has patented product sales within the same therapeutic category as the target firm prior to the acquisition. If an acquiring company has a patented product that meets this criterion we argue that the firm has to have some internal capabilities with respect to products in that therapeutic category – since

they had to successfully complete clinical testing and the FDA approval process in order to begin to sell the product. Finally, we include research experience. The research experience variable is an indicator that equals one if the acquiring firm has products in its own pipeline within the same therapeutic category as the target firm. We anticipate that the presence of prior alliances, sales and research experience should generate greater *CAR*s for acquiring firms. We present four separate specifications. We present univariate results in the first column for the entire sample. In columns two through four we present results for three smaller sub-samples. We break the sample into three types. Type I transactions are deals where a biotechnology firm or technology was acquired. Type II transactions are those deals where non-biotechnology related research and development firms were purchased. Type III transactions are those involving a mature product along with research and development capabilities.

The overall average abnormal return for acquiring firms, using a three-day window, is 3.91 percent and is significant at the 1 percent level.[31] Average abnormal returns to target firms were around 16.0 percent. The returns to the target firms are consistent with previous research, as discussed above. We find similar results across the various sub-types of acquisitions. Average abnormal returns for these sub-types were 2.81 percent, 4.29 percent and 5.29 percent, respectively. All are significant at the 1 or 5 percent level. We provide the distribution of the overall average abnormal returns in Table 6. We include several controls to ensure that our results are not being driven by outliers. Panel A of Table 6 breaks the individual abnormal returns down into magnitude ranges. From this panel, we find that only four *CAR*s are below negative 15.0 percent while sixteen *CAR*s are greater than positive 15 percent. Panel B contains a plot of the *CAR*s against their frequency. While the sample appears to be skewed slightly to the right of zero, no large outliers appear to exist. In addition to Table 6, we performed non-parametric tests to determine the sensitivity to outliers.[32]

The extant literature finds that cash-financed transactions generate superior returns than those financed with stock (Andrade *et at*, 2001). Our findings contradict this result. While cash transactions, on average, produce average cumulative abnormal returns of 2.38 percent, those transactions financed with equity yielded returns of 3.87 percent. Both results are significant at

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[31] Abnormal returns for our robustness measure for acquiring firms was 4.38 percent and significant at the 1 percent level. Recall, this *CAR* was a combination of results from a three and five day window, as discussed in Section 4.2.
[32] We perform a Wilcoxon signed rank test, which considers both the sign and magnitude of each transaction's cumulative the abnormal return. We reject the null hypothesis of zero CAR with a z-value of 5.692.

least at the 5 percent level and are also significantly different from each other at the 5 percent level. Equity payments in these acquisitions may help alleviate the moral hazard problem and align the interests of target-firm employees with those of the acquiring firm. As there is generally a large disparity in size between acquirer and target in terms of market capitalization, acquiring firms need to ensure that target firm managers or scientists remain committed to the overall success of a particular research project as they transition from being owners of the firm's research output to employees of the acquirer.

Our next three results examine different types of pre-acquisition information-gathering activities on the part of acquirers: prior alliances, sales experience, and research experience. We find that the presence of each of these activities generates greater abnormal returns for the acquirer. Acquirers that engaged in alliances with the target firm prior to the acquisition generated average abnormal returns of 4.30 percent versus returns of 3.36 percent for those firms that did not engage in these types of alliances. Both are significant at the 1 percent level and are significantly different from each other at the 1 percent level. Acquiring firms that had prior sales experience within the same therapeutic category as the acquisition experienced substantially greater average abnormal returns than those firms that did not. Firms that had prior sales experienced average abnormal returns of 6.99 percent while those that did not experienced average abnormal returns of only 3.08 percent. Both are significant at the 1 percent level and are significantly different from each other at the 5 percent level.[33] Finally, acquiring firms that have existing research experience within the same therapeutic category as the target generate greater average abnormal returns, 5.08 percent versus 3.24 percent. This result suggests that firms are rewarded for making acquisitions within their existing areas of expertise. Again, both are significant at the 1 percent level and are significantly different from each other at the 1 percent level. The presence of each of these activities allows the acquiring firm to "learn" about the true underlying value of the target. As a result, acquiring firms are able to place a more accurate value on the target firm and generate greater positive abnormal returns for their shareholders. It

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[33] A robustness check on a slight change in definition was performed. Currently, the variable includes sales of a patented product for which a firm may only be distributing the product and may have had limited or no involvement in the actual development of the product. Our alliance data set was utilized in an effort to identify only marketing deals. The relevant therapeutic category for these sales was removed from the acquiring company's list if they had no other sales experience for products that they internally or co-developed within that therapeutic category. We were unable to identify any situations for which this would be necessary. As a result, we are confident in our original measure.

is also likely that these pre-acquisition information gathering activities lead to more successful post-acquisition integration as well.

Cockburn and Henderson (2001) in their study of drug development performance find a strong correlation between the scope of a firm's development efforts and the success probability of individual projects. Scope is defined by the number of therapeutic categories in which a particular company operated. Our *pipeline experience* and *sales experience* variables are not scope measures. Rather they are a measure of the complementarty between the acquiring and target firm's research and product portfolios. As such, firms undertaking these types of outsourcing of research and development acquisitions are choosing to deepen their existing capabilities versus broadening their overall research scope. The results for our *relatedness* variable support this claim. We find positive average cumulative abnormal returns of 3.51 percent for acquirers that operate within the same broad therapeutic category as the target firm, as opposed to average cumulative abnormal returns of 2.57 percent for those firms that do not. Interestingly, in addition to the scope findings, Cockburn and Henderson (2001) also found that past successes in a therapeutic category were also positively associated with successful outcomes of a project. These results were robust across all of their specifications. Our *sales experience* variable is a measure of exactly this. It measures whether a firm has sales of a patented product -- which serves an indicator that the firm as experience taking a product in that therapeutic category through the various research phases -- within the same therapeutic category as the research being acquired from the target firm. Their finding of a greater likelihood of development success could also provide an alternative explanation for the magnitude of the positive abnormal return on the *sales experience* variable.

5.3   Cross-sectional analysis of abnormal returns

5.3.1   Information-gathering activities

Firms that engage in one of the three pre-acquisition information-gathering activities – alliances, prior sales of patented products and research experience within the same therapeutic category as the target – generate positive abnormal returns for their shareholders. Additionally, each of these significantly impacts the overall magnitude of the *CAR*. We report our cross-

sectional regression estimates in Table 7. Table 7 presents results for six separate specifications that test a series of independent variables hypothesized to have an impact on the magnitude of the *CAR* while at the same time controlling for various attributes of the firm and acquisition deals. The dependent variable for these regressions is the acquirer three day *CAR* for each acquisition in our sample. We include three groups of independent variables in our analysis. The first three variables include our pre-acquisition information gathering activities – prior research and sales experience and alliance activity. Next we include our *Desperation Index* measure and a measure of R&D intensity, defined as research and development expenditures divided by sales. We also include an indicator of whether or not the firm had engaged in any acquisitions in the previous three years. We include two financing variables indicators for cash and equity deals. Three other variables control for various financial characteristics of the acquiring firm – a measure of free-cash flow, Tobin's Q, and the log value of the market capitalization of the acquiring firm. Finally, dummies are included if the acquiring firm was based outside of the United States and if there was a contingent contract present in the deal.

Across the first four specifications we find mixed support for the pipeline experience variable. The coefficient, across these various specifications, ranges between 0.0184 and 0.0249 and is significant only once at the 10 percent level. Prior pipeline research – firms with products identified in the NDA pipeline – within the same therapeutic category as target firm positively impacts the overall magnitude of the *CAR*. In this case, firms are positively rewarded for buying "what they know."

Having prior sales experience -- our proxy for FDA approved products -- within the same therapeutic category as the target firm also positively impacts the magnitude of the *CAR*. We find strong evidence for this result across all six model specifications. In addition, the coefficient remains fairly stable and is significant at the 1 percent level. In addition to having the research capabilities for a specific therapeutic category, having sales experience and as a result having a product approved by the FDA demonstrates that the particular acquiring pharmaceutical firm has experience in taking that specific category of product through the formal FDA approval process. Phase III testing (human clinical trials) and the FDA approval process are very expensive and time-consuming. Firms have a clear advantage in taking new products into this process for which they already hold some experience. Additionally, the introduction of a new product within an existing therapeutic category would require less time to train sales

professionals and generate a new market than would a new class of products. Again, these results imply that acquiring firm shareholders are being rewarded for staying within areas in which they are already experts.

Alliance experience with the target firm prior to an acquisition positively impacts the magnitude of our *CAR* values across all specifications considered. Results ranged from 0.0321 to 0.0396 and were significant at the 1 percent level. On average, there were four alliances between the firms prior to the acquisition. Presumably this prior contact should provide learning opportunities for the acquiring firm resulting in a more appropriate valuation being placed on the target firm. These positive impacts are consistent with Chan et al (1997) and Porrini (2004).

Next, we look at the impact that the level of desperation has on the *CAR*. We find, across five of the six model specifications, a negative impact on the overall magnitude of the *CAR*. Results are significant at the 5 percent level. More importantly, while the presence of firm level desperation negatively impacts the *magnitude* of the *CAR*, the overall *CAR* for these desperate firms remains positive. The overall average abnormal return for the entire sample is 3.91 percent. Performing a univariate analysis similar to those in Table 5, the average abnormal return for the most desperate firms was 1.73 percent, significant at the 10 percent level. This suggests that even the most desperate firms are still able to employ pre-acquisition information-gathering activities in order to generate positive value for their firm's shareholders. The lower abnormal returns for these firms may be attributable to such factors as a lower internal required rate of return for the acquiring firm in addition to the less favorable negotiating position vis-à-vis target firms.

Of the remaining independent variables, R&D intensity, stock deal, cash deal, free-cash flow, Tobin's Q, contingent contracts and an international indicator, none are significant at any reasonable level across six specifications. However, acquiring firms experienced a negative impact on their *CAR* if they engaged in an acquisition within the three years prior to the current acquisition. This result is negative and significant at the 5 percent level across all six specifications. This finding is in contrast to Fuller et al (2002). One reason for the difference may be that the market is penalizing companies that engage in either multiple acquisitions or a program of acquisitions in an effort to grow their R&D business. The market may perceive this type of firm as having a weak internal research and development program that is unable to develop new projects independently. Since new product development is the life-blood of any

pharmaceutical firm, companies that are unable to produce potential products internally may be at a competitive disadvantage. Another reason for the difference may be the selection of firms analyzed. Whereas this study focuses solely on the pharmaceutical sector, the same sector only totaled 1.3 percent of the total firms analyzed in their study.

In additional unreported regression specifications, the public status of the target firm had no significant statistical impact on the magnitude of the cumulative abnormal return. This finding, in contrast to the extant literature, suggests that a "private company discount" does not exist in the current study. One of the justifications for the "private company discount" is the difficulty in valuing a company. This lends support to our argument that acquiring firms are able to use pre-acquisition information gathering activities to lessen the uncertainty as to the underlying value of the target firm.

5.3.2   Sensitivity Analysis

Additional specifications were tested in order to ensure the robustness of our main findings to changes in definitions. Repeating our procedure we parse the *Desperation Index* into its two main components – the *Score* and sales-weighted exclusivity horizon. In the first series of regressions we tested the *levels* of these two variables in the year prior to the acquisition. *Score* – the weighted measure of the health of a firm's research pipeline – while positive was not significant in the additional specifications. This would seem to suggest that a firm's pipeline status in the year prior to an acquisition has little impact on the abnormal returns generated over the three day event window. We found previously, however, that *Score* played a significant role in the probability that firm actually engaged in an acquisition. In contrast, we found both positive and significant results for our sales-weighted exclusivity horizon. We removed the exclusivity weighting and tested real sales and found similar results. Finally, we removed the sales data completely and used just a straight measure of the number of exclusivity years remaining in a firm's portfolio. Again, we found positive and significant results. These findings are all consistent with our findings on *Desperation Index* in Table 7. The desperation level of a firm negatively impacts the magnitude of its *CAR*.

Given the potential pitfalls of using exclusivity as an adequate measure of the health of a firms patented product portfolio we employ additional measures. First, in an attempt to control

for some of the "gaming" that may take place in order to garner additional years of exclusivity, for example, by engaging in patent litigation, we add 30 months of exclusivity onto each product in their last year of exclusivity if the drug had at least $100 million in revenues.[34] Arguably a company would not engage in the expense of patent litigation if the marginal benefit of doing so was less than the marginal cost. We find across various specifications a positive and significant (at the 5 percent level of significance) impact on the magnitude of the *CAR*. Again, this finding is consistent with our reported *Desperation Index* findings in Table 7.

We next remove the exclusivity variable and replace it with our patent data variable constructed from NERAC and Thomson Derwent in order to test robustness of our results across differing legal protections. Our findings here are mixed. The coefficient remains positive – consistent with the exclusivity findings – however the variable is only significant at the 10 percent level in a limited number of specifications. This finding only suggests there is potentially a real difference between the impact a firm's patent profile and a firm's exclusivity profile has on the magnitude of the *CAR*. Since this variable serves as an upper-bound measure, it is possible that these results are a function of the way the variable is constructed.

5.4   *Cross-sectional analysis of post-acquisition success measures*

In addition to the abnormal returns result discussed earlier, we find positive changes to the acquiring firm's *Score* value and product sales figures in the year following the acquisition. The *Score* value for a firm is a weighted measure of the health of a firm's research pipeline. An increase in the *Score* value of a firm after an acquisition is suggestive of improvements to the underlying pipeline. We present the distribution of firms across the various levels of desperation, both pre- and post-acquisition in Table 8. As presented in Panel A of Table 8, 94 firms or 59 percent of the firms in our sample improved their level of desperation through the use of acquisitions. This means that in the year following an acquisition, acquiring firms moved from one of the four levels of desperation, previously defined, to a less desperate level. In other words, through the use of acquisitions, firms are able to increase either their score value or weighted sales or both. Another 19 firms or 12 percent of firms maintained their level of

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[34]   This process was repeated for drugs with $50 million and $75 million in revenues in the final year of exclusivity.

desperation. In total, 71 percent of firms either improved or maintained their level of desperation.

Panel B presents the average change in sales and score values for the distribution of desperation categories *post-acquisition.* This panel suggests that firms that were able to improve their level of desperation in categories I (least desperate) or II were most successful in adding to their underlying research score value. As discussed in Panel A, 67.50 percent of firms fell into one of these two categories post-acquisition.   The average change in *Score* value for a category I firm (least desperate) post acquisition is positive, while the average change in *Score* value for a category IV firm (most desperate) is negative. Moreover, the average change in sales for category I firms was positive, while the average change in sales for category IV firms was negative. The post-acquisition change in product sales needs to be viewed very cautiously. As most research is acquired while still in phase testing, the sales impact will not be felt until some time in the future. The more important result, we feel, is the post-acquisition change in the *Score* value since this is a direct measure of the health of a firm's research portfolio.

Pisano (1991) suggests that that acquisition of biotechnology firms can be a "dangerous strategy" particularly when acquisitions are used to overcome a weakness in internal capabilities. As we discuss next, we find consistent with Chesbrough (2003) that this is not always the case. Table 9 presents cross-sectional regression results for these post-acquisition measures. The change in *Score* value ($score_{t+1} - score_t$) and change in product sales ($sales_{t+1} - sales_t$), respectively, are used as dependent variables. For both regression models we present five separate specifications. As before, we include and test a variety of independent variables that we feel have an impact on the two dependent variables. We find in the first regression model (Δ *Score post-acquisition* is the dependent variable) that the coefficient on the variable *Desperation Index* is positive and significant at least at the 5 percent level. This result suggests that desperate firms are experiencing positive post-acquisition changes to their *Score* value through the use of acquisitions. As the *Score* value is a measure of pipeline health, these improvements justify the use of acquisition activity as a tool to help improve the research portfolio of the firm. For the next regression model (Δ *Sales post-acquisition* is the dependent variable) focuses on the post-acquisition changes in product sales. Again, these results need to be viewed with caution since many of the acquisitions contained products still in various stages of phase testing. As a result, the financial impacts of their presence may not be realized until some period in the future, likely

greater than one year after an acquisition. Some acquiring firms, however, did purchase either mature products along with research capabilities or products in late-stage or FDA approval process. Again, the coefficient on the variable *Desperation Index* is positive and significant. Desperate firms that included these types of products in their acquisition were able to positively impact their post-acquisition change in product sales. Interestingly, firms that acquired a sales force as part of the acquisition showed positive changes to their post-acquisition change in sales. This result implies that target firms that had a sales force present also had products generating some type of revenues. As such, it is not surprising that the acquiring firm experienced a positive change in post-acquisition sales.

6.0   Conclusion

The pharmaceutical industry is characterized by large amounts of research and development. It is also an industry dependent upon that research to be productive and generate revenues in order to finance future research. As such, the protection and health of a firm's research pipeline is of paramount importance. Managers are faced with several options on how to go about replenishing that research pipeline. In this paper, we have sought to understand how pharmaceutical companies have employed acquisitions in an effort to combat deteriorating research pipelines and declining patented product portfolios. For acquisitions characterized by information asymmetries, we find evidence consistent with the proposition that acquirers are able to avoid the winner's curse. Specifically, we find a positive and significant correlation between acquirer returns and pre-acquisition information-gathering activities. We also find, on average, that companies experiencing a deterioration of their research pipeline and product sales were more likely to engage in an acquisition. Moreover, these firms were either able to stabilize or to reverse the pipeline declines that they were experiencing.

We believe considerable opportunities exist for further empirical research into these issues. It would be of interest to see if these results generalize across other high-tech industries; for example, the software industry. In this project, we employed a broad view of firm level research activities being undertaken by pharmaceutical firms. Extensions of the current analysis such as tracking research further into the future post-acquisition should yield additional

important insights. Finally, exploring more fully how firms employ alliances to complement internal research programs should be a rewarding area for future research.

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Table 1

Definition and description of regression-model independent variables. Different dependent variables are utilized - cumulative abnormal returns (CAR$_j$) are used in *Table 7* and Δ Score and Δ Sales are used in additional cross section analyses presented in *Table 9*.

Variable	Definition/Description
Score	Weighted value (non-monetary) of company research pipeline
Δ score pre-acquisition	Pre-acquisition change in weighted value of research pipeline (score$_t$ – score$_{t-1}$)
Δ score post-acquisition	Post acquisition change in pipeline weighted value (score$_{t+1}$ – score$_t$)
Log Sales Level	Log value of real life-cycle-weighted pharmaceutical sales
Δ sales pre-acquisition	Pre-acquisition change in weighted sales (log sales level$_t$ – log sales level$_{t-1}$)
Δ sales post-acquisition	Post acquisition change in weighted sales (log sales level$_{t+1}$ – log sales level$_t$)
R&D Intensity	R&D expenses/sales (real 1999 dollars)
Pipeline Experience	Dummy = 1 if acquiring company has NDA pipeline research in the same therapeutic category as the target firm
Sales Experience	Dummy = 1 if acquiring company has patented pharmaceutical product sales in the same therapeutic category as the target firm
Alliance	Dummy = 1 if acquiring company has alliance with target firm *prior* to the acquisition
Royalty	Dummy = 1 if acquiring company was paying a royalty to the target firm prior to the acquisition
Early Stage Alliance	Dummy = 1 if acquiring company has early stage product alliance with target firm prior to acquisition
Desperation Index (pre-acquisition)	Dummy = 1 if acquiring company was assigned to desperation categories III or IV
Δ Desperation Index post-acquisition	Dummy = 1 if acquiring company improved level of desperation post acquisition
Prior Acquisition	Dummy = 1 if acquiring company has prior acquisition experience in the three years prior to the latest acquisition
Stock Deal	Dummy = 1 if acquisition was stock financed
Cash Deal	Dummy = 1 if acquisition was cash financed
Contingent Contract	Dummy = 1 if contingent contract was present
Related	Dummy = 1 if acquiring and target firms operate within the same therapeutic category(s)
Sales Force	Dummy = 1 if sales force personnel were part of acquisition
Free-cash flow	Free-cash flow
Tobin	Tobin Q
Log Market Cap	Log of market capitalization
International	Dummy = 1 if acquiring firm was an international firm

Table 2

Descriptive statistics for firms making 160 research and development related acquisitions in the 1994-2001 period; these variables are used in (1) probit results analyzing the characteristics that impact the probability a firm engages in an acquisition, *Table 4*; (2) analysis of the event study results, *Table 5*; (3) cross-section results utilizing the cumulative abnormal return as the dependent variable, *Table 7*; and, (4) cross-section results utilizing two separate measures of success as the dependent variable, *Table 9*.

Variable	Mean	Standard Deviation	Minimum Value	Maximum Value
Free-cash flow	438.03	943.77	-250.87	4669.00
Tobin Q	3.69	3.53	-0.96	32.25
Log Market Cap	7.26	2.42	2.15	12.58
Score (in year of acquisition)	4.49	8.66	0	51.54
Δ score pre-acquisition	1.39	5.06	-9.95	28.15
Δ score post-acquisition	0.51	191.4	-10.6	114.4
Log Sales Level	3.51	5.67	0	15.58
Change Sales Level	0.30	1.72	-9.71	12.15
R&D Intensity	3.06	26.05	0	324.98
Pipeline Experience	0.36	0.48	0	1
Sales Experience	0.23	0.42	0	1
Alliance	0.67	0.29	0	1
Royalty	0.03	0.17	0	1
Desperation Index	0.60	0.26	0	1
Prior Acquisition	0.28	0.45	0	1
Stock Deal	0.36	0.48	0	1
Cash Deal	0.18	0.39	0	1
Contingent Contract	0.21	0.41	0	1
Related	0.81	0.39	0	1
Sales Force	0.13	0.34	0	1
International	0.24	0.43	0	1

Table 3

Correlation matrix for relevant variables utilized in the following analyses: (1) probit estimation (*Table 4*); (2) cumulative abnormal return cross-sectional regressions (*Table 7*); and, (3) post-acquisition cross-sectional regressions (*Table 9*). The numbers listed horizontally across the top row correspond to the numbers and variables listed vertically on the table. See *Table 1* for variable definitions.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1.	Pipeline Experience	1.0000														
2.	Sales Experience	0.1292	1.0000													
3.	Royalty	-0.0669	-0.0260	1.0000												
4.	Early Stage Alliance	-0.0474	0.0306	-0.0007	1.0000											
5.	Equity Stake	0.0428	0.1841	0.1921	0.2491	1.0000										
6.	Desperation Index	0.1373	0.3467	0.0264	0.1888	0.1258	1.0000									
7.	R&D Intensity	-0.0494	-0.0641	-0.0010	-0.0580	-0.0109	-0.0512	1.0000								
8.	Prior Acquisition	0.1238	0.2685	-0.0484	0.0824	0.0292	0.2744	-0.0797	1.0000							
9.	Stock Deal	0.0861	0.0254	0.0017	0.1438	0.1692	0.0284	-0.0821	-0.0446	1.0000						
10.	Cash Deal	-0.0318	0.1644	0.1162	-0.0871	-0.0896	0.0199	-0.0517	0.0574	-0.3697	1.0000					
11.	Free Cash Flow	0.1975	0.1786	0.0217	0.0689	-0.0064	0.2630	-0.0632	0.2848	-0.0440	0.0527	1.0000				
12.	Tobin's Q	-0.0077	-0.0661	-0.0663	-0.0511	-0.0575	0.0763	-0.0224	0.0103	-0.1106	-0.0490	0.1642	1.0000			
13.	Log Market Cap	0.0637	0.2251	-0.0730	0.1195	0.0531	0.4156	-0.1420	0.3667	-0.0447	0.1032	0.5913	0.1421	1.0000		
14.	Contingent Contract	0.1865	-0.1283	-0.0139	-0.0616	0.1009	-0.1353	0.1784	-0.0415	0.0468	-0.0237	-0.1558	-0.1099	-0.2093	1.0000	
15.	International	-0.0318	0.2948	-0.0882	0.0079	0.0369	0.2325	-0.0563	0.1802	-0.0582	0.0431	-0.0024	-0.0058	0.2003	-0.2046	1.0000

Table 4

Probit estimates for our data regress an acquisition indicator (= 1 if an acquisition took place) on a series of independent variables expected to impact a firm's probability of engaging in an acquisition. The period for this analysis runs from 1994-2001. The universe of firms for this analysis includes all firms contained in the Recombinant Capital alliance data set that have pipeline and patented product information available. *Count* is defined as the total number of alliances that the acquiring firm is engaged in on a year-by-year basis. Desperation Index categories III and IV are the most severe levels of firm desperation. The variable *Desperation Index* is an aggregated indicator variable that assumes a value of one if the acquirer is in Categories III or IV and is zero otherwise. Φ is the standard cumulative normal distribution. See *Table 1* for all other variable definitions. Firm and time effects were included. We use White's (1980) heteroscedasticity-consistent standard errors to compute the appropriate test statistics included in parentheses below the coefficient estimates. We test the following model:

$$P(y_{i,t} \neq 0 | x_{i,t}) = \Phi(x^1_{i,t} + x^2_{i,t} + x^3_{i,t} + x^4_{i,t} + x^5_{i,t} + x^6_{i,t} + x^7_{i,t} + x^8_{i,t} + x^9_{i,t} + FE + c)$$

$$\partial\Phi/\partial x_i = \phi(\mathbf{xb})b_i$$

Dependent variable: *Acquisition Indicator*

Independent Variable	Model 1	$\partial\Phi/\partial x$	Model 2	$\partial\Phi/\partial x$	Model 3	$\partial\Phi/\partial x$	Model 4	$\partial\Phi/\partial x$
x^1: Change Score (Pre-Acquisition)	-0.0545 (1.91)*	-0.0111						
x^2: R&D Intensity	0.0016 (1.84)*	0.0003	0.0014 (1.98)**	0.0003	0.0016 (2.34)**	0.0003	0.0012 (1.89)*	0.0002
x^3: Log Market Cap	-0.0457 (1.09)		-0.0965 (2.77)***	-0.0214	-0.0881 (2.83)***	-0.0196	-0.0894 (2.62)***	-0.0201
x^4: Count	0.0086 (0.80)		0.0033 (0.37)				0.0019 (0.22)	
x^5: Desperation Index – Category I								
x^6: Desperation Index – Category II			-0.4640 (1.44)		-0.4497 (1.39)			
x^7: Desperation Index – Category III			0.4416 (2.14)**	0.1141	0.4537 (2.24)**	0.1177		
x^8: Desperation Index – Category IV			0.5668 (1.83)*	0.1601	0.5776 (1.86)*	0.1638		
x^9: Desperation Index							0.5314 (2.96)***	0.1386
c : Constant	-0.8285 (2.02)**		-0.3479 (1.08)		-0.3874 (1.21)		-0.3867 (1.21)	
Fixed Effects:	Yes		Yes		Yes		Yes	
N	424		424		424		424	
Pseudo R^2	0.04		0.04		0.05		0.05	
Log likelihood	-122.96		-172.09		-172.17		-173.23	

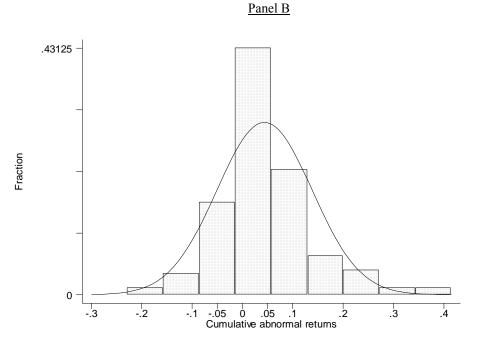|	
***	significant at the 1% level
**	significant at the 5% level
*	significant at the 10% level

Table 5

Event study estimates evaluating the cumulative abnormal return versus the presence of various independent variables. Type I transactions involve the acquisition of biotechnology R&D; Type II transactions involve the acquisition of general R&D; and, Type III transactions involve the acquisition of a mature product along with R&D. *t*-statistics are reported in parentheses. The second column reports the *t-statistic* that tests whether each of the sub-categories (for the overall sample) are statistically different from each other (difference of the means). See *Table 1* for definitions of variables. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

	Overall	*t-test*	Type I	Type II	Type III
Acquirer CAR	3.91 percent (4.95)*** N=160		2.81 percent (2.61)*** N=91	4.29 percent (2.41)** N=27	5.29 percent (3.27)*** N=42
Relatedness	3.51 percent (4.24)*** N=130		2.49 percent (2.25)** N=68	4.00 percent (2.01)** N=24	4.32 percent (2.88)*** N=36
Financing		2.19**			
Stock Payment	3.87 percent (2.92)*** N=58		3.22 percent (2.13)** N=35	3.36 percent (0.68) N=8	3.71 percent (1.67)*** N=14
Cash Payment	2.38 percent (2.47)** N=29		2.35 percent (1.36) N=13	2.24 percent (1.71)* N=7	4.08 percent (1.47) N=9
Alliances		2.58***			
Prior Alliances	4.30 percent (4.14)*** N=94		4.58 percent (3.25)*** N=54	2.11 percent (1.39) N=18	4.22 percent (1.82) N=21
No Prior Alliances	3.36 percent (2.73)*** N=66		0.17 percent (0.13) N=35	8.65 percent (2.07)** N=9	6.37 percent (2.77)*** N=21
Sales Experience		2.12**			
Prior Sales	6.99 percent (3.29)*** N=128		4.28 percent (2.19)** N=75	4.50 percent (1.49) N=17	10.56 percent (1.91)* N=31
No Prior Sales	3.08 percent (4.85)*** N=34		2.58 percent (2.46)** N=14	4.17 percent (4.36)*** N=10	3.43 percent (3.32)*** N=11
Research Experience		2.10***			
Prior Experience	5.08 percent (3.71)*** N=103		2.40 percent (2.46)** N=61	9.08 percent (4.36)*** N=15	12.35 percent (3.32)*** N=25
No Prior Experience	3.24 percent (4.52)*** N=57		3.03 percent (2.19)** N=28	6.95 percent (1.49) N=12	0.50 percent (1.91)*** N=17

Table 6

The dispersion of cumulative abnormal returns *(CARs)* are presented. Following Dodd & Warner (1983), standardized abnormal returns *(SARs)* are computed by dividing the abnormal return (AR) by its standard deviation. These standardized abnormal returns *(SARs)* are then aggregated over the number of the days in the event window, *k* to generate a cumulative abnormal return *(CAR)*. Panel A provides a simple count of the number of *CARs*. Panel A provides for a simple count of the number of *CARs* that are located in various intervals. Panel B presents the same information in a bar graph with a standard normal distribution overlapping the presented data.

Magnitude	Number of observed abnormal returns
$CAR \leq -15.0\%$	4
$-15.0\% < CAR < -10.0\%$	3
$-10.0\% \leq CAR < -5.0\%$	12
$-5.0\% \leq CAR < 0.0\%$	41
$0.0\% \leq CAR < 5.0\%$	38
$5.0\% \leq CAR < 10.0\%$	29
$10.0\% \leq CAR < 15.0\%$	17
$15.0\% \leq CAR$	16
	160

Panel B

43

Table 7

Cross-sectional regression estimates and independent variables from regressing the cumulative abnormal return (CAR) on selected independent variables for 160 announcements of acquisitions relating to the outsourcing of research and development. CARs are from the three day event window. The period for this analysis runs from 1994-2001. Year fixed effects are included in all specifications. White's (1980) heteroskedasticity-consistent *t*-statistics are reported in parentheses. See *Table 1* for variable definitions.

Dependent variable: Acquirer *CAR*

Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Pipeline Experience	0.0249	0.0227	0.0184	0.0211		
	(1.73)*	(1.11)	(1.24)	(1.14)		
Sales Experience	0.0565	0.0527	0.0544	0.0529	0.0557	0.0408
	(3.01)***	(2.89)***	(3.12)***	(2.93)***	(3.12)***	(2.65)***
Alliance	0.0348	0.0374	0.0396	0.0347	0.0321	0.0355
	(3.21)***	(3.28)***	(3.11)***	(3.59)***	(2.99)***	(2.67)***
Desperation Index	-0.0442	-0.0428	-0.0436	-0.0406	-0.0362	
	(2.41)**	(2.34)**	(2.42)**	(2.24)**	(2.26)**	
R&D Intensity	0.0003		0.0004			
	(0.91)		(0.95)			
Prior Acquisition	-0.0211	-0.0204	-0.0185	-0.0204	-0.0174	-0.0219
	(2.34)**	(2.31)**	(2.17)**	(2.31)**	(2.12)**	(2.41)**
Stock Deal	-0.0117	-0.0069				
	(0.65)	(0.42)				
Cash Deal	-0.0202					
	(0.99)					
Free-cash flow	-0.0005	-0.0041		-0.0040		
	(0.41)	(0.39)		(0.45)		
Tobin	0.0003	0.0002		0.0002		-0.0002
	(1.14)	(0.11)		(0.11)		(0.11)
Log Market Cap	-0.0024	-0.0031	-0.0035	-0.0028	-0.0041	-0.0057
	(0.45)	(0.62)	(0.98)	(0.56)	(1.22)	(1.73)*
Contingent Contract	0.0036					
	(0.16)					
International	0.0108	0.0085	0.0159			
	(0.66)	(0.54)	(0.75)			
Constant	0.0576	0.0591	0.0528	0.0535	0.0711	0.0816
	(1.39)	(1.58)	(1.77)*	(1.38)	(2.43)**	(2.86)***
N	155	155	160	155	160	155
R²	0.26	0.25	0.22	0.24	0.22	0.22
F-Statistic	2.78	2.64	2.91	2.87	3.12	2.58

***	significant at the 1% level
**	significant at the 5% level
*	significant at the 10% level

Table 8

Panel A: Distribution of acquiring firms across desperation categories

Changes in desperation index prior to and post acquisition. Classifications are as follows: Class 1 indicates firms with increasing or constant score values and increasing weighted-sales; class 2 indicates firms with increasing or constant score values and decreasing weighted-sales; class 3 indicates firms with decreasing score values and increasing or constant weighted-sales; and, class 4 indicates firms with decreasing score values and decreasing weighted-sales. Class 1 firms are "less desperate" than those firms in class 4.

Improvement in level of desperation	Number of firms
Improved level of desperation	94 (59%)
Level of desperation remained constant	19 (12%)
	141 (71%)
Worsened level of desperation	47 (29%)

Pre-Acquisition Distribution of Firms Across Desperation Categories

Category	Frequency	Percent
Category 1 (least desperate)	17	10.63%
Category 2	47	29.38%
Category 3	24	15.00%
Category 4 (most desperate)	72	45.00%

Post-Acquisition Distribution of Firms Across Desperation Categories

Category	Frequency	Percent
Class 1 (least desperate)	36	22.50%
Category 2	72	45.00%
Category 3	33	20.63%
Category 4 (most desperate)	19	11.88%

Panel B: Distribution of acquiring firms across various post-acquisition measures

Changes in sales and NDA pipeline score values in the calendar year following the acquisition. The NDA score value is a proxy for the overall health of a firm's research pipeline. An increase in score value would signal that the firm's pipeline has strengthened. Δ Score is defined as $score_{t+1} - score_t$. Δ Sales is defined as $sales_{t+1} - sales_t$. Classifications are as follows: Class 1 indicates firms with increasing or constant score values and increasing weighted-sales; class 2 indicates firms with increasing or constant score values and decreasing weighted-sales; class 3 indicates firms with decreasing score values and increasing or constant weighted-sales; and, class 4 indicates firms with decreasing score values and decreasing weighted-sales. Weighted sales values are log values of 1999 constant dollars.

Variable	Class	Number of firms	Mean	S.D.	Min.	Max.
Δ Score	1	36	116.91	167.14	0	636.2
Δ Score	2	72	40.83	142.34	0	1143.8
Δ Score	3	33	-173.10	228.06	-1059.6	-3
Δ Score	4	19	-71.34	66.07	-273.6	-3
Δ Sales	1	36	1.0966	2.4109	0.2436	10.82
Δ Sales	2	72	-0.2784	1.4465	-9.7067	-0.0067
Δ Sales	3	33	0.4872	1.5877	0	6.5853
Δ Sales	4	19	-0.8373	3.2896	-14.345	-1.5194

Table 9

Cross-sectional regression estimates and independent variables from two separate regressions are reported. First, Δ Score, defined as score$_{t+1}$ − score$_t$, is regressed on a series of independent variables thought to have an impact on the firm's underlying research portfolio. Second, Δ Sales, defined as sales$_{t+1}$ − sales$_t$, is regressed on a series of independent variables thought to have an impact on the firm's underlying weighted-sales. The period for this analysis runs from 1994-2001. White's (1980) heteroskedasticity-consistent *t*-statistics are reported in parentheses. See *Table 1* for variable definitions. *** 1% level of significance; ** 5% level of significance; and, * 10% level of significance.

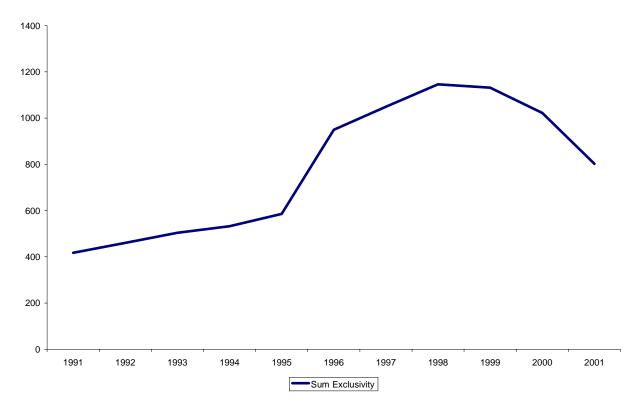| Dependent Variable	Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Δ Score post-acquisition	R&D Intensity	-0.0357 (0.35)	-0.1566 (1.63)	-0.1910 (2.02)**	-0.2131 (2.38)**	-0.0041 (0.40)
	Pipeline Experience	40.883 (1.41)	32.041 (1.09)	38.200 (1.23)		
	Sales Experience	57.169 (1.14)	73.316 (1.44)			
	Desperation Index	68.592 (2.10)**	58.326 (1.80)***	64.637 (1.94)***	64.857 (1.94)***	77.116 (2.42)**
	Free-cash flow	-0.0641 (1.65)***	-0.0373 (1.10)	-0.0301 (0.84)	-0.0262 (0.71)	-0.0574 (1.40)
	Tobin	-2.476 (0.73)		-2.104 (0.83)	-2.339 (0.98)	
	Log Market Cap	19.784 (2.46)**				20.356 (2.51)**
	Constant	-176.25 (3.14)***	-46.119 (1.70)*	-30.651 (0.96)	-18.081 (0.64)	-169.80 (3.06)*
	N	155	155	155	155	155
	R^2	0.12	0.08	0.06	0.05	0.09
	F-Statistic	13.41	17.76	16.10	20.37	23.02
Δ Sales post-acquisition	R&D Intensity	0.0011 (1.08)				
	Pipeline Experience	0.7572 (2.18)**	0.7596 (2.19)**	0.7257 (2.10)**	0.5264 (1.32)	0.5098 (1.32)
	Sales Experience	-0.2547 (0.57)	-0.2303 (0.52)			
	Desperation Index	0.6012 (1.67)*	0.6143 (1.71)*	0.5713 (1.78)*	0.5742 (1.73)*	0.5841 (1.80)*
	Free-cash flow	-0.0059 (1.43)	-0.0006 (1.51)	-0.0005 (1.59)		
	Tobin	-0.0322 (0.72)			-0.0435 (1.06)	
	Log Market Cap	-0.0456 (1.32)	-0.0397 (0.35)		-0.1003 (1.32)	-0.1041 (1.42)
	Sales Force	1.4304 (2.11)**	1.3800 (2.11)**	1.3027 (2.13)**	1.4068 (2.10)**	1.3618 (2.09)**
	Constant	-0.5992 (1.24)	-0.6622 (1.41)	-0.3994 (1.36)	-0.3017 (0.60)	-0.1675 (0.36)
	N	155	155	155	155	160
	R^2	0.15	0.15	0.15	0.11	0.10
	F-Statistic	1.74	1.86	2.31	1.65	2.04

Table 1: Sum of Exlcusivity Exclusivity Protection

Table 2: Industry Pipeline Breakdown 1993-2001